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Evaluation of CMIP6 precipitation simulations across different climatic zones: Uncertainty and model intercomparison

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ABSTRACT

This study analyzes the performance of precipitation estimates from historical runs of the CMIP6 (Climate Model Intercomparison Project Phase 6) over the climatic regions of Iran. In order to capture the spatio-temporal precipitation patterns, using a set of evaluation metrics, 12 GCMs (General Circulation Models) are compared to the observation data from the GPCC (Global Precipitation Climatology Centre) at the common 1° spatial resolution for 1950–2014. A comprehensive assessment is performed at different temporal scales including monthly, seasonal and annual. Results indicate that the reliability of precipitation estimates varies significantly across space and time. The CMIP6 models best reproduce the climatological features of precipitation and its spatio-temporal changes over the arid and hyper arid areas of the country. The outputs of the models exhibit less systematic biases in the arid zone. In addition, a strong underestimation is detected throughout the rainiest zone, indicating high uncertainty in wet regions. All models tend to show some level of underestimation in summer months with the lowest rainfall. The findings illustrate substantial inter-model variability over different climatic zones. Each of the CMIP6 models appears to be more suitable in a specific climatic zone. The models that performed reasonably well in the humid zone (CNRM-CM6-1 and MRI-ESM2-0), did not perform well in the hyper arid and arid zones. Similarly, models (HadGEM3-GC31-LL, BCC-CSM2-MR, and CanESM5) that performed well in the arid and hyper arid zones did not perform as well in the humid zone. Results inform what types of models are suitable for different climate zones.

1. Introduction

Climate change is expected to alter the magnitude and spatio-temporal patterns of hydro-climate variables, including precipitation (e.g., Trenberth, 2008; Black, 2009; Willems and Varc, 2011; Allan and Soden, 2008; Mukherjee et al., 2018; Ragno et al., 2018; Papalexiou and Montanari, 2019; Guo et al., 2020). Such changes can have significant implications for the ecosystem, human societies and current and future water resources (Sun et al., 2018; Kamworapan and Surussavadee, 2019). GCMs (General Circulation Models) are widely employed to simulate historical and projected precipitation (and other climate variables) for climate change and variability studies (Hwang and Graham, 2013; Stouffer et al., 2017; IPCC, 2013).

Despite significant progress over the past decade, model simulations are subject to biases and uncertainties for a wide range of reasons including simplifying assumptions, errors in model parameterization, boundary conditions, model structure/physical processes, and input variables (e.g., Tebaldi et al., 2006; Reichler and Kim, 2008; Kay et al., 2009; Liepert and Previdi, 2012; Khan et al., 2018). For this reason, performance evaluation of available GCMs and characterization of the underlying uncertainties and biases in climate model simulations are fundamental to understanding their value and potential for climate change impact assessment studies (Kumar et al., 2013; Purich et al., 2013; Rupp et al., 2013; Su et al., 2013; Miao et al., 2014; Ahmadalipour et al., 2017; Gulizia and Camilloni, 2015; Moise et al., 2015; Lovino et al., 2018; Raghavan et al., 2018; Zazulie et al., 2018; Rivera and Arnould, 2019).

With support from several international programs, historical and future climate simulations from many modeling groups from around the world have been made for Intergovernmental Panel on Climate Change

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(IPCC) Assessment Reports and other regional and local climate assessments (Das et al., 2012; Zhou et al., 2014; Stouffer et al., 2017). Recently, the CMIP6 (Coupled Model Intercomparison Project Phase 6; Eyring et al., 2016) released the latest suite of coordinated climate model simulations to facilitate the 6th Assessment Report. Previous modeling experiments (e.g., CMIP3 and CMIP5) have been widely evaluated and used in numerous studies (Maxino et al., 2008; McAfee et al., 2011; Taylor et al., 2012; Rana et al., 2013; Rupp et al., 2013; Almagro et al., 2020; Onol et al., 2014; Wojcik, 2014; Anandhi and Nanjundiah, 2015; Jiang et al., 2015; Bozkurt et al., 2018; Cai et al., 2018; Yazdandoost and Moradian, 2019). The results of recent regional evaluation studies have shown that CMIP6 models have improved relative to the previous phases (Rivera and Arnould, 2019; Gusain et al., 2020).

Performance assessment is either on the direct GCM outputs (e.g. Khan et al., 2018; Shi et al., 2018) or outputs of secondary models that use GCMs as input variables (e.g., hydrologic simulations forced by GCMs; Chiew et al., 2009; Wilby, 2010; Teutschbein et al., 2011; Chen et al., 2012). Either way, evaluation is typically based on a series of statistical and/or categorical metrics applied at different space-time scales. Several studies have introduced performance metrics (including categorical and volumetric) for evaluation of model simulations versus reference observations (AghaKouchak and Mehran, 2013).

The results of previous precipitation evaluations have shown that the outputs of GCMs may significantly overestimate or underestimate the observed precipitation across different seasons – i.e., substantial variability of performance in hot and cold seasons (Johnson et al., 2011; Gouda et al., 2018; Liu et al., 2014; Busuioc et al., 2001; Debebe and Mengistu, 2020). In addition to seasonal variability, model performance may also significantly change across different spatial domains and topographic properties (Pan et al., 2001; Niu and Yang, 2003; Ashiq et al., 2011). For example, Lv et al., 2020 showed that CMIP5 model simulations tend to overestimate and underestimate precipitation in northern and southern parts of China, respectively.

In this study, we have evaluated the recently released CMIP6 precipitation simulations over Iran. Given that previous simulations (e.g., CMIP5) have shown substantial seasonal variability (Liu et al., 2014), we have conducted both annul and monthly assessment of precipitation simulations. Also, previous studies have shown that even when precipitation simulations were in broad agreement with observations, there were substantial variability in performance across different climate regions (e.g., Mehran et al., 2014). For this reason, we have evaluated CMIP6 across different climate zones of Iran. Given Iran's limited water resources and substantial variability in precipitation, a good understanding of the performance of climate model is fundamental for climate change impact assessment on water resources. The reminder of this paper is organized as follows: Section 2 introduces the study area and methods. Section 3 presents the results; and Section 4 summarizes the findings and conclusions.

2. Materials and method

2.1. Study area

This study focuses on CMIP6 precipitation evaluation over Iran, the second largest country in the Middle East. The average annual rainfall in the country is about 230 mm, a mere 30% of the global average precipitation of 810 mm. Spatial pattern of precipitation in Iran is very heterogeneous: the central regions receive less than 50 mm annually, while the average precipitation in northern Iran reaches about 1000 mm per year. In addition, 75% of the country's total annual precipitation falls over only 25% of its area (Karandish and Hoekstra, 2017).

Ineffective water resources management along with climate change and variability, have resulted in major water resource challenges including desiccation of Urmia Lake shrinkage which is the largest lake in the country (Ahmadaali et al., 2018; Alborzi et al., 2018; Khazaei et al., 2019), drying of the Hamun Lake in the eastern part (Modaresi et al., 2019), substantial groundwater depletion (Ashraf et al., 2017) and seasonal disappearance of Zayandeh River in central part (Foltz, 2002). Given the observed changes in water resources there is a great deal of interest in using climate model simulations to assess potential future changes (e.g., Abbaspour et al., 2009; Ashraf et al., 2019). Therefore, model evaluation is really important to understand whether available simulations are consistent with the observation in the historical period.

Table 1
The climatic zones of Iran and their characteristics.

Climatic zone		Mean precipitation (mm/year)	Area (Km^2)	Number of provinces
1	Hyper Arid	132	437,488	3
2	Arid	294	848,417	13
3	Semi-Arid	451	304,125	12
4	Dry-Sub Humid	273	20,367	1
5	Humid	941	37,798	2

In this paper, in order to better evaluate the spatio-temporal performance of GCM precipitation simulations, the study area was divided into five different climatic zones (based on Karandish and Hoekstra, 2017). This classification is based on the general climate and geographic features to study how models perform in different climatic zones. Detailed information about the climatic regions is provided in Table 1. It should be noted that climatic zones are not defined just based on precipitation, but also other factors such as plant density (Fig. 1). As shown in Table 1, the dry-sub humid zone receives less precipitation than the arid zone because of considering different bio-physical properties in addition to precipitation. The authors note that the climatic zones used in this study differ with respect to size. The differences in the number of simulations used for regional evaluations can be a potential source of uncertainty.

2.2. Data and model simulations

Climate model simulations were obtained from the historical runs of 12 CMIP6 (Eyring et al., 2016) models (Table 2). When there was more than one ensemble member, the arithmetic mean of the members was used. The CMIP6 estimations were evaluated against the GPCC (Global Precipitation Climatology Centre; Schneider et al., 2018) data on a common 1° spatial resolution for the historical period of 1950–2014. GPCC, established in 1989, gathers in-situ precipitation data to analyze it over global land regions. Previous studies have introduced it as a reliable dataset for rainfall over Iran (Raziei et al., 2011; Azizi et al., 2015; Darand and Zand Karimi, 2016; Yazdandoost et al., 2020). CMIP6 climate model simulations were obtained from https://esgf-node.llnl.gov/search/cmip6/, whereas gauge-based GPCC precipitation data were obtained from https://opendata.dwd.de/climate_environment/GPCC/html/download_gate.html.

2.3. Methodology

This paper evaluates precipitation data from 12 CMIP6 models against the GPCC data at monthly, seasonal, and annual scales. Here, the bicubic interpolation method (Keys, 1981) was used to achieve a common spatial resolution of 1°. Bicubic is an extension of the cubic method for interpolating data on a two-dimensional regular grid network. Detailed information about the method is provided in Keys (1981).

There are wide range of metrics that can be used for validation and verification purposes. Table 3 shows several metrics used in this study including bias (Bias), Correlation Coefficient (CC), Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) (e.g., Duan et al., 2016). We note that CMIP6 model simulations are not forced with all the available historical oceanic and climatic boundary conditions (Griffies et al., 2016; Meinshausen et al., 2017). For this reason, they are not

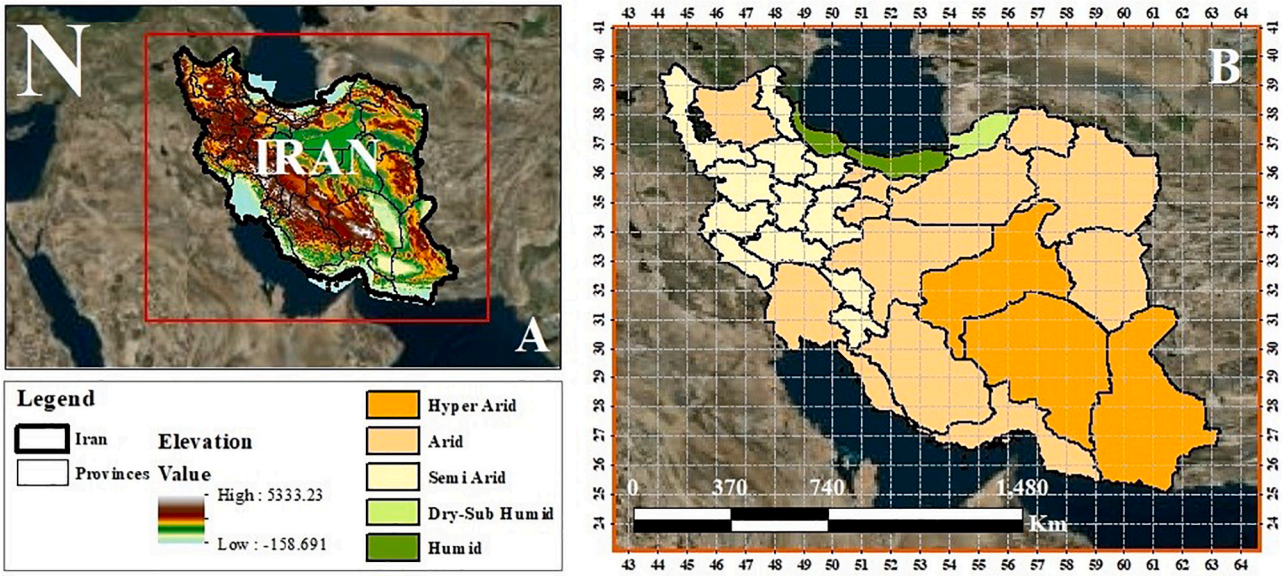

Fig. 1. (a) Topography and (b) climatic zones of Iran.

Table 2
List of the 12 CMIP6 models, utilized in the present study.

Model		Institute	Country	Horizontal resolution		Number of ensemble members
				longitude	latitude	
1	BCC-CSM2-MR	Beijing Climate Center, China Meteorological Administration	China	1.125°	1.125°	3
2	CanESM5	Canadian Centre for Climate Modeling and Analysis	Canada	2.81°	2.81°	50
3	CESM2	National Center for Atmospheric Research (NCAR)	USA	1.25°	0.94°	3
4	CNRM-CM6-1	National Center of Meteorological Research	France	1.4°	1.4°	10
5	FGOALS-g3	LASG, Institute of Atmospheric Physics, Chinese Academy of Sciences	China	2°	2°	3
6	GFDL-ESM4	NOAA Geophysical Fluid Dynamics Laboratory	USA	1.25°	1°	1
7	GISS-E2-1	Goddard Institute for Space Studies (NASAGISS)	USA	2.5°	2°	5
8	HadGEM3-GC31-LL	Met Office Hadley Centre	UK	1.88°	1.25°	4
9	IPSL-CM6A-LR	Institute Pierre Simon Laplace	France	2.5°	1.25°	10
10	MIROC6	Japan Agency for Marine-Earth Science and Technology (JAMSTEC)	Japan	1.4°	1.4°	3
11	MRI-ESM2-0	Meteorological Research Institute	Japan	1.125°	1.125°	2
12	NorESM2-LM	Norwegian Climate Service Centre	Norway	2.5°	1.9°	3

Table 3
List of the metrics used in the present study for evaluation of CMIP6 precipitation simulations against observations.

Evaluation Metrics	Equation	Unit	Range	Optimal value
bias (Bias)	$\text{Bias} = \frac{\sum_{i=1}^{N}(P_i - O_i)}{N}$	mm	$(-\infty \sim +\infty)$	0
Correlation Coefficient (CC)	$CC = \frac{\sum_{i=1}^{N}\left(P_i - \overline{P}\right)\left(O_i - \overline{O}\right)}{\sqrt{\sum_{i=1}^{N}\left(P_i - \overline{P}\right)^2} \times \sqrt{\sum_{i=1}^{N}\left(O_i - \overline{O}\right)^2}}$	NA	[−1–1]	1
Mean Absolute Error (MAE)	$\text{MAE} = \frac{\sum_{i=1}^{N}\lvert P_i - O_i\rvert}{N}$	mm	$[0 \sim +\infty)$	0
Root Mean Squared Error (RMSE)	$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{N}(P_i - O_i)^2}{N}}$	mm	$[0 \sim +\infty)$	0

note: Oi and Pi refer to the observed precipitations from the GPCC and the precipitation estimates from the CMIP6 models, respectively. Also, $\overline{O}$ and $\overline{P}$ are the average of corresponding data between N samples.

expected to simulate the timing of wet and dry periods consistent with observations at high spatial resolutions. Evaluation typically should focus on the general statistical properties of simulations against observations. For this reason, we have used different temporal (monthly, seasonal, annual) and spatial scales (country scale and climate zones) for model evaluation.

The GPCC and climate model anomalies were calculated based on the long-term average of models/observations in the historical period (1950–2014). Above-average and below-average precipitation are considered as positive anomaly and negative anomaly, respectively (Madadgar et al., 2016).

3. Results

3.1. Spatial assessment of precipitation simulations

Since Iran has a diverse climate with a wide range of precipitation variability, we first focused on the capability of models in capturing the observed spatial variability of precipitation. The spatial maps of monthly average rainfall from ground-based GPCC data (top left) and

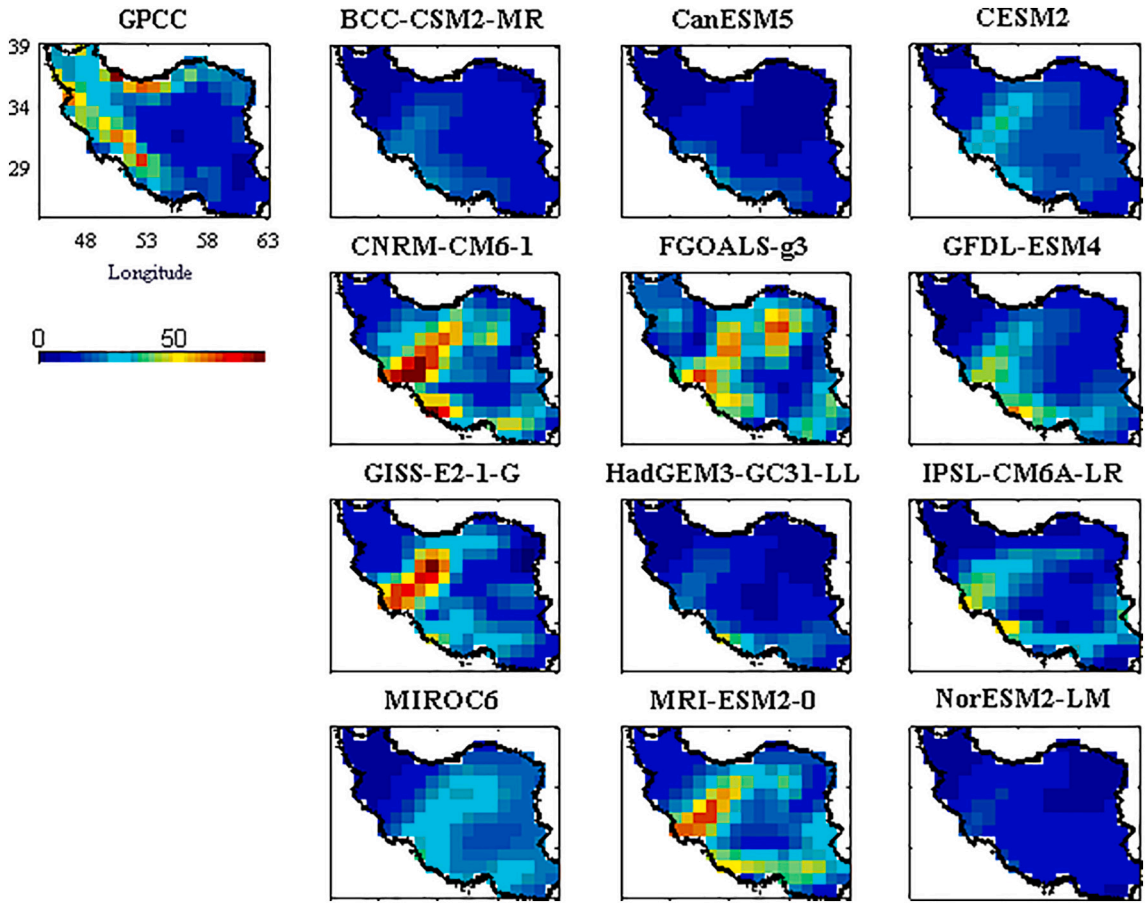

Fig. 2. Spatial maps of monthly average precipitation (mm) over the study area (1950–2014).

CMIP6 model simulations are presented in Fig. 2. Comparing the subplots in Fig. 2 with the elevation map of the country (Fig. 1) indicates that none of the CMIP6 models can reproduce the orographic precipitation pattern, apparent in GPCC (top left panel). Given that the observed precipitation is consistent with the high mountains in northern and western Iran, it seems that relatively coarse resolution of models have led to spatially inconsistent precipitation patterns. Among all models, FGOALS-g3 has the most similar spatial precipitation pattern relative to the GPCC data. Also, BCC-CSM2-MR, CanESM5, HadGEM3-GC31-LL and NorESM2-LM correctly simulate precipitation in areas that do not receive substantial precipitation (e.g., southeastern Iran). We note that most of the models can capture relatively high coastal rainfall in the southwest of the country. Investigating the monthly average rainfall biases (Fig. 3) shows that there are substantial biases between climate model simulations and ground-based observations. In fact, comparing biases reported in Fig. 3 with the GPCC monthly average precipitation (Fig. 2 top left), one can see that in some pixels, the bias (difference between simulations and observations) is larger than the monthly mean value of the same pixel for the period 1950–2014. This indicates that using the models for hydrologic applications without bias correction may lead to unreasonable results. Further, while FGOALS-g3 simulations were spatially more consistent with observations compared to the rest of the models, the biases of FGOALS-g3 were significantly higher than most models (specially in central and northeastern parts of Iran). Overall, the relative biases of all models are higher in the northern and northwestern parts of Iran. Fig. 4 shows the spatial correlation coefficients of mothly precipitation simulations relative to the observations. As shown, the spatial correlations vary significantly across the country and in different climatic zones. This figure indicates that the lowest values of CC are found in the coastal parts of the country (specially in humid northern parts of Iran) and higher values of the CC are found in relatively drier regions (e.g., central and southeastern parts).

3.2. Temporal assessment of precipitation simulations

As mentioned earlier, CMIP6 simulations are not forced with all the available historical oceanic and climatic boundary conditions, and hence they are not expected to simulated observations at high spatial and temporal scales. For this reason, assessment is often performed over a relatively large spatial domain averaged over a period of time. Fig. 5 shows time series of spatially averaged annual precipitation data over the study area (1st and 3rd columns) and the corresponding monthly climatology (2nd and 4th columns). The figure shows that some models significantly underestimate the averaged annual precipitation (e.g., CanESM5 and IPSL-CM6A-LR) while some other models overestimate (at least at some time steps) precipitation (e.g., FGOALS-g3 and MRI-ESM2-0). In CanESM5, for example, the largest value is around a quarter of the largest value in the observations. While bias is a major issue, it can often be corrected using bias corrections techniques such as using a multiplicative factor based on the ratio of observations over simulations. However, this method would work best when the general pattern of precipitation is simulated reasonably well. For this reason, the monthly climatology is presented in Fig. 5 (2nd and 4th columns). Monthly climatology plots show that most of precipitation falls between November and April, with sharp transitions into dry conditions. While most models do capture the general climatology, some exhibit substantial differences relative to the observations (e.g., CanESM5, NorESM2-LM, BCC-CSM2-MR). On the other hand, some climate models reproduce the monthly climatology very well (e.g., MRI-ESM2-0,

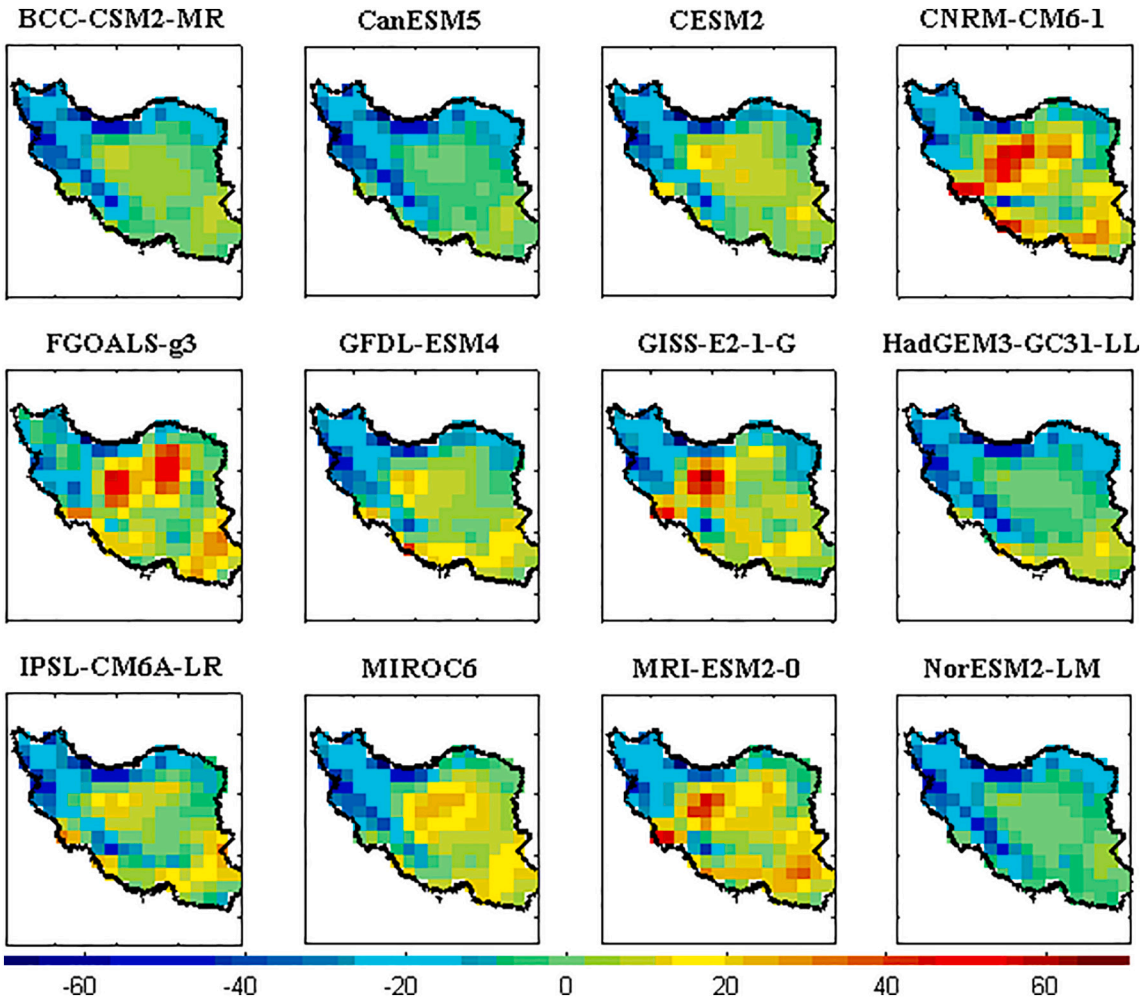

Fig. 3. Spatial maps of monthly Bias over the study area (1950–2014).

MIROC6, GISS-E2-1).

Previous studies showed that performance of some climate models varies seasonally (Busuioc et al., 2001; Liu et al., 2014; Debebe and Mengistu, 2020). For this reason, we have also investigated climate model simulations against observations across different seasons and climate zones (Fig. 6). In Fig. 6 the lowest bar in each panel represents the observations (GPCC). Results from the figure, along with previous studies (Liu et al., 2014; Debebe and Mengistu, 2020), highlight biases in seasonal precipitation patterns and also seasonal fractions of rainfall. For example, based on observation in hyper-arid climate zone, most of the precipitation occurs in winter followed by spring. FGOALS-g3, however, shows the most of the rainfall occurs in spring followed by winter. Overall, in terms of the relative contribution of each season, most models are broadly consistent with observations, though the seasonal biases are generally very high consistent with the earlier results.

Fig. 6 indicates that almost all climate models are highly biased in estimating seasonal precipitation in rainy areas (see the humid panel in Fig. 6). In humid zone, almost all models systematically miss the summer precipitation in the region (Fig. 6 right panel), whereas in the arid zone most models reasonably simulate summer rainfall (Fig. 6 Arid panel). Our results highlight that substantial seasonal variations across CMIP5 models observed in previous studies (Liu et al., 2014) is still a major issue in CMIP6 simulations.

Results presented in Fig. 6 displayed substantial biases in spatially averaged annual precipitation simulations. Fig. 7 shows the annual precipitation anomalies after removing the overall mean of each time series. This can be considered as a form of bias correction in which the means of all time series have been adjusted to be the same and consistent with the observations. Blue areas indicate wet (above average rainfall) periods, whereas, red areas indicate dry (below average precipitation) periods. Given that CMIP6 outputs are not forced with real historical forcings, we cannot expect the occurrence of wet and dry periods to match exactly with the observations. One can see that with respect to duration and amplitude some of the model simulations (e.g., MIROC6, MRI-ESM2-0) are consistent with observations (i.e., in terms of durations and amplitudes and not the timing of the events). However, the wet and dry durations in some other models such as GFDL-ESM4 and CanESM5 are substantially different from observations. This is important for drought analysis using climate model simulations (Nasrollahi et al., 2015). For example, if GFDL-ESM4 is used for wet and dry period analysis, it will lead to prolonged wet periods never observed in the historical record (compare the blue areas in GFDL-ESM4 and GPCC in Fig. 7).

Fig. 8 offers a more quantitative way of climate model biases by showing the MAE and RMSE (left) and the Taylor diagram (right) of CMIP6 precipitation simulations against ground-based observations across different climatic zones. This figure clearly shows model biases are lower in the arid regions (lower left in the left panel of Fig. 8), whereas biases are highest in the humid zone (upper right in left panel of Fig. 8). Recall from Fig. 6 that models overestimate precipitation in the hyper arid areas while they underestimate rainfall the humid zone. Fig. 8 offers quantitative information on the model overestimations/underestimations for each of the climate zones. This figure shows that mean absolute error of some of the models, such as CanESM5, in the

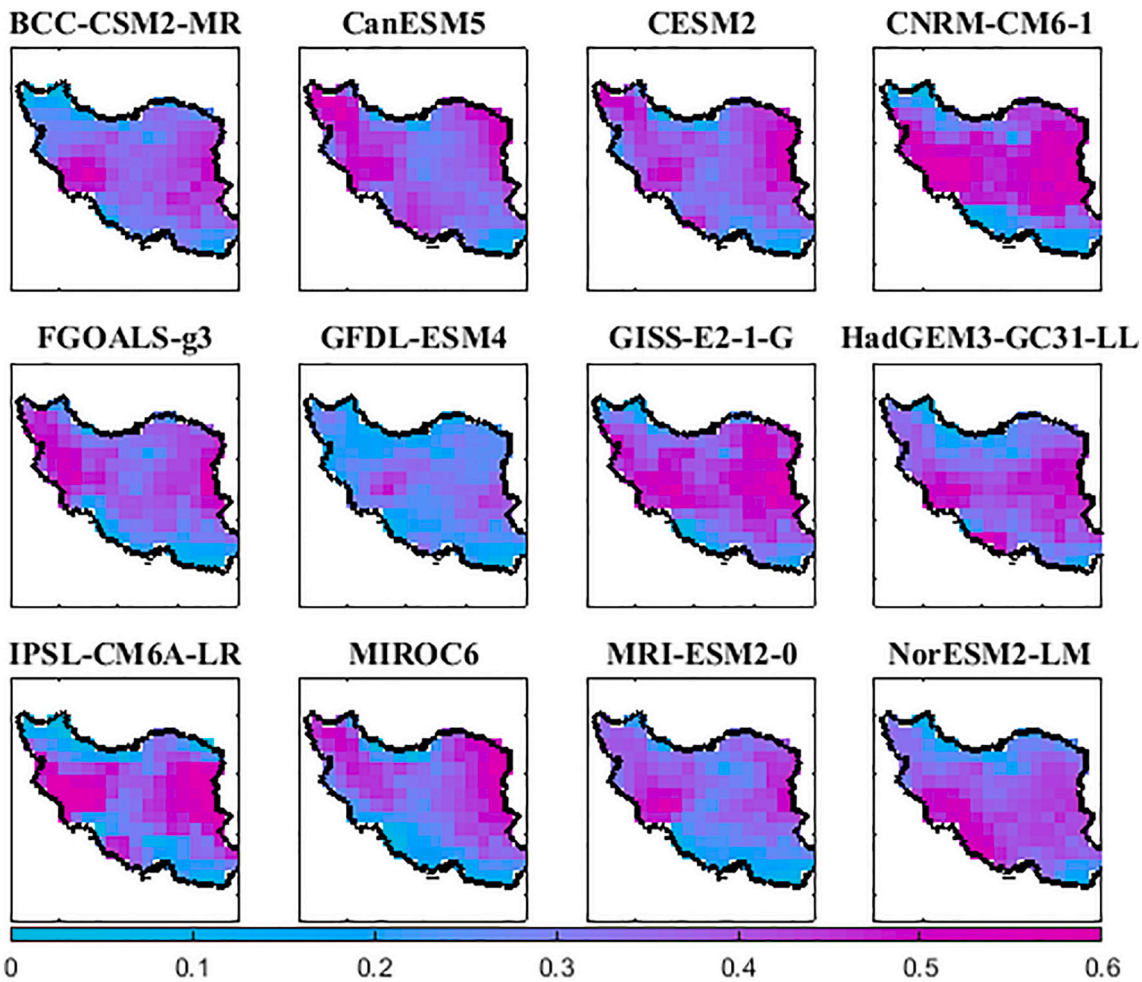

Fig. 4. Spatial maps of monthly correlation coefficient over the study area (1950–2014).

humid zone is nearly similar to the rainfall climatology of the region. The same model, however, offers the least error in the hyper arid zone. This indicates that for different applications using selected models based on regional performance may be more appropriate. Taylor diagram (Fig. 8 right panel) shows the normalized correlation coefficient (CC) along with the RMSE information. Here, the CC values were normalized to the range of zero to one for better visualization of differences (Suarez-Alvarez et al., 2012; Shi et al., 2018). The figure highlights not only large RMSE, especially in the humid zone, but also relatively low CC for some of the models such as FGOALS-g3 and MRI-ESM2-0.

4. Discussion and conclusions

In recent years, climate model simulations have become more accessible for research and assessment studies (Eyring et al., 2016). Reliable rainfall simulations are fundamental to both historical climate studies, and also future projections of water availability (Flato et al., 2013). However, model simulations are still highly uncertain, and a good understanding of the underlying errors and biases is critical before the simulations are used in climate assessment studies (Notz, 2015).

This paper evaluated the performance of 12 CMIP6 precipitation simulations over different climatic regions of Iran. In order to study the performance of the model simulations in space and time, we have conducted our analysis at monthly, seasonal and annual scales and also across individual climate zones and the entire country. The model simulations were evaluated against the ground-based GPCC data. A review of all the results indicate that the overall performance of CMIP6 models varies significantly across different climatic zone. While no model can be considered ideal, some models (e.g., CNRM-CM6-1 and MRI-ESM2-0) that performed relatively well in the humid zone, did not perform as well in the hyper arid zone. Conversely, HadGEM3-GC31-LL, BCC-CSM2-MR, and CanESM5 that relatively performed well in the hyper arid zone, did not perform as well in the humid zone.

Overall, all CMIP6 models showed less systematic biases in the arid zone, and elevated systematic bias (underestimation) in the rainiest (humid). Consistent with the previous CMIP6 studies (e.g., Liu et al., 2014), the performance of CMIP6 simulations vary substantially across seasons. For example, in the humid zone, almost all models systematically miss the summer precipitation, whereas in the arid zone most models reasonably simulate summer rainfall (Fig. 6).

The US Global Change Research Program (USGCRP (US Global Change Research Program), 2009) highlights that uncertainties in climate model simulations limit our ability to reliably project future projections for adaptation and mitigation studies. Characterization of biases in climate model simulations is hence a critical step for future model development and research studies. It is hoped that more efforts in this direction sheds light on capabilities of models for practical applications.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

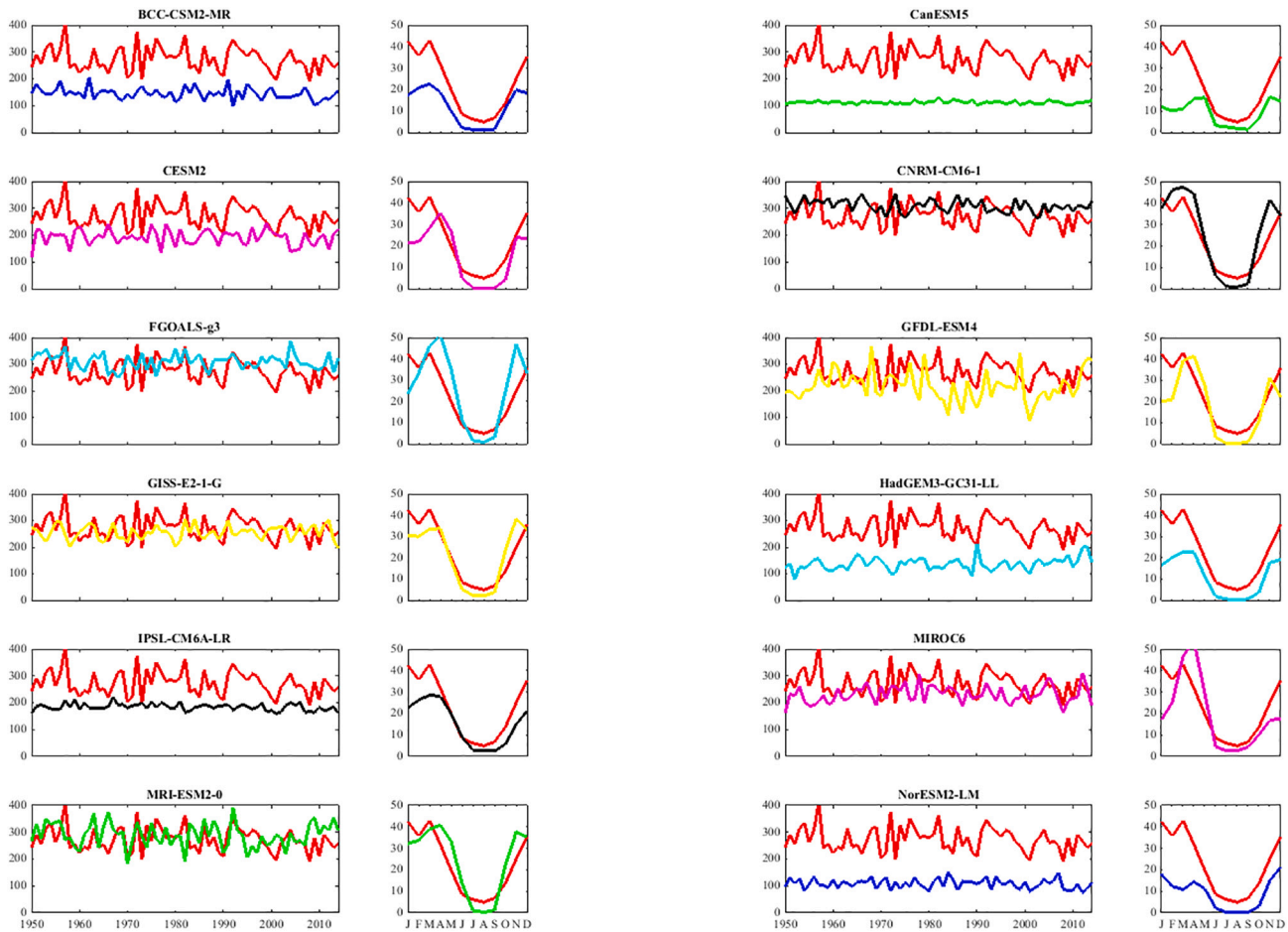

Fig. 5. Long-term observed GPCC and CMIP6 annual precipitation time series (1st and 3rd columns) and monthly climatology (2nd and 4th columns) spatially averaged over the study area (1950–2014).

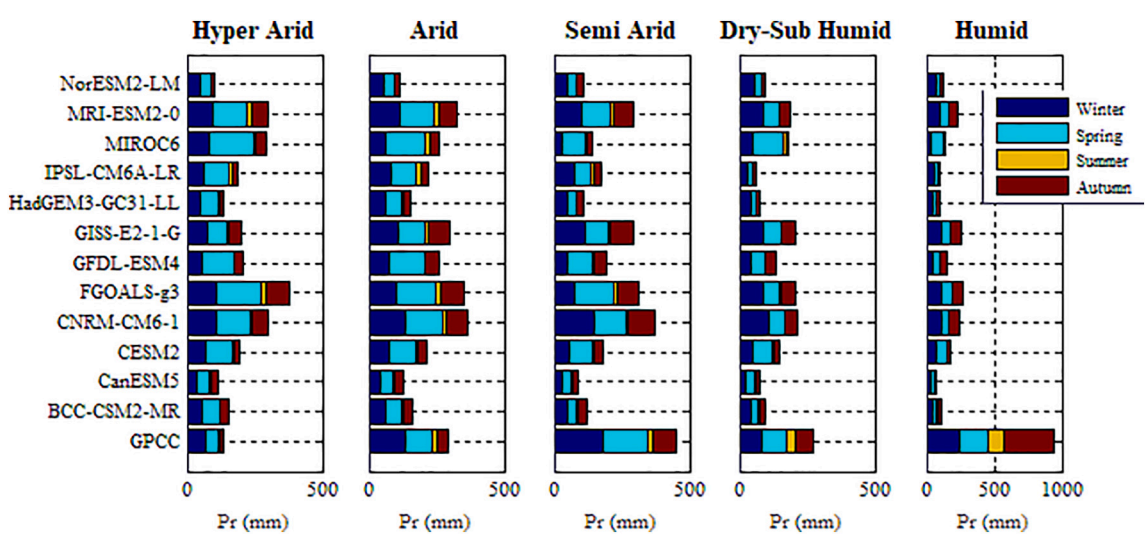

Fig. 6. Seasonal precipitation means based on observations (GPCC) and CMIP6 climate model simulations over the study area in different climatic zones (1950–2014).

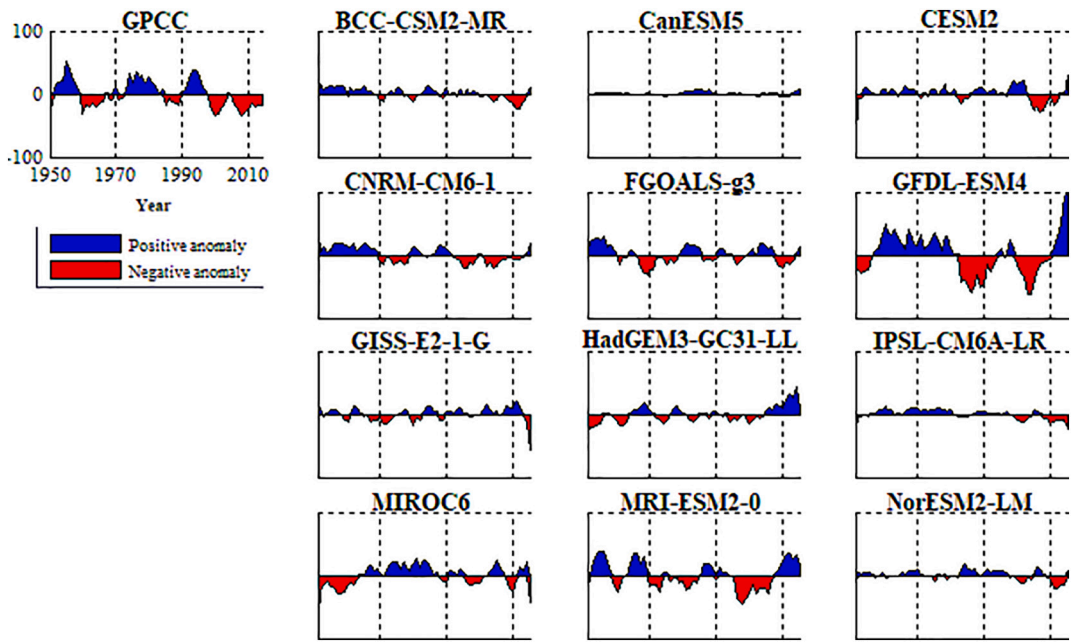

Fig. 7. Annual precipitation anomalies based on observations (GPCC) and CMIP6 climate model simulations over the entire study area (1950–2014).

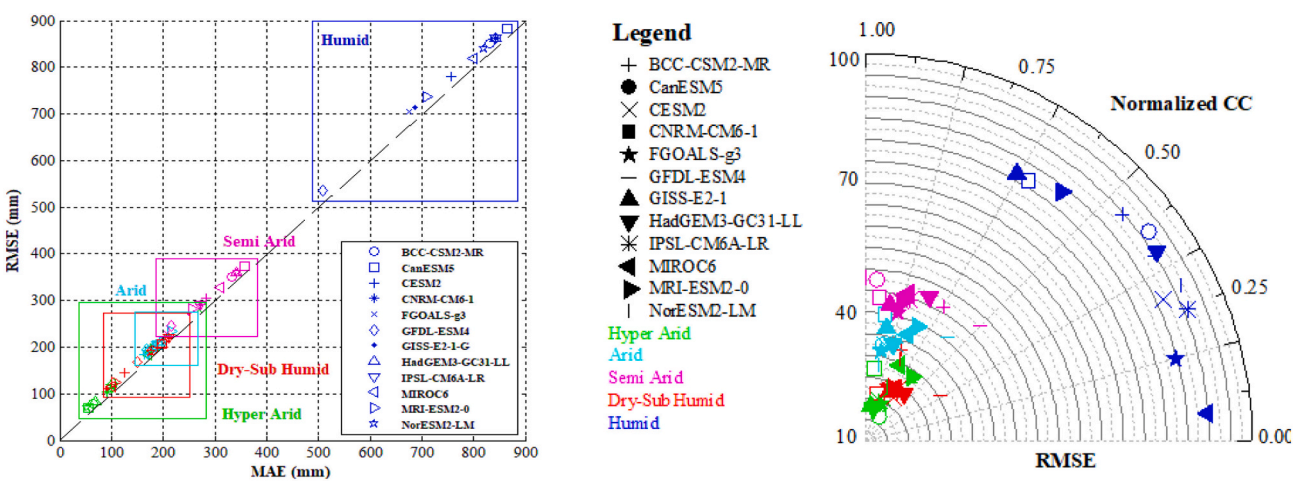

Fig. 8. (left) Annual MAE and RMSE and (right) Monthly Taylor diagram of CMIP6 precipitation simulations against ground-based observations across different climatic zones (1950–2014).

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