ORIGINAL PAPER

Evaluation of reanalysis-based, satellite-based, and "bias-correction"-based datasets for capturing extreme precipitation in Iran

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Abstract

This study compares seven global gridded daily precipitation datasets against gauged precipitation to evaluate their accuracy for capturing extreme precipitation in Iran. We evaluated the performance of satellite-based (CHIRPS and MSWEP-V220), reanalysis-based (CFSR and MERRA-2), ensemble-based (MRE3ensemble), and "bias-correction"-based (MRE3ensemble, EWEMBI, and W5E5) precipitation datasets for the period of 1980–2016. The extreme precipitation indices that we examined consist of intensity indices [the maximum consecutive 1-day precipitation (Rx1day) and simple precipitation intensity (SDII)], duration indices [the consecutive dry days (CDD) and the consecutive wet days (CWD)], and frequency indices [heavy precipitation events (R10mm) and very heavy precipitation events (R20mm)]. The results showed that MSWEP-V220 had the best performance in Iran and Bias-Correction W5E5 was the second-best dataset to estimate precipitation in Iran. Although RMSE and MBE statistics showed high error and bias for all precipitation datasets in northern Iran, the evaluation of the PBIAS showed the share of bias value in the northern regions of Iran compared to the total precipitation in the climate zone of Iran is less than 5%. In contrast, most datasets showed a high percentage of bias in the eastern and interior regions of Iran. The results showed that all the studied datasets in the rainy areas of Iran (Cfa, Csa, and Dsa) underestimate maximum one-day precipitation (Rx1day), precipitation intensity (SDII), and heavy and very heavy precipitation (precipitation > 10 and 20 mm). In addition, MERRA-2 and CFSR overestimate the indices related to intensity and frequency in the most desert (BW) and semi-desert (BS) climates of Iran, respectively. CHIRPS data in all climate zones of Iran—except the CWD index in Cfa climate zone – overestimate the CDD index and underestimated the CWD. Accordingly, CHIRPS data show a drier climate for Iran unrealistically.

1 Introduction

Precipitation plays a vital role in issues related to hydrology (Poonia et al. 2021), meteorology, climatology, and climate change (Trenberth 2011). In addition, an essential part of water balance and the energy cycle is related to precipitation changes (Wang et al. 2020). Precipitation directly affects runoff generation and soil moisture (Sofia et al. 2019). Hence, careful study of precipitation, especially extreme precipitation, is essential in water resource management such as flood forecasting and drought monitoring (Funk et al.

2014), environment (Su et al. 2007), and scientific and social applications (Funk et al. 2015). However, precipitation estimating is very challenging in a country like Iran, with a complex topography and high climate diversity. Changes in extreme precipitation are generally heterogeneous compared to extremes temperature both spatially and temporally. The Fifth Assessment Report of the IPCC (AR5) expressed that probably, the frequency of extreme precipitation events in many parts of the globe has statistically increased since 1951 (IPCC 2014). However, some areas also showed a decrease (Stocker 2014), and global observations generally showed an increase in the frequency and intensity of wet extremes over the past century (Donat et al., 2016).

Climate extremes often occur on relatively short time scales, and it is important that the daily data used to study climate extremes be able to reflect this time scale (Donat et al. 2020). Temperature waves (hot or cold) usually last for days or weeks. In contrast, heavy precipitation occurs

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at intervals of several days, daily, or even relatively less than one day. Therefore, to adequately describe this type of extreme with high temporal and spatial variability, data with relatively high temporal and spatial resolution are required. So, we need long-term reliable data (at least five to six consecutive decades) to study long-term changes.

The availability of daily data with a suitable temporal and spatial scale is critical for examining climate extremes. Although a large number of datasets relating to the last century are available (Schneider et al. 2018), the accessibility of daily data is limited globally, resulting in a limitation for studying extremes. Generally, three gridded climate datasets can be used for studying precipitation extremes: (1) Observational data, (2) Reanalysis data, and (3) Satellite data.

Observational data are the most reliable data for studying global climate variables. However, this dataset remains sparse and problematic for many regions in developing countries, such as most parts of Iran, resulting in a lower ability to establish changes both in terms of spatial and temporal scales. Reanalysis datasets are generated by combining specific types of observational data in atmospheric numerical models (Dee et al. 2011) and provide variables on a regular grid within continuous spatial and temporal coverage over the entire globe. Therefore, they have become a popular dataset for studying climate variables. However, we must be careful in using this data due to three reasons: (1) Lack of homogeneity of observational data that is used as input to this dataset; (2) Imperfections in data assimilation schemes and (3) Model uncertainty (Thorne and Vose 2010). From this perspective, removing the bias of this dataset is an excellent approach to using this data.

The availability of daily precipitation based on satellite data is a significant turning point in climate studies. Extracting data from satellites is one of the most reliable methods for studying climate variables despite the limitations of the period and the algorithm used in satellite sensors. This dataset has been available since the 1960s when the first meteorological satellite (TIROS-1) was launched; however, daily data with the appropriate horizontal resolution has not been accessible before the 1980s. Today, an extensive range of satellite products such as CHIRPS v2.0 (Funk et al. 2015), PERSIANN-CDR (Ashouri et al. 2015), 3B42 RT v7.0 (Huffman et al. 2007), CMORPH V1.0 (Xie et al. 2017) and most recently MSWEP_V220 (Beck et al. 2019a, b) are available to use.

On a regional scale, many studies have used gridded precipitation datasets to estimate precipitation extreme indices to assess the fitness of various methods and innovations of the gridded dataset (Ou et al. 2013; Rhodes et al. 2015; Li et al. 2018; Alexander et al. 2020). However, many studies conducted in Iran (Rahimzadeh et al. 2009; Soltani et al. 2016; Ghiami-Shamami et al. 2019; Rahimi and Fatemi 2019; Fathian et al. 2020) used only limited existing station datasets to study extreme precipitation and the reanalysis, ensemble, and satellite dataset was not used in most of these studies. However, these datasets have good validity at some regional levels (Beck et al. 2017; 2019a, b). Few studies (Katiraie-Boroujerdy et al. 2017; Pour et al. 2020) that examined precipitation extremes with gridded data over Iran stated that they are reliable. None of these studies have used more than one gridded dataset and compared available datasets in terms of accuracy.

Monitoring and forecasting precipitation extreme indices have been used in various studies. Considering the extreme indices have consistently been the subject of climate change studies in different parts of the world. In the meantime, most of these studies have been performed using observation or reanalysis data purely. Locations examined in these studies include a basin (Su et al. 2006; Zandonadi et al. 2016; Chen et al. 2021), geographical area (Rahimzadeh et al. 2009; Molanejad et al. 2014; Iqbal et al. 2019) or world (Alexander et al. 2006). Few studies at the level of a geographical area also examined the output of ensemble data (Soares et al. 2012) to study precipitation extremes. The number of studies that have used multiple datasets to study precipitation extremes has grown significantly in recent years (Donat et al. 2016; Herold et al. 2017; Gupta et al. 2020; Zhao et al. 2020). An essential advantage of this type of study over similar studies using an individual dataset is the non-dependence of the results on a specific dataset and the careful examination of their uncertainty despite this important feature, this type of study has not been done in Iran so far.

The primary purpose of this study is to compare Iran's precipitation extreme indices with multiple gridded datasets with high horizontal resolution. In addition, another primary purpose of this study is to investigate the intensity, duration, and frequency of extreme precipitation in different climate zones of Iran. Due to the lack of observational data on the one hand and the insufficient length of data, on the other hand, we have to use gridded data. Since the performance of the different datasets is not similar and relying on an individual dataset is associated with high uncertainty, we have compared the performance of seven global gridded datasets in terms of capturing extreme precipitation over Iran.

This study is done to achieve the following goals: (1) To evaluate routinely used reanalysis and satellite gridded datasets in Iran (2) Highlighting the fundamental differences in gridded datasets to capture extreme precipitation, (3) Reviling value of integration of different precipitation data, and (4) Estimating extensive precipitation in mountainous areas and especially Caspian coasts of Iran where the observation data scare. The results of this study may have essential achievements for data assimilation, water resources management, and the identification of critical areas of heavy precipitation.

2 Material and methods

2.1 Study area

Iran is located in southwest Asia in a region called the Middle East. It is a vast plateau bounded on the south by the Persian Gulf and the Sea of Oman and on the north by the Caspian Sea, the Central Asian steppes, and the Caucasus Mountains (Fig. 1). Westerly winds in the cold period (Razei et al. 2013; Mofidi et al. 2015) of the year and subtropical high pressure in the warm period (Zarrin et al. 2010) mainly control the country's climate. At the same time, it is extended along the latitude; the relatively complex topography and the proximity to the seas have created a very diverse climate for this country and high temporal and spatial variability are its predominant features. Since the purpose of this study is to investigate different gridded

daily precipitation datasets for the study of extreme precipitation indices in Iran, we have classified the country into climate zones to analyze better the performance of each of the selected datasets whose full description is given in Table (1). Köppen–Geiger climate classification method used for climate zoning. Iran has 13 climate zones (out of 31 Köppen–Geiger climate classification), so it is a country with a diverse climate. Considering the four conditions examined in the next section, 49 stations were selected to study Iran's observational extremes and verify the dataset. Of all selected stations, 6.12% are in the Bsh zone, 24.48% are in BSk zone, 30.61% are in BWh zone, 16.32% are in BWk zone, 2.04% are in Cfa zone, 10.20% are in Csa zone and 10.21% is in the Dsa zone. A large number of stations in the hot and cold desert and semi-desert areas in the Köppen–Geiger classification is due to the prevailing climate of Iran, which is desert (BW) and semi-desert (BS).
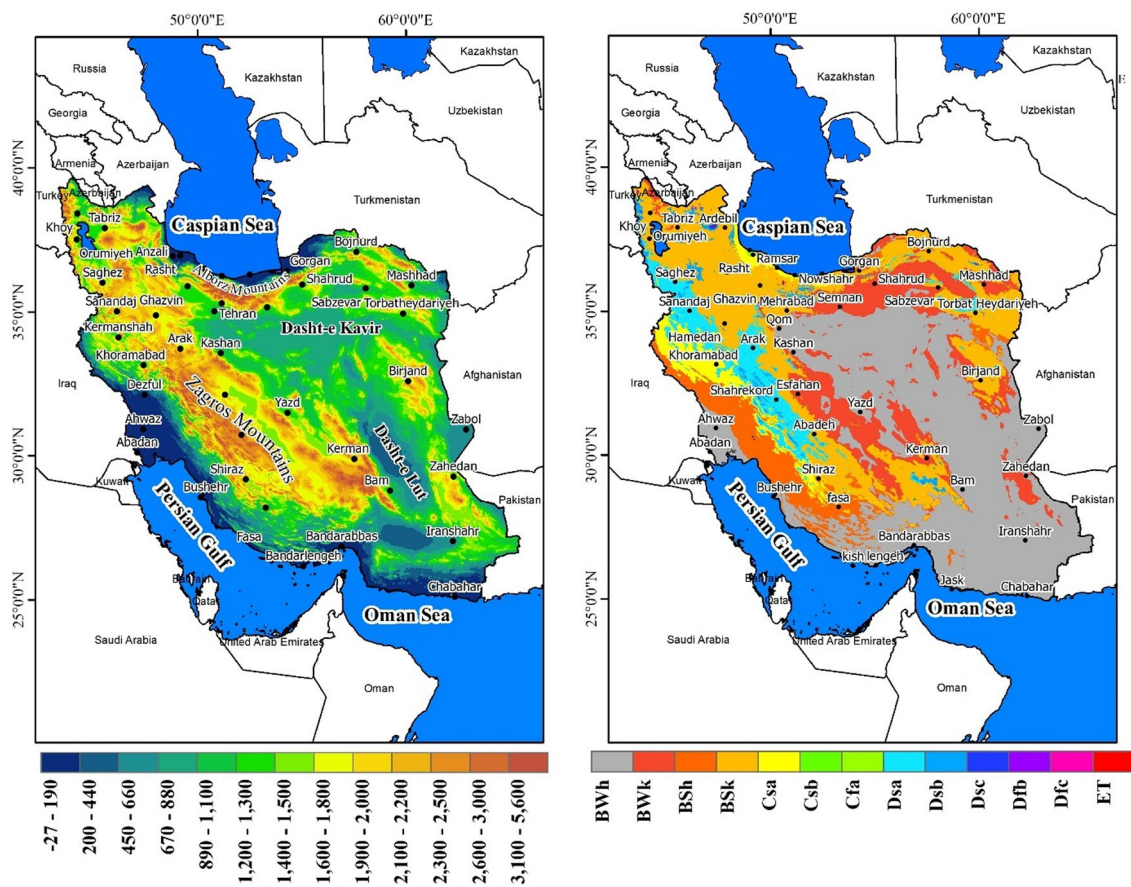

Fig. 1 Spatial distribution of Synoptic stations over Iran, with Digital Elevation Model (DEM), derived from the SRTM elevation data (~1 km²) and 1-km resolution Köppen-Geiger climate classification maps (Fick and Hijmans 2017). These Synoptic stations provided consistent observations from 1980 to 2016

2.2 Data used in the study

2.2.1 Observational data

In Iran, there are 53 synoptic stations with 40 years records that are of high study value for the study of extremes. However, there is still no data for many parts of Iran, so the use of gridded data is required. To select the stations four main conditions were considered: (1) The period of the observation data should be the same as the data of the selected global daily gridded precipitation datasets (as shown in Table 1, only the CHIRPS data started in 1981), so stations selected that have had data in Iran since 1980, and 53 stations selected based on the first condition. (2) The maximum missing data from the entire time series of stations should not be 10% (Zolina et al. 2005); accordingly 4 out of 53 stations omitted. (3) Data with more than three standard deviations from daily values and repeated data relating to more than ten days with non-zero values were then examined (Alexander et al. 2006), and none of the 49 stations has these two problems. (4) The uniformity of data was examined by the Standard Normal Homogeneity Test (SNHT) (Alexandersson 1986), and their accuracy was confirmed at the level of 0.05.

2.2.2 Global daily gridded precipitation datasets

New precipitation datasets are released regularly following innovations in weather forecasting models, satellite recovery methods, and multi-source integration techniques. There are more than 400 synoptic stations in Iran and 13% of these stations (53 stations) have data for forty years (beginning in 1981), and only 16 stations have data for seventy years (beginning in 1951). On the other hand, there is no station in the interior desert areas and the highlands (the highest station in Iran located at an altitude of 2985 m) of Iran. Therefore, using only the station data will not provide a good understanding of Iran's climate. However, as the observational data is limited by the arid environment and complex topography, sufficient and reliable information about precipitation in Iran has not been available so far. To improve the accuracy of estimation precipitation, this study examined various precipitation datasets, including satellite, reanalysis, and bias-correction data for 1980–2016 (Table 1).

2.3 Assessment metrics to quantify the evaluation of the multi precipitation datasets

Statistical measures of Root Mean Square Error (RMSE), correlation, bias, and variability hybrid performance measures, the Kling—Gupta efficiency (KGE) (Knoben et al.

2019; Gupta et al. 2009; Kling et al. 2012), mean bias error (MBE), and percentage of bias (PBIAS) used to evaluate the performance and amount of bias of precipitation dataset (Table 2).

Where, S_i is the estimated value of the variable in O_i is the observational value of the variable, n is the number of points with the observational variable (Knoben et al. 2019). σ is the standard deviation, and μ is the mean. Moreover, r is the linear correlation between the observed and simulated data.

2.4 Selected precipitation extremes indices

In this study, six extreme precipitation indices of an Expert Team on Climate Change Detection and Indices (ETCCDI) (Alexander et al. 2006) were used to examine the aspects of Duration, Frequency, and intensity of the precipitation. These indices are computed from the total amount of daily precipitation. Table 3 shows an overview of the indicators discussed in this study.

3 Results and discussion

3.1 Evaluation of selected dataset

Figure 2 shows the spatial distribution of seven selected precipitation datasets in Iran with four validation methods, and Table 2 shows the changes in these statistics in different climate zones. The maximum value of RMSE is for the CHIRPS and CFSR, respectively. These datasets showed an RMSE above 100 mm (Cfa, and Csa climate zones). This value is 103 mm for the CHIRPS and 101.261 mm for the CFSR. The lowest value of RMSE was calculated with 64.37 mm for EWEMBI. For all datasets, the maximum MBE values are the same as RMSE, and the bias value increases from south to north of Iran. All datasets underestimate precipitation in southern Alborz (diverse climate zones of BSK, BWk, and Dsa) and Zagros (climate zone of Dsa). The CFSR has shown the highest bias range, so this dataset is not reliable in Iran. The RMSE and MBE statistics of all precipitation datasets show a significant error in the northern regions of Iran (Cfa and Csa climate zones). However, a different result was obtained by PBIAS and KGE metrics which are more efficient in estimating precipitation bias. The reason is the different calculation methods of RMSE and MBE statistics. Since the values of RMSE and MBE statistics are a function of precipitation range, large amounts of RMSE and MBE in the Caspian Sea region (Cfa and Csa: Bandar Anzali, Babolsar, Gorgan, Ramsar, and Rasht stations) seen due to heavy precipitation. Therefore, the use of only two statistics of MBE and RMSE does not represent good results.

Table 1 Overview of the seven global daily gridded precipitation datasets evaluated in this study

Name	Details	Spatial resolution	Type	Temporal coverage	References
MRE3ensemble	Data sources: 1980–2015: CFSR, ECMWF Reanalysis v5 (ERA5), ERA-Interim, The Japan Meteorological Agency (JMA) JRA-55-mdl-iso, MERRA, MERRA2: 2016–2018: CFSR, ERA5, ERA-Interim, JRA-55-mdl-iso, MERRA-2	0.62°×0.74°	Ensemble Gauge, Satellite, Reanalysis	1980–2018	NASA-NCCS web page, 2020
MERRA-2	The Modern-Era Retrospective analysis for Research and Applications, version 2 (MERRA-2)	0.5°×0.62°	Gauge, Satellite, Reanalysis	1980–present	Gelaro et al. 2017
CFSR	Climate Forecast System Reanalysis (CFSR)	0.5°×0.5°	Reanalysis	1980–present	Saha et al. 2010
CHIRPS V2.0	Climate Hazards Group InfraRed Precipitation (CHIRP) V2.0	0.05°×0.05°	Gauge, Satellite, Reanalysis, and Analysis	1981–present	Funk et al. 2015
MSWEP_V220	Multi-Source Weighted-Ensemble Precipitation (MSWEP) Data sources: WorldClim, Global Historical Climatology Network-Daily (GHCN-D), Global Summary of the Day (GSOD), Global Precipitation Climatology Centre (GPCC), and others], satellites [Climate Prediction Center morphing technique (CMORPH), Gridded Satellite (Grid-Sat), Global Satellite Mapping of Precipitation (GSMaP), and Tropical Rainfall Measuring Mission (TRMM) Multi-satellite Precipitation Analysis (TMPA) 3B42RT]	0.1°×0.1°	Gauge, Satellite, Reanalysis, and Analysis	1979–2017	Beck et al. 2019a, b
W5E5	Data sources of W5E5 are version 1.0 of WATer and global CHange (WATCH) Forcing Data (WFD) methodology applied to ERA5 data (WFDE5), ERA5 reanalysis data, and precipitation data from version 2.3 of the Global Precipitation Climatology Project	0.5°×0.5°	Bias-Correction Reanalysis	1979–2016	Weedon et al. 2014; Cucchi et al. 2020
EWEMBI	Data sources of EWEMBI are ERA-Interim reanalysis data (ERAI), WATCH forcing data methodology applied to ERA-Interim reanalysis data (WFDEI), eartH2Observe forcing data (E2OBS), and NASA/GEWEX Surface Radiation Budget data (SRB). The SRB data was used to bias-correct E2OBS shortwave and longwave radiation	0.5°×0.5°	Bias-Correction Reanalysis	1979–2016	Weedon et al. 2014; Lange 2019

Table 2 Metrics for evaluation of reanalysis-based, satellite-based, and "bias-correction"-based datasets precipitation versus observation

Evaluation Metrics	Equation	Unit	Range
Root Mean Squared Error (RMSE)	$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (S_i - O_i)^2}$	mm	$[0 \sim +\infty)$
Mean Bias Error (MBE)	$MBE = \frac{1}{n} \sum_{u=1}^{N} (S_i - O_i)$	mm	$(-\infty \sim +\infty)$
Percent Bias (PBIAS)	$PBIAS = \left[\frac{\sum_{i=1}^{n} (Y_i^{O_i} - Y_i^{S_i}) \times 100}{\sum_{i=1}^{n} (Y_i^{O_i})} \right]$	%	$(0–100)$
Kling–Gupta Efficiency (KGE)	$KGE = 1 - \sqrt{(r-1)^2 + \left(\frac{\sigma_{S_i}}{\sigma_{O_i}} - 1\right)^2 + \left(\frac{\mu_{S_i}}{\mu_{O_i}} - 1\right)^2}$	NA	$(-1) - (+1)$

Table 3 Climate Extreme Indices (CPIs) analyzed in this Study

Category	Short name	Long name	Calculation	Description	Units
Duration Indices	CDD	Consecutive Dry Days	The maximum annual number of consecutive dry days (when precipitation $< = 1.0$ mm)	The longest dry spell	Days
	CWD	Consecutive Wet Days	The maximum annual number of consecutive wet days (when precipitation $> = 1.0$ mm)	The longest wet spell	Days
Frequency Indices	R10mm	Number of heavy precipitation days	Number of days when precipitation $> = 10$ mm	Days when precipitation is at least 10 mm	Days
	R20mm	Number of very heavy precipitation days	Number of days when precipitation $> = 20$ mm	Days when precipitation is at least 20 mm	Days
Intensity Indices	SDII	Daily precipitation intensity	Annual total precipitation divided by the number of wet days (when total precipitation $> = 1.0$ mm)	Average daily wet-day precipitation intensity	mm/day
	Rx1day	Max 1-day precipitation	Maximum 1-day precipitation total	The maximum amount of precipitation that falls in one day	mm

To achieve accurate results, this study uses two-hybrid methods of PBIAS and KGE.

The results of PBIAS statistic showed that despite the high amount of MBE for the northern zones of Iran, it consists of a small percentage of annual precipitation. For example, MBE in MSWEP-V220 was calculated at 58.58 mm in the Cfa climate zone, which is up to less than 4% of annual precipitation. Examining the PBIAS and KGE, the southeast, northeast, southwest, and southern slopes of the Alborz mountains and the coasts of the sea of Oman show the highest value of PBIAS.

In the Cfa and Csa zones of Iran, where the precipitation intensity is heavy, the performance of satellite products and reanalysis data is poor. In contrast, bias-corrected data provide a better estimate of the absolute values in these areas. However, one of the significant advantages of satellite data and reanalysis data is the availability of them in the observation scares areas. EWEMBI and W5E5, are bias-corrected data, and their bias-corrected using gauged precipitation data. They approximately perform better when the maximum amount of precipitation is between 30 and 100 mm in the arid zone (BSh, BSk, BWh, and BWk) of Iran. Satellite data with Multi Weighted Measurement (MW) performs better than InfraRed-based data. This is observed in CHIRPS, which underestimates heavy precipitation, especially in the southern regions. In contrast, MSWEP-V220, which uses a hybrid method, tends to overestimate the maximum precipitation in the north of Iran (Cfa and Csa climates).

As part of bias-correction precipitation datasets, the reanalysis (CFSR and MERRA-2) performs worse than the satellite (CHIRPS) datasets (KGE score for CFSR and MERRA-2 is equal to 0.53 and 0.54, while the KGE score of CHIRPS is 0.61) (Figs. 2 and 3). However, it should be noted that as CHIRPS uses gauge, satellite, reanalysis, and analysis inputs, it significantly performs better in estimating precipitation than the PERSIANN and PERSIANN-CCS, which are merely infrared-based datasets (Katiraie-Boroujerdy et al. 2017). In addition, ensemble reanalysis data of NASA MRE3 with a KGE score of 0.63 shows the best performance among the not bias-corrected dataset. This result confirms significant progress in earth system modeling and precipitation estimation based on ensemble data.

The vital point about third-generation analysis data (CFSR) is its high horizontal resolution. The CFSR with

a KGE score of 0.533 showed the worst performance for Iran precipitation following MERRA-2 with a KGE score of 0.525 (Fig. 3). Therefore, it is suggested that CFSR would not use in future studies on Iran. It should be mentioned that the KGE score of CFSR is area-averaged, and the errors are much higher in different climate zones.

The evaluations of the EWEMBI (ERA-Interim corrected) and W5E5 (ERA5 corrected) bias-correction data were done by KGE and scores of 0.699, and 0.715, were calculated, respectively. Among the 7-dataset studied over Iran, the best overall performance was obtained by MSWEP V2.2 (with an average KGE score of 0.725), and this shows the importance of daily gauge corrections and accounting for gauge reporting times. This result has also been obtained in the United States, examining 26 datasets (Beck et al. 2019a, b) and confirming the high performance of the second version of MSWEP.

In the following, precipitation datasets in Iran's climate zones were investigated. All, not bias-corrected datasets showed lower performance on the north and northwest coasts, including the Csa, Cfa, and Dsa climate zones. This is due to the complex topography and high temporal-spatial heterogeneity of precipitation in these areas.

Except for CHIRPS (which has been modified for systematic bias using gauged observations), the not bias-corrected datasets have shown a considerable bias for precipitation on the northern coast of Iran. The bias of CFSR, MERRA-2, and MRE3 was 72.86, 57.42, and 59.54 mm, respectively. Even MSWEP-V220, as the best gridded daily precipitation dataset over Iran, showed a bias of 58.58 mm for the northern coast of Iran. In contrast, bias-corrected data showed a much lower bias.

The maximum bias of EWEMBI and W5E5 was 34.95 and 43.84 mm for the northern coast of Iran. These results reflect the difficulty of retrieving and simulating orographic and convective precipitation. MSWEP-V220 and W5E5 show the most accurate performance due to the use of the algorithm of reanalysis and hybrid satellite data (Figs. 2 and 3), and so these two datasets should be paid more attention.

Although W5E5 and EWEMBI have similar performance (the average KGE score of Iran was 0.725 and 0.715, respectively), there are regional differences in northwestern and mountainous areas of Iran (Fig. 2). Comparing W5E5 with MSWEP-V220 in mountainous areas (including Alborz and Zagros Mountain chains), the performance of both datasets decreases is not too far from expectations. The findings of this study show that topography and type of climate zone should be considered for choosing satellite and, or reanalysis datasets.

The main findings of this study for evaluating precipitation data show that the output of re-analysis and satellite products is highly over (under) estimated in Iran. In contrast, multi-source weighted-ensemble datasets have higher performance. The maximum precipitation of Iran occurs in two climates of Cfa and Csa, where all datasets, even bias-corrected data, have overestimated precipitation.

3.2 Heavy and very heavy precipitation (R10mm and R20mm)

The spatial distribution of days with heavy precipitation has been shown in Fig. 4, and the number of days with very heavy precipitation is shown in Fig. 5. The maximum R10mm and R20mm (Figs. 4 and 5) can be seen in northern Iran, Alborz Mountain (from northwest to northeast of the country). All studied datasets correctly showed the spatial pattern of heavy and very heavy precipitation (Figs. 3 and 4). The minimum and maximum of R10mm occurs in the BWh and Cfa climate zones with 3.80 and 48.66 days based on observation data.

In examining the maximum and minimum of R10mm and R20mm indices of MSWEP _V220 and W5E5 (Figs. 4 and 5) datasets which were found to have the best performance, they have not only identified the exact climate zones but also, there estimated values are very close to the observational data. The MSWEP _V220 and W5E5 data estimated the minimum value in the BWh zone as 3.60 and 2.98 days and the maximum value in the Cfa climate zone as 33.07 and 36.63 days, respectively (Fig. 6). This is also true for R20mm, with the difference that the maximum of R20mm seen in the BWk climate zone with a long-term average of 0.92 days.

The general investigation of heavy precipitation in all datasets shows that geographically the minimum and maximum amount of heavy precipitation days with the values between 0 to 48.82 are seen in southeastern Iran and the high Zagros Mountains, and southwest of the Caspian Sea. Meanwhile, observation data showed 1.27 days for the minimum amount of heavy precipitation and 48.66 days for the maximum amount.

The minimum and maximum values for R20mm were 0–28.32 days and 0.13–28.66 days for gridded datasets compared to the observation data. As mentioned, there are significant differences in the minimum and maximum amount of heavy precipitation in Iran with a different dataset. Due to the lower density of stations in the Zagros Mountains and the heights of northeastern Iran, heavy and very heavy precipitation in some parts of the western and northeastern regions of Iran is not very well captured by the observational data.

In northwestern Iran, where there are few numbers of stations, heavy and very heavy precipitation has shown in an unrealistic pattern due to the incorrect interpolation. The multi-source weighted-ensemble precipitation
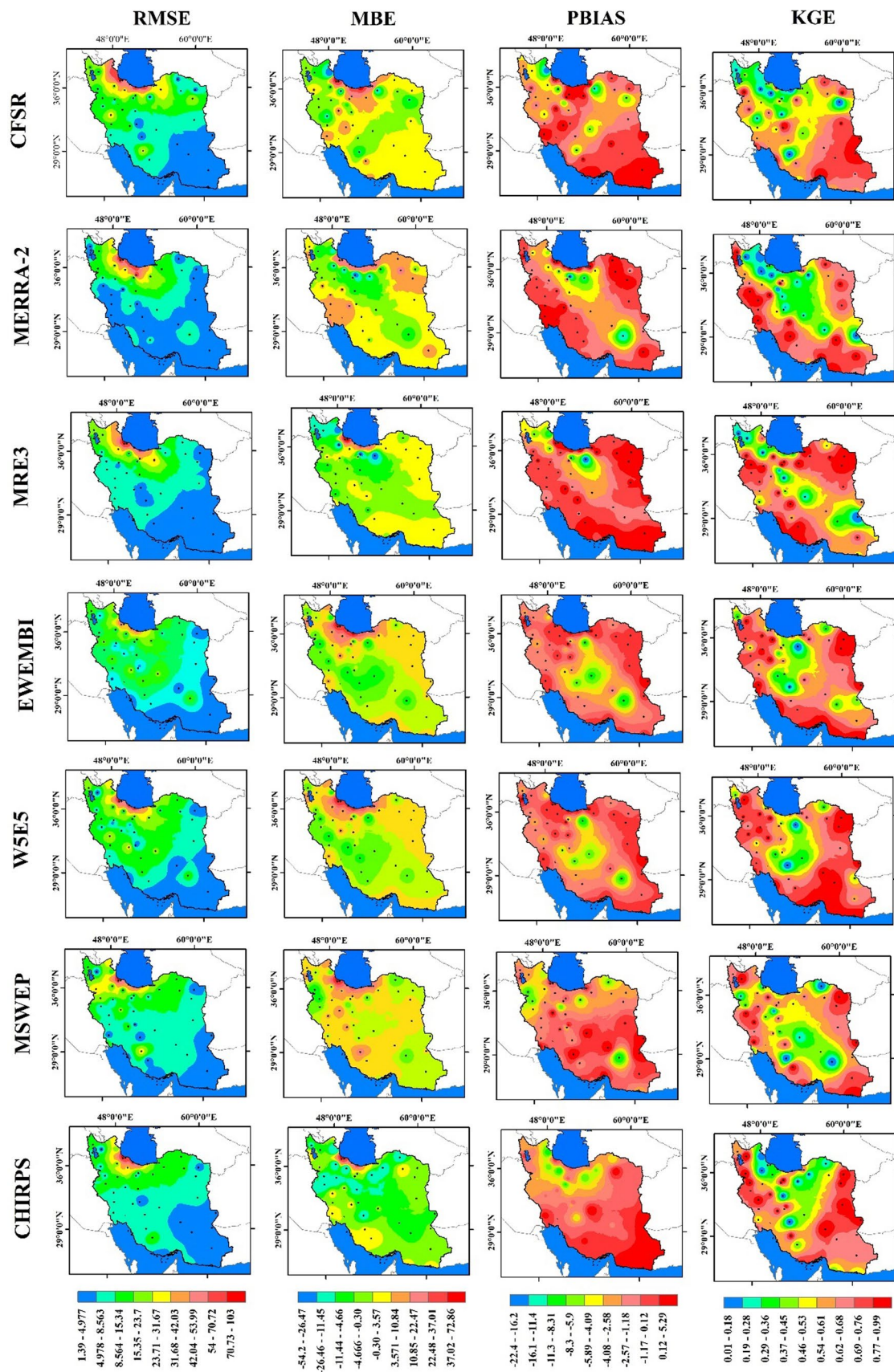
	RMSE	MBE	PBIAS	KGE
CFSR				
MERRA-2				
MRE3				
EWEMBI				
W5E5				
MSWEP				
CHIRPS				

RMSE legend: 1.39 – 4.977, 4.978 – 8.563, 8.564 – 15.34, 15.35 – 23.7, 23.71 – 31.67, 31.68 – 42.03, 42.04 – 53.99, 54 – 70.72, 70.73 – 103

MBE legend: −54.2 – −26.47, −26.46 – −11.45, −11.44 – −4.66, −4.666 – −0.30, −0.30 – 3.57, 3.571 – 10.84, 10.85 – 22.47, 22.48 – 37.01, 37.02 – 72.86

PBIAS legend: −22.4 – −16.2, −16.1 – −11.4, −11.3 – −8.31, −8.3 – −5.9, −5.89 – −4.09, −4.08 – −2.58, −2.57 – −1.18, −1.17 – −0.12, 0.12 – 5.29

KGE legend: 0.01 – 0.18, 0.19 – 0.28, 0.29 – 0.36, 0.37 – 0.45, 0.46 – 0.53, 0.54 – 0.61, 0.62 – 0.68, 0.69 – 0.76, 0.77 – 0.99

◄**Fig. 2** Spatial distributions of Root Mean Square Error (RMSE: mm year^{-1}), Mean Bias Error (MBE: mm year^{-1}), Percentage of Bias (PBIAS: % year^{-1}), and Kling—Gupta efficiency (KGE) derived from MRE3ensemble, MERRA-2, CFSR, CHIRPS V2.0, MSWEP _V220, W5E5 and EWEMBI datasets concerning Synoptic stations data from 1980 to 2016

of MSWEP _V220 provides an accurate spatial pattern in this area.

3.3 Consecutive dry and wet days (CDD and CWD)

Consecutive dry days gradually decrease from south to north in Iran (Fig. 7). although all datasets show a similar pattern for CWD and CDD over the territory of Iran, their values vary in each climate zone (Fig. 8). The average of minimum CDDs in Iran is 21.46 days, and the average of maximum CDDs in Iran is 196.29 days. The maximum CWD in Iran is seen in the Cfa climate zone located southwest of the Caspian Sea, and the minimum one is seen in the BWh climate zone.

The highest annual CDD (Fig. 7) is found in the southeast, the coast of the Sea of Oman, and central parts of Iran in all datasets. Hence, we can say that this region, from east to southeast, is an extensive arid hotspot. In this region, there are two main deserts of Iran, Dasht-e Lut (51,800 km^2) and Dasht-e Kavir (77,600 km^2) (Fig. 1a), which together cover about 8% of the total area of Iran. This is the reason for the significant increase in CDD. In this region, gridded datasets show CDD much more than observational data, and this is not because of the bias of gridded datasets but the lack of observations.

If we focus on the climate zones of Iran, we can see that the same CDD (CWD) difference can be seen over climate zones. For example, the significant difference of nearly 50 days for the BSh climate zone and about 20 days for the BWk climate zone is seen between gridded datasets and observation data.

Considering MSWEP _V220 as the most appropriate dataset for estimating precipitation in Iran, CDD was calculated at 187.96, 174.55, 156.63, 147.37, 131.68, 122.47, and 36.89 days in BWh, BSh, BWk, Dsa, Csa, BSk, and Cfa climate zones, respectively. It is interacting that the CDD in the mountainous climate zone (Dsa) is more than the steppe climate zone (BSk) in Iran.

In addition, it is worthy to note that many parts of Iran, especially central and eastern parts of it, have faced severe droughts over the past decades. Based on observation data, minimum and maximum CDD is observed in Cfa and BWh climate zones with 33.08 and 184.15 days. The noteworthy point is that MSWEP_V220 and W5E5 data are consistent with each other and with observation data to capture consecutive dry days in both the values and geographical

distribution. The maximum of 187.96 and 180.77 days and the minimum of 36.89 and 35.16 days for BWh and Cfa climate zones were obtained (Fig. 9). There is also a great deal of consistency between MERRA-2 and the observation data in the BSk, BWh, and BWk climate zones for the CDD and CWD indices (Figs. 7 and 8). Accordingly, using MERRA-2 data in the arid climate zone of Iran to determine dry and wet days provides good results. In contrast, the performance of MERRA-2 is drastically reduced in a temperate climate such as Cfa and Csa and in mountainous areas such as Dsa (Fig. 9).

One other dataset that we examined is CFSR, which shows Iran much drier in all except the Cfa climate zone. As we mentioned earlier, this dataset is not recommended for examining CDD and CWD in Iran (Figs. 7 and 8).

3.4 Intensity of extreme precipitation (SDII and Rx1day)

We used two intensity indices of SDII and Rx1day to quantify the temporal variability of precipitation among different datasets (Figs. 10, 11 and 12). Figure 10 shows the maximum daily precipitation (Rx1day) for the long-term period (1980–2016) of 49 synoptic stations and seven gridded daily precipitation datasets in Iran. The result shows that all datasets except MERRA-2 are highly consistent in the geographical pattern. The Rx1day has not captured the correct pattern in central Iran in the observation figure (Fig. 10) because the density of observations in this area is scarce (Fig. 1). Six datasets of W5E5, EWEMBI, CFSR, MERRA-2, CHIRPS, and MRE3 estimated the amount of Rx1day in the southern Alborz Mountain chain to be the same as the eastern Caspian Sea, which is not an accurate estimation. A comparison of the MSWEP_V220 dataset with observation shows its high accuracy for estimating Rx1day over Iran.

The highest value of Rx1day is seen in the Cfa climate zone, with 113.52 mm, and the lowest value of this index is seen in the BWk climate zone, with an average value of 22.96 mm. A comparison of Rx1day spatial distribution in the studied datasets shows an essential point about the CHIRPS dataset. This dataset, unlike others, shows considerable underestimation in the value of Rx1day on the southern coast of Iran. This may be because CHIRPS data relies on infrared information to retrieve precipitation, and this has been attributed to the indirect nature of the relationship between cloud-top temperature and surface precipitation (Scofield and Kuligowski 2003). Salio et al. (2015) showed that IR-based algorithms have difficulty retrieving maximum precipitation values. Similar results have been reported for underestimation in East Africa (Kimani et al. 2017) and Brazil (Palharini et al. 2020).

Central Iran, along with the eastern parts of it -as mentioned earlier- are the driest regions of Iran. However,
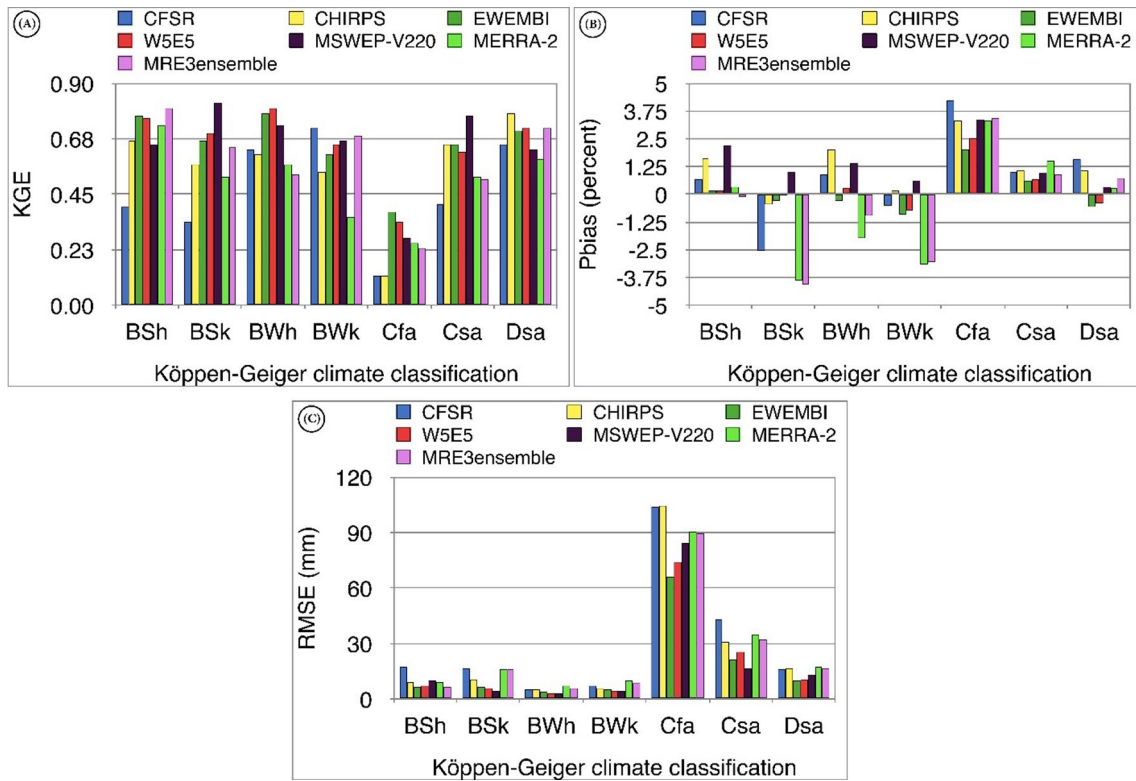
Fig. 3 Evaluation metrics for the MRE3ensemble, MERRA-2, CFSR, CHIRPS V2.0, MSWEP _V220, W5E5, and EWEMBI datasets against observations in different climate classes of Iran; **A** KGE; **B** PBIAS and **C** RMSE
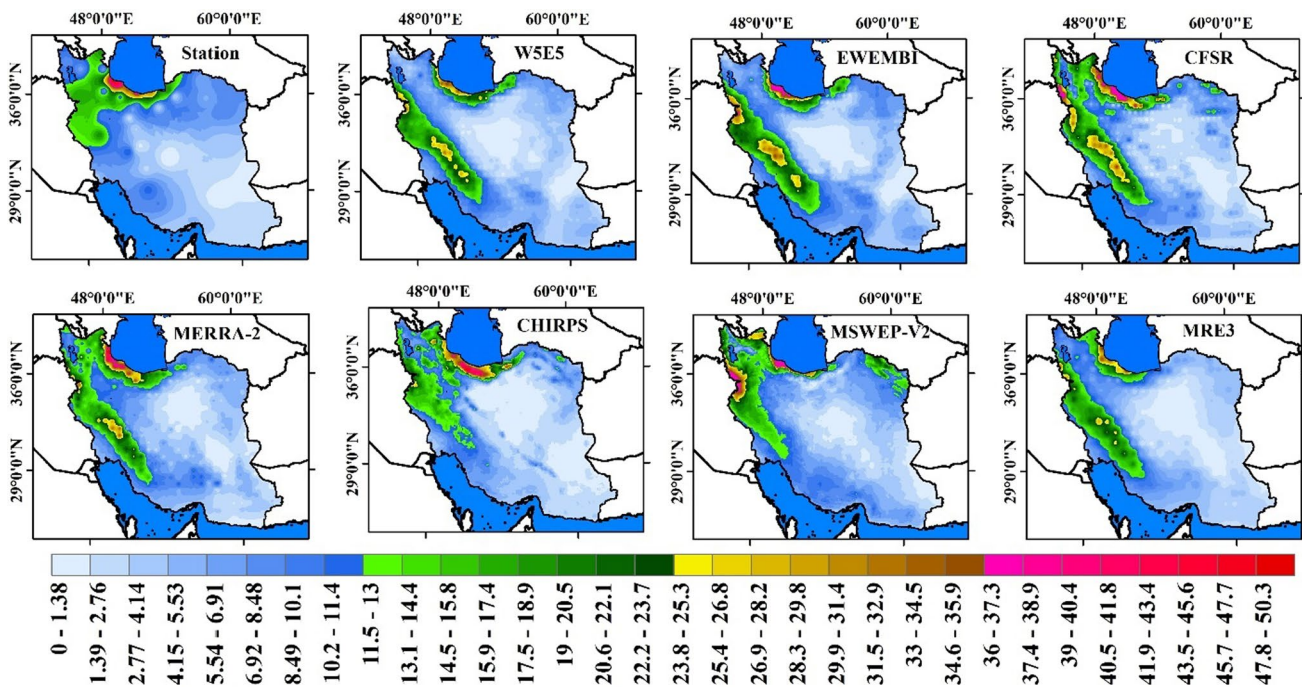

Fig. 4 The spatial distributions of the heavy precipitation (R10mm) of observation, W5E5, EWEMBI, CFSR, MERRA-2, CHIRPS, MSWEP, and MRE3ensemble datasets (Units: Day year^{-1})
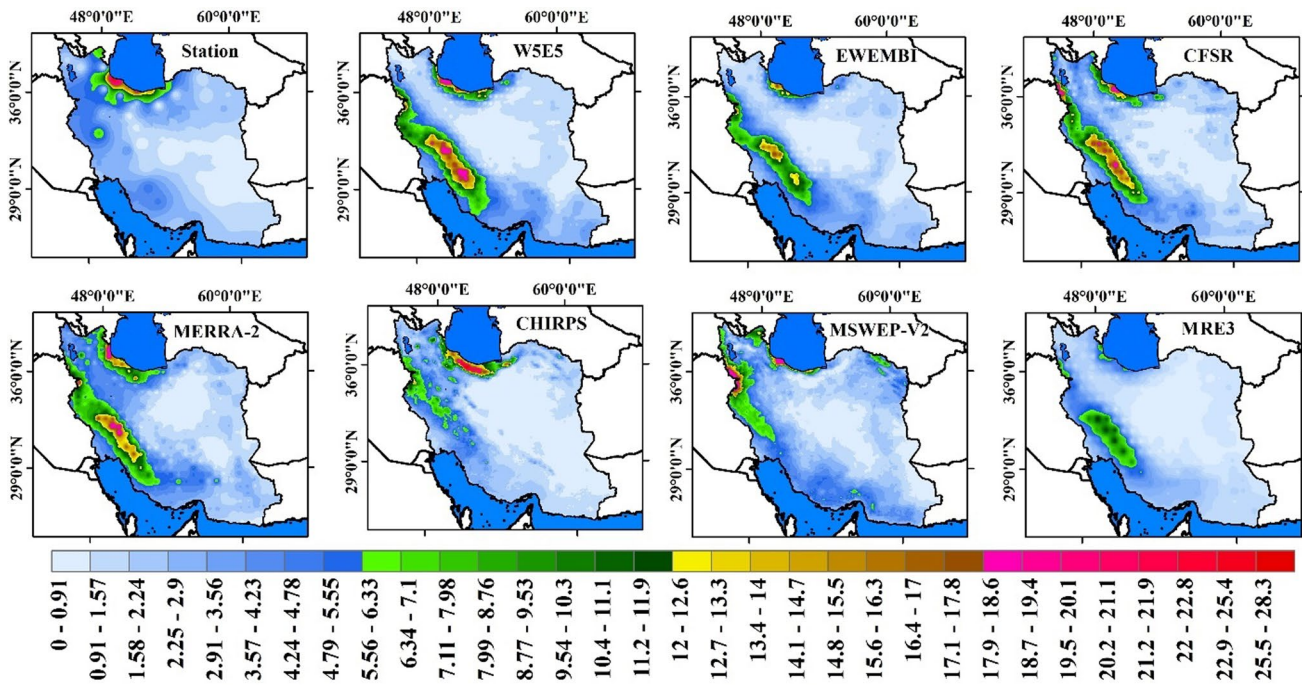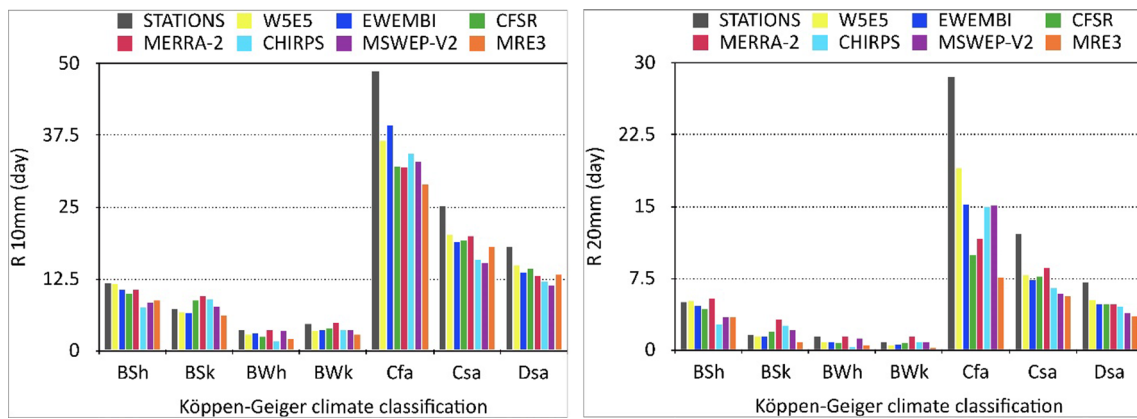
Fig. 5 The spatial distributions of the very heavy precipitation (R20mm) observation, W5E5, EWEMBI, CFSR, MERRA-2, CHIRPS, MSWEP, and MRE3ensemble datasets (Units: Day year^{-1})

Fig. 6 Area-averaged heavy and very heavy precipitation (R10mm and R20mm) for the MRE3ensemble, MERRA-2, CFSR, CHIRPS V2.0, MSWEP _V220, W5E5, and EWEMBI datasets against obser- vation in different Köppen-Geiger climate classification over Iran (Units: Day year^{-1})

MERRA-2 estimated the amount of Rx1day in these areas as the same as the northwestern Iran, which is not an accurate estimate of the intensity of the precipitation. The MERRA-2 performs well in estimating CDD and CWD in the BSk, BWh, and BWk climate zones. This good performance is because the CDD and CWD indices only represent the occurrence of precipitation and do not take into account the absolute amount of precipitation.

Another index that is used to investigate precipitation intensity is SDII (Fig. 11). Examining the SDII in climate zones, the maximum precipitation intensity is related to the Cfa zone with 16.32 mm/day, and the minimum one is related to the BWk zone with 5.49 mm/day (Fig. 12), based on observation.

The intensity of precipitation is very high on the north- ern and southern coasts of Iran and the western part of it over the Zagros mountains. All of these areas have a high
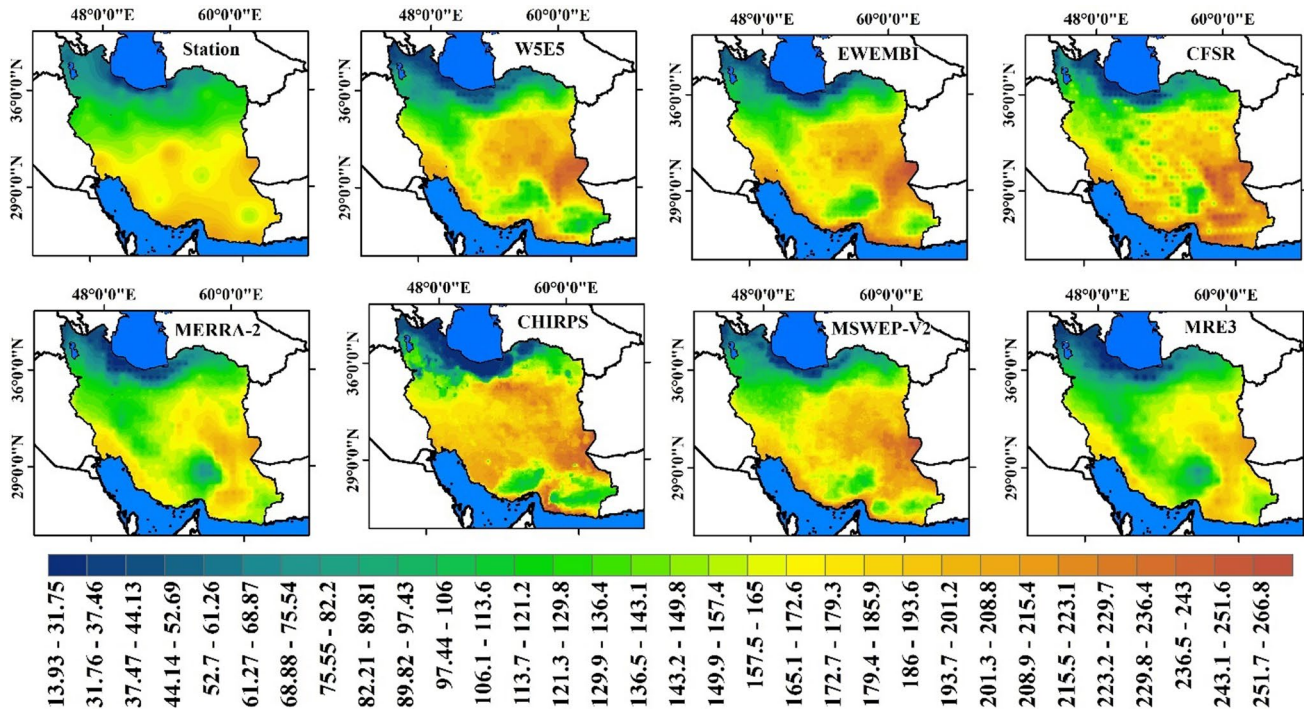
Fig. 7 The spatial distributions of the Consecutive Dry Days (CDD) of observation, W5E5, EWEMBI, CFSR, MERRA-2, CHIRPS, MSWEP, and MRE3ensemble datasets (Units: Day year^{-1})
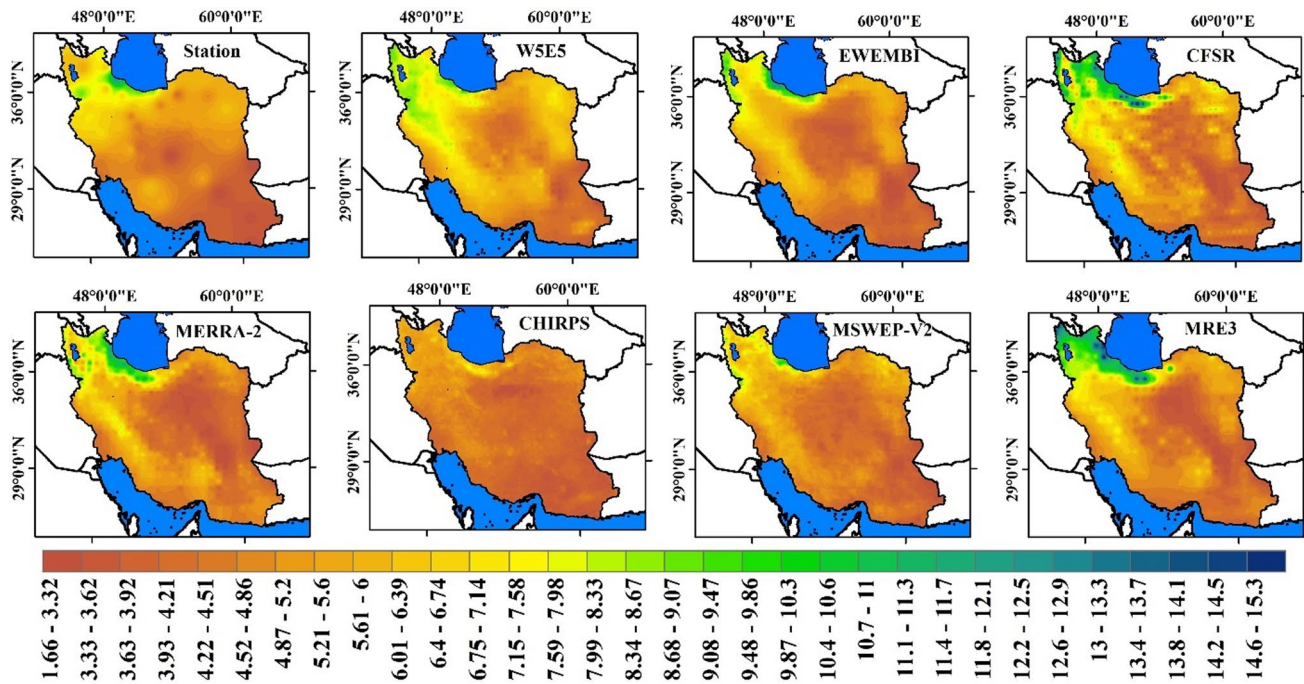

Fig. 8 The spatial distributions of the Consecutive Wet Days (CWD) of observation, W5E5, EWEMBI, CFSR, MERRA-2, CHIRPS, MSWEP, and MRE3ensemble datasets (Units: Day year^{-1})
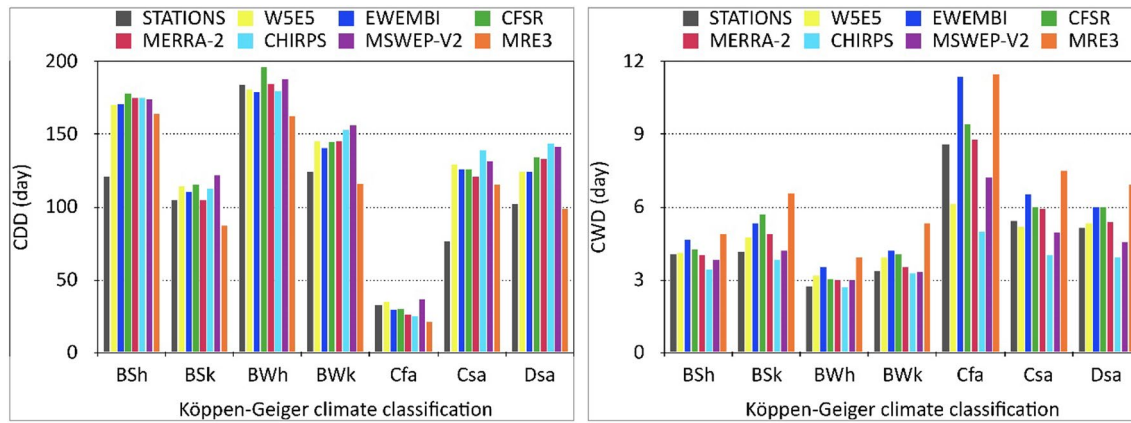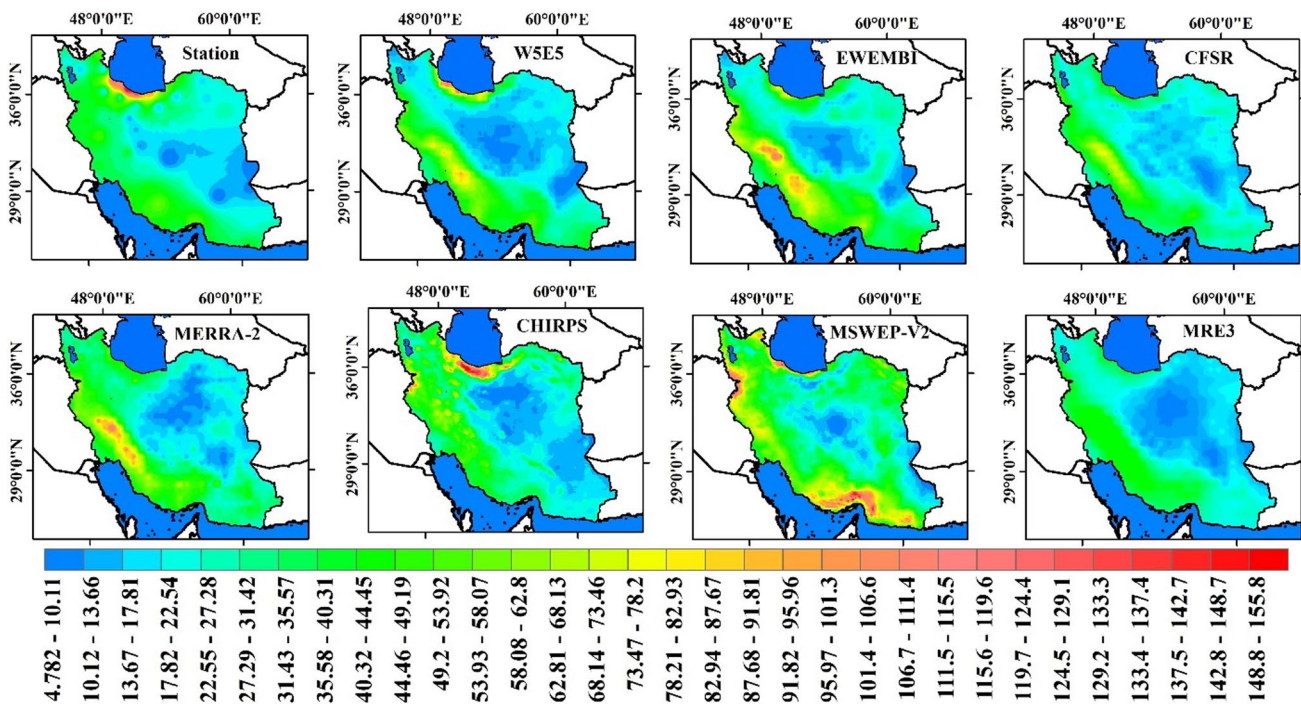
Fig. 9 Area-averaged consecutive dry and wet days (CDD and CWD) for the MRE3ensemble, MERRA-2, CFSR, CHIRPS V2.0, MSWEP _ V220, W5E5, and EWEMBI datasets against observation in different Köppen-Geiger climate classification over Iran (Units: Day year^{-1})

Fig. 10 The spatial distributions of the Maximum amount of precipitation that falls in one day (RX1day) of observation, W5E5, EWEMBI, CFSR, MERRA-2, CHIRPS, MSWEP, and MRE3ensemble datasets (Units: mm year^{-1})

potential of being flooded during extreme precipitation events. The minimum precipitation intensity of less than 5 mm per day is observed in central parts and southeastern Iran. Looking into the intensity of precipitation in climate zones, all datasets estimated it with only a 1 to 2 mm/day difference with observation, except for the Cfa climate zone. According to observational data, the precipitation intensity in the Cfa climate zone is 16.32 mm/day.

The CFSR and MRE3 estimated this at 7.69 and 6.28 mm/day, respectively. Even MSWEP_V220, which

showed the highest performance in Iran, estimated the precipitation intensity as 10.85 mm/day in the Cfa climate zone, which is 5.47 mm/day less than observed. In contrast, W5E5, with an estimated 14.58 mm/day, has the best performance for estimating precipitation intensity in the Cfa climate zone.
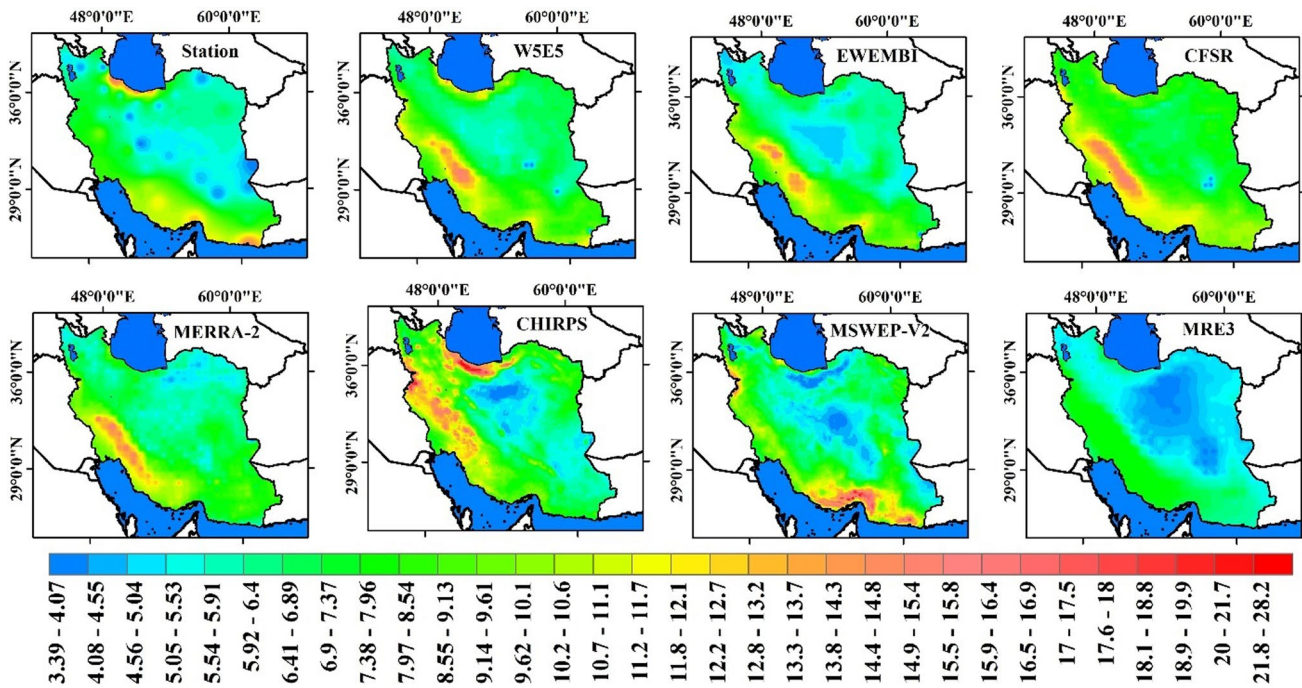
Fig. 11 The spatial distributions of the Simple Daily precipitation Intensity Index (SDII) of observation, W5E5, EWEMBI, CFSR, MERRA-2, CHIRPS, MSWEP, and MRE3ensemble datasets (Units: mm/day year^{-1})
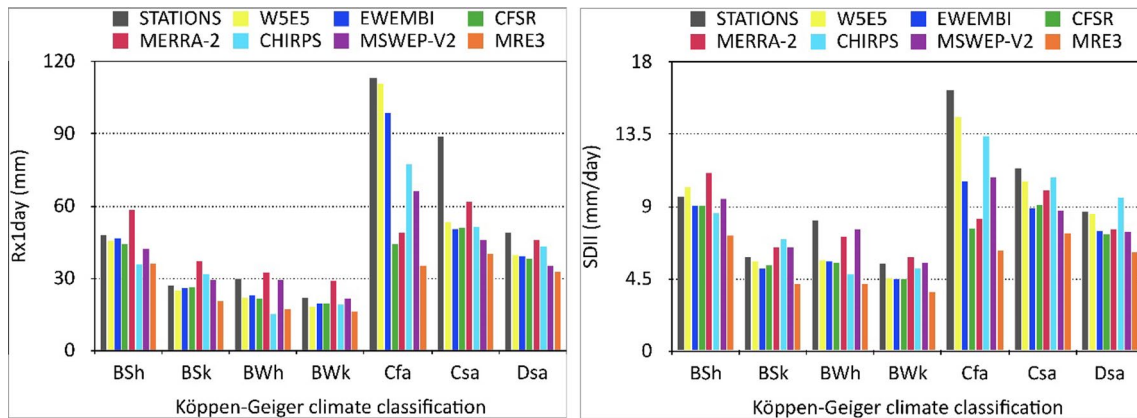

Fig. 12 The area-averaged intensity of extreme precipitation (SDII and Rx1day) for the MRE3ensemble, MERRA-2, CFSR, CHIRPS V2.0, MSWEP _V220, W5E5, and EWEMBI datasets against observation in different Köppen-Geiger climate classification over Iran (SDII Units: mm year^{-1}; Rx1day Units: mm/day)

4 Conclusion

To clarify the strength and weakness of the global gridded daily precipitation datasets, we examined the performance of seven daily precipitation datasets. Examination of different datasets showed that the bias-correction datasets (EWEMBI and W5E5) and the MSWEP_V220 have better performance than the reanalysis and satellite datasets. The main findings of this study to evaluate the performance of datasets can be summarized as follows:

1. Comparing the satellite-based precipitation products and reanalysis datasets, satellite products perform better than the reanalysis data on average.
2. Comparing the reanalysis data, MRE3ensemble showed acceptable performance; So the overall performance, of this ensemble dataset is equal to the CHIRPS product in Iran.

3. Among the precipitation datasets produced using gauge data, the MSWEP-V220 represents better performance compared to MERRA-2. The very high performance of MSWEP-V220 is related to applying daily gauge corrections and accounting for gauge reporting times (Beck et al. 2019a, b).

4. Bias-Correction precipitation data showed better performance in providing Intensity, Frequency, and Duration than reanalysis and satellite-based data (meaning CHIRPS).

5. The W5E5 dataset (ERA5 data, the bias was corrected with CRU TS4.03 and GPCCv2018) for all indices performed better in most climate zones and average of Iran from EWEMBI dataset (ERA-Interim base data). The superiority of the W5E5, which uses the new version of ERA, reflects significant advances in climate system modeling and data assimilation data based on rain gauge stations, satellites, and sounding observations over the past decades.

6. The MSWEP-V220 and W5E5 overall had the best performance among all the datasets, although each has better performance in different zones. The MSWEP-V220 performed better in the climate zones (BWk and Dsa), while the W5E5 performed much better in the BSh, BSk, BWh, Cfa, and Csa climate zones.

The spatial distribution of extreme precipitation during the study period for MSWEP-V220 and W5E5 datasets in Iran has provided acceptable results; the MERRA-2 dataset on KGE score showed the lowest performance among the datasets. The MERRA-2 does not provide an accurate estimate of heavy and very heavy precipitation and high-intensity daily precipitation events in central and southeastern Iran, which are arid areas. In contrast, it demonstrated high agreement with observational data in the BSk, BWh, and BWk climate zones for CDD and CWD indices. In addition, among the satellite data, CHIRPS underestimated precipitation intensity, especially for the southern regions of Iran, because it relies on infrared precipitation estimates (Darand and Khandu 2020; Ghozat et al. 2021).

Based on precipitation gridded datasets, the results of estimating extreme precipitation in the climate zone of Iran are as follows:

1. All seven precipitation datasets underestimate the frequency indices (R10mm and R20mm) and precipitation intensity (Rx1day and SDII) in the rainy climate zones of Iran (Cfa, Csa, and Dsa);

2. The highest overestimation of intensity and frequency indices in the desert (BW) and semi-desert (BS) climate zones of Iran are seen in MERRA-2 and CFSR datasets, respectively;

3. Heavy precipitation (R10mm) in the two climate zones of BSh and BWh is underestimated compared to observational data;

4. Very heavy precipitation (R20mm) is underestimated in the BWh desert climate.

5. Consecutive dry days in Iran's two semi-desert climate zones (BSh and BSk) are overestimated in most datasets.

6. The MRE3 has overestimated the CDD index in cold semi-desert climate zones compared to the other datasets;

7. The significant difference between global precipitation datasets and observation data in estimating CDD and CWD in the arid interior of Iran is the lack of synoptic stations (Zarrin and Dadashi-Roudbari 2021) in these areas.

8. In the hot desert climate zone of Iran (BWh), consecutive dry days are underestimated for Bias-Correction (W5E5 and EWEMBI), CHIRPS, and MRE3 datasets.

9. An interesting result is related to CHIRPS while retrieving consecutive dry and wet days in Iran; in all zones except Cfa, this dataset overestimated CDD and underestimated CWD; In other words, CHIRPS unrealistically shows Iran drier. Based on this, it is recommended that infrared-based gridded data may be used more cautiously in arid area

10. Global daily precipitation datasets, in agreement with observational data, were showed the highest frequency of CDD in the southern and eastern regions of Iran; While the lowest values were, seen in the northern coasts of Iran (Cfa and Csa);

11. All datasets have a good performance in estimating dry and wet days (days with precipitation thresholds less than and more than 1 mm) and can reasonably identify the presence or absence of rainy days in Iran. What causes a significant difference in these data is the precipitation intensity indices (SDII and Rx1day).

In future studies, more precipitation datasets from various climate regimes should be used to generalize the conclusions drawn from this study. In addition, the impacts of using different reanalysis-based, satellite-based, and "bias-correction"-based datasets to calibrate the climate models also need to be investigated.

Author contributions Conceived and designed the analysis: AZ and AD-R. Collected the data: AZ and AD-R. Contributed data or analysis tools: AZ and AD-R. Performed the analysis: AZ and AD-R. Wrote

the paper: AD-R. Writing—review, and editing: AZ. Corresponding author: AZ.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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