Evaluation of the performance of CMIP6 models in simulating precipitation over Morocco

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Abstract

Morocco is encountering record daily maximum temperatures, severe rainfall deficits, intense thunderstorms, droughts, and powerful wind gusts, causing significant harm to people and property. Therefore, it is crucial to understand the course of these occurrences and to determine to what extent the global climate models (GCMs) used to project climate can replicate rainfall before they can be used in downscaling or impact assessment studies. GCMs are essential tools for climate studies, but selecting the best-performing ones remains challenging. This study aims to assess the extent to which certain climate models from the Coupled Model Intercomparison Project's 6th phase (CMIP6) reproduce the spatial and temporal variability of precipitation across Morocco between 1981 and 2014. Total monthly precipitation from the Climate Hazards Group Infrared Precipitation with Station data (CHIRPS) were used as observational references. We used six robust statistical metrics on monthly and annual scales, including relative bias, correlation coefficient, root means square error, relative error, Taylor diagram, and Kling–Gupta efficiency. The outcomes demonstrated that the ability of GCMs to simulate precipitation varied over space and time. The spatio-temporal properties of precipitation were well reproduced by all GCMs, with correlation values ranging from 0.78 to 0.87. The research also revealed that only a few models accurately captured the spatial patterns of the detected trends. According to the KGE metric, the GCM INM_CM5_0 is ranked first among the models with the highest KGE value (0.45), followed by GCM FGOALS_f3_L with a value of around 0.41. The study results can be applied to climate projections using CMIP6 under different IPCC scenarios.

1 Introduction

Morocco's geographical position and geomorphological characteristics confer a remarkable range of bio-climates from humid and sub-humid to semi-arid and arid. The country is highly vulnerable to climate change due to its location in the Mediterranean, a climate change hot spot (Almazroui

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et al. 2020). Morocco is largely dependent on agriculture, fishing, and tourism, which are economic sectors already suffering the effects of climate change. In addition, there is a growing strain on the natural resources. Recent studies have shown the negative impact of climate change on socio-economic development (Ferreira Fernandes and Alves 2022), water resources (Schilling et al. 2020; Mounir et al. 2023), agriculture (Ouraich et al. 2019), forests (Ghazali et al. 2021; Ifaadassan et al. 2021), coastline (Aitali et al. 2020), biodiversity (El Morabet et al. 2019; Kassout et al. 2022), energy (Soares et al. 2019; Meir et al. 2022), extreme events (Karmaoui et al. 2021), water erosion (Alitane et al. 2022), and food security (Hall et al. 2017).

Changes in precipitation that would impact both its amount and spatio-temporal distribution could reduce water supply and availability and have severe socioeconomic consequences (Tume 2021). In recent decades, several studies have assessed the impact of climate change on precipitation in Morocco. These studies focused on

the spatio-temporal variation of rainfall and the occurrence of droughts. The results showed that precipitation would decrease over most territories by 2050 (Filahi et al. 2017; El Asri et al. 2019; Lachgar et al. 2022). However, the degree of its reduction will vary from one region to another. Contrary to most studies that pointed to an expected precipitation decrease under the different climate scenarios, those of Kessabi et al. (2022) and Huebener and Kerschgens (2007) indicated increased precipitation over parts of Morocco. The difference in predicting precipitation frequency and magnitude between models raises questions about the accuracy of the climate model used.

Global climate models (GCMs) are fundamental for studying global climate change and its short-, medium-, and long-term consequences (Ahmadi and Azizzadeh 2020). They are used to simulate the past climate and project future climate under different anthropogenic greenhouse gas emissions scenarios (Fajardo et al. 2020). These models are continuously evaluated to improve their performance and reliability (Zhao et al. 2020) and to implement the most appropriate adaptation and mitigation measures to address the repercussions of climate change (Shiru and Chung 2021). However, GCMs simulations are not perfect, and are associated with uncertainties arising from initial conditions, internal model variability forced by the governing equations, and the characterization of the land surface processes within the spatio-temporal resolution of the model, which limits the use of GCMs for reliable climate projections at all spatial and temporal scales. Given these constraints, selecting an appropriate subset of GCMs remains challenging for any climate change impact assessment. Over time, considerable efforts are being made to improve GCMs (Meher et al. 2017). The Coupled Model Intercomparison Project (CMIP) is a World Climate Research Program (WCRP) project established more than 20 years ago to promote international cooperation among climate modeling centers (Eyring et al. 2016). Numerical climate simulations from CMIP feed into numerous scientific projects for understanding mechanisms and evaluating models and multidisciplinary impact studies and serve as a reference for IPCC reports. Each phase of this program, thus, advances the knowledge base on climate, particularly its probable evolution, a base on which policies are formed (Stockhause and Lautenschlager 2022). These simulations also feed into the emerging climate services (Kulkarni and Huang 2014). The current phase, CMIP6, started in 2014 following the publication of the IPCC 5th Assessment Report. More than 20 climate modeling centers were involved in many countries and used for the IPCC 6th Assessment Report published in April 2022. Approximately 200 targeted "numerical experiments" make up CMIP6 and aim to answer various scientific questions (Juckes et al. 2020). Modeling centers improve their climate models and perform these experiments before making the results available to researchers worldwide (Juckes et al. 2020). With the advancement of understanding about climatic processes and the availability of increasingly precise terrestrial and atmospheric data and information, GCMs simulation abilities have increased over time (Hadipour et al. 2022).

In the 6th phase, scientists minimized biases, improved spatial resolution, and simulated climate processes by incorporating additional terrestrial components such as ice sheets and biogeochemical cycles (Eyring et al. 2019). As a result, GCMs from the most recent CMIP6 project typically offer a better estimate of the climate than their prior iterations from older CMIP projects (Chen et al. 2021). Despite improvements, simulating climate in all regions remains challenging for GCMs (Chen et al. 2019). Several researchers have shown interest in evaluating the performance of CMIP6 models, comparing simulation results with available observational data. Yang et al. (2021) evaluated temperature and precipitation in China under 20 GCMs from CMIP6 and concluded that the GCMs provided satisfactory results, producing spatial distributions of temperature and precipitation. Nie et al. (2020) evaluated the capacity of CMIP6 to generate more precise assessments of the amplitude of global temperature extremes. Iqbal et al. (2021) used 35 CMIP6 models in Southeast Asia to evaluate their ability to simulate precipitation. The findings showed that most GCMs could replicate changes in local precipitation with some degree of accuracy. Rivera and Arnould (2020), through a study conducted in southwestern South America, demonstrated the ability of CMIP6 models to simulate precipitation decline and drought. Babaousmail et al. (2021) evaluated how well the CMIP6 models performed in simulating the spatial and temporal variability of precipitation across North Africa and discovered that they satisfactorily simulated the climatology. The models selected in the above publications are all different, clearly showing the spatial and temporal complexity of climate conditions and the need to identify the most effective models for each region of the world.

This study aims to evaluate the performance of nine CMIP6 models to reproduce the temporal and spatial characteristics of monthly and annual precipitation over Morocco. Due to the lack of robust and homogeneous observation datasets over the country, high-resolution gridded data analysis was necessary. This study will provide a scientific reference for future climate change projections over Morocco. The best-performing models will be used to examine possible future climate patterns, decision-making, resource planning and management,

development of robust adaptations, and to implement sound sustainable development policies.

## 2 Materials and methods

2.1 Study area

Morocco is located in the northwest of Africa between latitudes 21°N to 36°N and longitudes 1°W to 17°W. It is bordered by the Atlantic Ocean from the west and the Mediterranean Sea to the north. Its entire eastern border is continental (Fig. 1). Thanks to its great latitudinal extension, it benefits from an important maritime facade on the Atlantic Ocean (2934 km) and 512 km on the Mediterranean Sea. The Moroccan territory covers an area of 710.850 km².

From the geomorphological point of view, Morocco has a remarkable topography reaching about 4106 m above the mean sea level (MSL) at the summit of the High Atlas, which makes it possible to hold snow past springtime.

The country is located between temperate low-pressure systems and the Azores subtropical anticyclone, which conditions weather events (Tatlı and Türkeş 2014). It is a transition zone between two major climate regimes, the temperate climate regime on the one hand and the tropical climate regime on the other (Zhao et al. 2019). It is also characterized by important variations in its regional climates. Indeed, the Moroccan climate comes in various shades, including oceanic in the west, continental in the interior, Mediterranean in the north, and Saharan in the south. The climate is also affected by seasonal changes, with a hot and dry summer with virtually no precipitation and high potential evaporation and a mild winter on the coastal strip, cold inland, on the Atlas Mountains, the Rif, and the highlands of the Oriental region. The configuration of the relief strongly modulates the climate of Morocco: erratic rainfall, cold temperatures, heat waves,

Fig. 1 Map of Morocco showing the elevations, bordering countries, and grid points centroids 1°×1° considered in the analysis
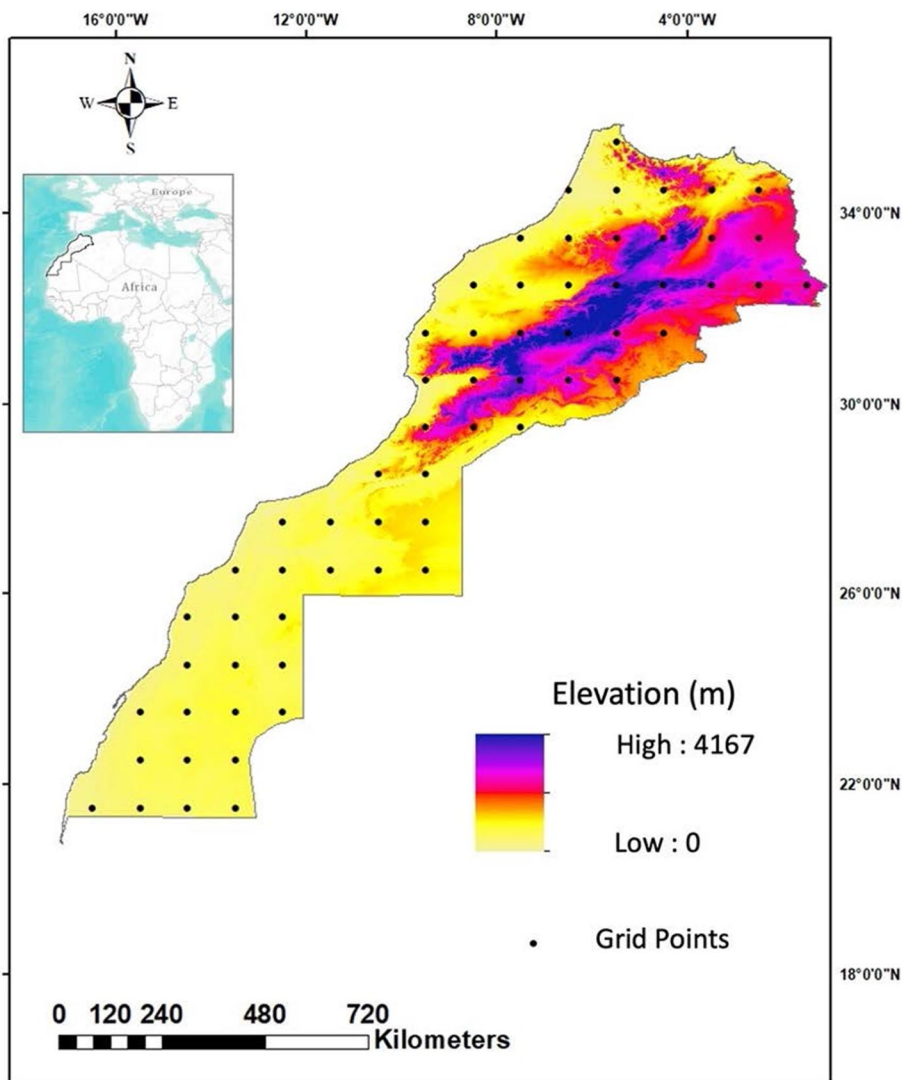
and unpredictable droughts, which became more frequent (Ezzine et al. 2014), all of which affected the economic and social life of the country.

In terms of rainfall, there is a high spatio-temporal and interannual variability across the country's different regions. The average annual rainfall is about 100 mm in the south to 1200 mm in the northwest, with two seasonal peaks, winter and spring, depending on the region. This amount gradually decreases in the west-to-east gradient to reach less than 200 mm in the Oriental region. In Morocco, snowfall regularly occurs from November to March at elevations above 1500 m, and it is common for snow cover to last for several months above 2500 m (Marchane et al. 2015). The amount of snow varies significantly yearly, mirroring the interannual variation in the local climate. In Morocco, however, agriculture predominantly occurs in low-altitude plains, which generally offer fertile soil and favorable climatic conditions, including adequate water availability from rivers or groundwater sources, essential for crop growth. The relatively flat terrain facilitates efficient irrigation systems, enabling effective water management and distribution to the fields.

In addition, low-altitude plains often have better accessibility for transportation and infrastructure development and allow for easier distribution of agricultural products to markets. Moreover, the lower altitudes typically experience milder temperatures than higher elevations, reducing the risk of frost and snow damage and providing longer growing seasons conducive to a wider variety of crops. Overall, these factors contribute to the preference for low-altitude plains as primary agricultural areas in Morocco and make the CHIRPS rainfall data an excellent proxy relevant to our study. The performance of CHIRPS data in plains compared to high mountains is also discussed in Bai et al. (2018).

Water resources, characterized by their scarcity and spatial and temporal irregularity, are subject to increasing pressure from population growth, expansion of irrigated agriculture, urban expansion, as well as industry and tourism development. The tremendous regional disparity of precipitation induces a significant spatial variation of surface water runoff (Bouizrou et al. 2022). The surface water resources are produced at 51% at the level of four watersheds, which cover 7.1% of the country's area. In addition, the overexploitation of groundwater resources, an exploited volume of 4.3 billion m^3 against an exploitable volume of 3.4 billion m^3, generates an annual deficit of nearly 1 billion m^3, especially in the basins of Oum Er Rbia, Souss-Massa-Drâa, Tensift, Sebou, and Bouregreg (MFNC 2021).

2.2 Data

Observed data at local weather stations have several gaps in both temporal and spatial dimensions. Thus, we used high-resolution precipitation datasets as a surrogate for observed data. The datasets are from the Climate Hazards Group Infrared Precipitation corrected with Station data (CHIRPS) (Funk et al. 2015). CHIRPS 2.0 is a near-global precipitation dataset developed by the Climate Hazards Group at the University of California, Santa Barbara, and experts at the U.S. Geological Survey Earth Resources Observation and Science Center. CHIRPS is a satellite precipitation dataset combined with rainfall from ground-based weather stations. The corrected final product is at a spatial resolution of 0.05° × 0.05°. CHIRPS

Table 1 CMIP6 GCMs assessed in the study

Model	Institution	Country	Resolution (latitude × longitude)	Doi
CNRM-CERFACS -CM6-1-	Centre National de Recherches Metéorologiques; Centre Europeen de Recherche et de Formation Avancée en Calcul Scientifique	France	0.5 × 0.499	10.22033/ESGF/CMIP6.1387
FGOALS-f3-L	Chinese Academy of Sciences	China	1.25 × 1	10.22033/ESGF/CMIP6.3054
CMCC-CM2-SR5	Fondazione Centro Euro-Mediterraneo sui Cambiamenti Climatici	Italy	0.942 × 0.942	10.22033/ESGF/CMIP6.13230
E3SM-1–0	Lawrence Livermore National Laboratory	United States	1 × 1	10.22033/ESGF/CMIP6.2294
CAMS-CSM1-0	Chinese Academy of Meteorological Sciences	China	1.121 × 1.121	10.22033/ESGF/CMIP6.11004
EC-Earth3-Veg	EC-Earth Consortium	Europe	0.701 × 0.701	10.22033/ESGF/CMIP6.727
TaiESM1	Research Center for Environmental Changes, Academia Sinica	Taiwan	1.25 × 0.942	10.22033/ESGF/CMIP6.9702
INM-CM5-0	Institute for Numerical Mathematics, Russian Academy of Science	Russia	2 × 1.5	0.22033/ESGF/CMIP6.5081
BCC-CSM2-MR_esm	Beijing Climate Center	China	1.125 × 1.121	10.22033/ESGF/CMIP6.2901

is a new quasi-global (50°S–50°N) daily and monthly precipitation estimation product, available from 1981 to the present (Funk et al. 2014). Several satellite data have been combined to create CHIRPS. These data are Climate Hazards Precipitation Climatology (CHPClim), which are in the form of high spatial resolution (0.05°) derived from the combination of satellite observations, average precipitation weather stations and rainfall forecasts (Funk et al. 2014); thermal infrared satellite data from two NOAA sources, the National Climatic Data Center (NCDC) and the Climate Prediction Center (CPC), which extract thermal infrared data from various geostationary satellites Meteosat-5, Meteosat-7, GOES-8, GOES-10, GMS-5 (Sun et al. 2018), as well as passive microwave observations (from NOAA-15, NOAA-16, and NOAA-17); precipitation data from NASA's Tropical Rainfall Measuring Mission (TRMM); precipitation fields from NOAA's Climate Prediction System atmospheric model (CFSv2 version); and in situ precipitation observations obtained from various weather stations (Funk et al. 2015). Due to their high resolution and capacity to capture the effects of topography and local features, the CHIRPS datasets were determined to have sufficient accuracy over the research area compared to other satellite datasets (Tramblay et al. 2021). However, it is worth noting that CHIRPS, due to its limited capability in detecting snowfall, performs better in plain areas compared to high mountains (Bai et al. 2018).

CHIRPS satellite rainfall data were extracted from the CHIRPS website (https://www.chc.ucsb.edu/data/chirps).

We also used historical monthly precipitation simulations from nine GCMs from the CMIP6, accessible online from the Earth System Grid Data Portal (https://esgf-node.llnl.gov/search/cmip6). The models selected under this study are high resolution and have produced at 50 km, 70 km, and 100 km nominal resolution described in CMIP6 attributes. Specific information about the selected GCMs is presented in Table 1. This analysis uses data from the gridded observational datasets from 1981 to 2014 to maintain consistency.

2.3 Methodology

This paper evaluates the performance of nine GCMs in simulating precipitation data against observed data from CHIRPS over the period 1981–2014 at monthly and annual scales. To unify the different resolutions, the GCMs and the observed data were resampled to $1° \times 1°$ grids using the bilinear interpolation approach, a technique often used to analyze GCMs output worldwide (Ahmed et al. 2019b; Hadipour et al. 2022).

First, the annual average was generated based on the monthly precipitation series from observations and model outputs. Then the GCMs were evaluated by examining their ability to reproduce the observed precipitation. To assess the spatio-temporal performance of each model, several statistical metrics were calculated, including the pattern correlation coefficient (PCC), mean monthly bias (MMB), root mean square error (RMSE), standard deviation (SD), The Pearson correlation coefficient, Taylor diagram, and the robust Kling–Gupta efficiency (KGE) metric for classification of the different models. More details on the empirical approaches and equations used are given below.

The PCC was calculated to compare the spatio-temporal simulation abilities of GCMs with the CHIRPS data. The PCC ranges from -1 to 1, with values closer to 1 indicating a greater ability of the GCMs to capture the spatio-temporal patterns of the observed series over the region. The equation used to compute the PCC is given below.

$$PCC = \frac{\sum_{i=1}^{n}\left(X_{simi} - \overline{X_{sim}}\right)\left(X_{obsi} - \overline{X_{obs}}\right)}{\sqrt{\left[\sum_{i=1}^{n}\left(X_{simi} - \overline{X_{sim}}\right)^2 \sum_{i=1}^{n}\left(X_{obsi} - \overline{X_{obs}}\right)^2\right]}} \quad (1)$$

where $X_{sim\,i}$ and $X_{obs\,i}$ are the particular GCM and observed data at the i grid point, respectively, and the overbars refer to the mean value over the n grid points.

The MMB represents the tendency of the models to overestimate or underestimate observed data by subtracting the means of the GCMs from CHIRPS observations. A model is considered to perform well when the values are close to zero. The evaluation of the MMB is performed as follows:

$$MMB = \frac{1}{n}\sum_{i=1}^{n}\left(X_{simi} - X_{obsi}\right) \quad (2)$$

where n represents the number of observations, $X_{obs\,i}$ is the mean precipitation value acquired from the CHIRPS observation dataset; $X_{sim\,i}$ represents the mean precipitation value obtained from particular GCM precipitation data.

The RMSE provides a good measure of accuracy by measuring the magnitude of errors in the predictions for different times. Smaller RMSE values that tend toward zero indicate a stronger model performance (Komaragiri et al. 2017). In this study, RMSE was calculated using:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\left(X_{simi} - \overline{X_{sim}}\right) - \left(X_{obsi} - \overline{X_{obs}}\right)\right)^2} \quad (3)$$

where n represents the number of observations, $X_{sim\,i}$ is the value obtained from the particular GCM precipitations data, $\overline{X_{sim}}$ is the average of the simulated values, $X_{obs\,i}$ stands for the ith observed value from the CHIRPS, and $\overline{X_{obs}}$ is the average of the observed values.

The standard deviation is a parameter that measures the degree of dispersion of two sets of data of similar size and approximately the same mean. A low standard deviation implies that the values are around the mean, while a high standard deviation indicates that the values are scattered. Equation (4):

$$SD = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(X_i - \overline{X})^2} \qquad (4)$$

where n stands for the shape of the set, Xi is the i th value, and $\overline{X}$ is the set's average.

The Pearson correlation coefficient measures the strength of the linear relationship between the CHIRPS data and the simulated data. The correlation coefficient R can vary between -1 and $+1$. The approach is to compare the distance of each data point with the mean of the variable and determine the extent to which the relationship of the variable follows an imaginary line. The equation adopted to calculate the R is given below (Eq. (5)).

$$R = \frac{\frac{1}{n}\sum_{i=1}^{n}\left[\left(X_{obsi} - \overline{X_{obs}}\right)(X_{simi} - \overline{X_{sim}})\right]}{\partial_{obs}\partial_{sim}} \qquad (5)$$

where ∂ is the SD.

A goodness-of-fit test is also used to evaluate the spatial performance of GCMs. The KGE is developed by Gupta et al. (2009). It considers three statistical measures: Pearson correlation, variability ratio, and bias ratio. KGE values can range from $-\infty$ to 1, with optimal values near 1, Eq. (6).

$$KGE = 1 - \sqrt{(r-1)^2 + (\beta-1)^2 + (\gamma-1)^2} \qquad (6)$$

In Eq. (6), r is the Pearson correlation between observed and GCM data, β is the bias ratio, and γ is the variability ratio (Gupta et al. 2009).

We also used the Taylor diagram to visualize Pearson correlation, RMSE, and SD to explicitly summarize the degree of correspondence between simulated and observed precipitation. In the Taylor diagram, these parameters are indicated by a single point on a 2D graph (Taylor 2001). The angular coordinate shows the Pearson correlation coefficient, the radial coordinate plots the SD, and the concentric half-cycle shows the RMSE difference.

3 Results and discussion

We calculated the mean annual precipitation over the research area using the monthly precipitation data from CHIRPS. The spatio-temporal distribution of annual precipitation from 1981 to 2014 is depicted in Fig. 2. The CHIRPS dataset showed a striking spatial distribution of precipitation, where the northwestern part of the region is the rainiest, with a mean annual reaching 1100 mm/year. At these latitudes, precipitation is closely related to the values of the North Atlantic Oscillation (López-Moreno et al. 2011). Also, the results showed that the precipitation decreases from north to south and west to east and is concentrated around the Rif and Atlas Mountains. The minimum precipitation is recorded in the southern regions, well under 170 mm/year. These results are consistent with Hanchan and Bijou (2018), who pointed out the dependence of the total annual precipitation on geographical location, indicating its increase from south to north and decrease from west to east.

Since Morocco is characterized by a diverse climate with a wide range of precipitation variations, we were primarily interested in the models' ability to capture the observed spatio-temporal precipitation variation. The spatio-temporal map of mean annual precipitation from GCMs simulations is presented in Fig. 3. The results showed that all models underestimated the mean annual precipitation, except for the CNRM-CERFACS-CM6-1-HR model, which showed a clear overestimation, especially in the northwestern region where the highest annual precipitation is observed. The performance of the CNRM-CERFACS-CM6-1-HR model is similar to what was reported in a recent study by Babaousmail et al. (2021) over northern Africa, in which the model overestimated precipitation compared to all other models. On the other hand, all the GCMs showed similar spatial distribution of precipitation and its dependence on geographical position and elevation. The lowest mean annual precipitation is recorded over the arid southern regions of Morocco, while the highest is recorded over the northern parts. Therefore, no GCMs have captured the effect of continental location and the effect of altitude in the High Atlas in central Morocco.

The spatio-temporal performance of each GCM against the CHIRPS dataset in simulating rainfall over the region was further assessed by statistical metrics, including PCC and MBB (Table 2). All GCMs showed a positive PCC with the observed patterns. The CNRM-CERFACS-CM6-1-HR model showed the highest correlation of 0.87, while the four models showed a lower but still robust correlation of 0.78. Most other models were centered around a correlation coefficient of 0.79. The estimated MMB shows the existence of significant biases between GCMs simulations and CHIRPS observations over Morocco (Fig. 4). Also, seven GCMs indicated a negative precipitation bias over the region. We note that the CNRM-CERFACS-CM6-1-HR model showed a moderate positive bias over the whole country, and the E3SM1-0 model showed a positive monthly bias in the south and northeast. In contrast, all other models showed negative biases over the entire country, reaching an amount of 100 mm/month in some areas.

Figure 5 shows the annual cycle of the monthly precipitation averages over the period 1981–2014. Each month's value
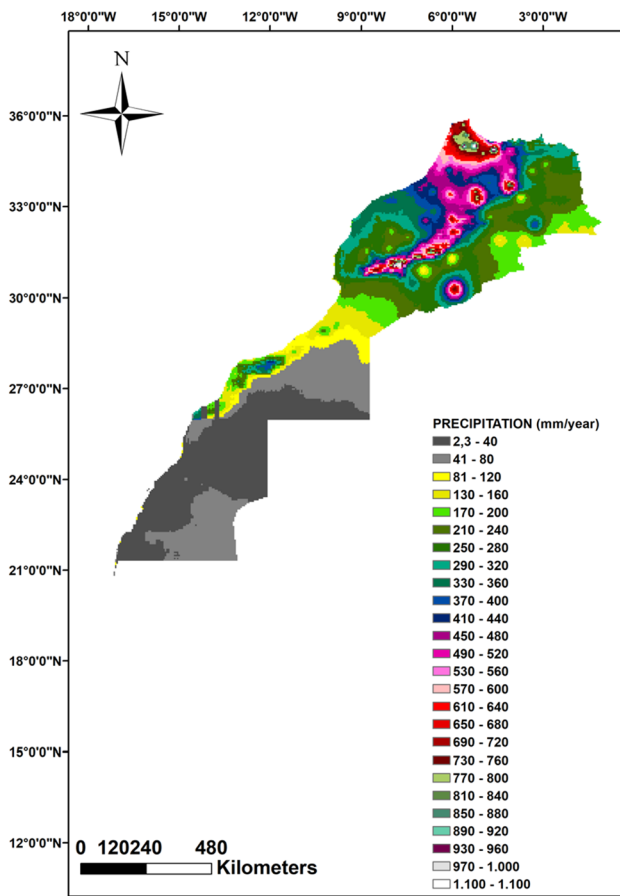
Fig. 2 CHIRPS mean total annual precipitation calculated over the period 1981–2014

is the temporal mean over 30 years for GCMs outputs and CHIRPS data. The CHIRPS data show climatological mean monthly precipitation ranging from 2 mm in July to 32 mm in December, with a well-marked fall rainy season showing a maximum increase between October and November. December marks the peak of the rainy season, followed by January, after which a gradual decrease in monthly precipitation is observed until July. Although there were large differences in monthly precipitation, all CMIP6 models captured the seasonal cycle except the CNRM-CERFACS-CM6-1-HR model, which generated maximum precipitation in October. However, most models underestimated the monthly rainfall over the study area, except the CNRM-CERFACS-CM6-1-HR and E3SM1-0, which overestimated the monthly precipitation throughout the year. Furthermore, in line with observations, all models have a good convergence for the dry months of June, July, and August, where little or no precipitation is recorded.

We also evaluated the GCMs simulation performance using Taylor's diagram, which quantitatively measures the correspondence between simulated and observed patterns in terms of spatial correlation coefficient, RMSE, and standard deviation ratio. The Taylor plot was used for both monthly and annual precipitation over the period 1981–2014. Figure 6 shows the Taylor diagram for monthly precipitation based on CMIP6 models and CHIRPS observations. The analyses revealed that the CNRM-CERFACS-CM6-1-HR and E3SM1-0 models show very high spatial variability compared to the CHIRPS data with a high standard deviation value. The CAMS-CSM1-0, FGOALS- f3-L L, INM-CM5-0 models showed close agreement in terms of precipitating spatial variability with respect to CHIRPS, while the BCC-CSM2-MR_esm, CMCC-CM2-SR5, EC-Earth3-Veg, TaiESM1 presented
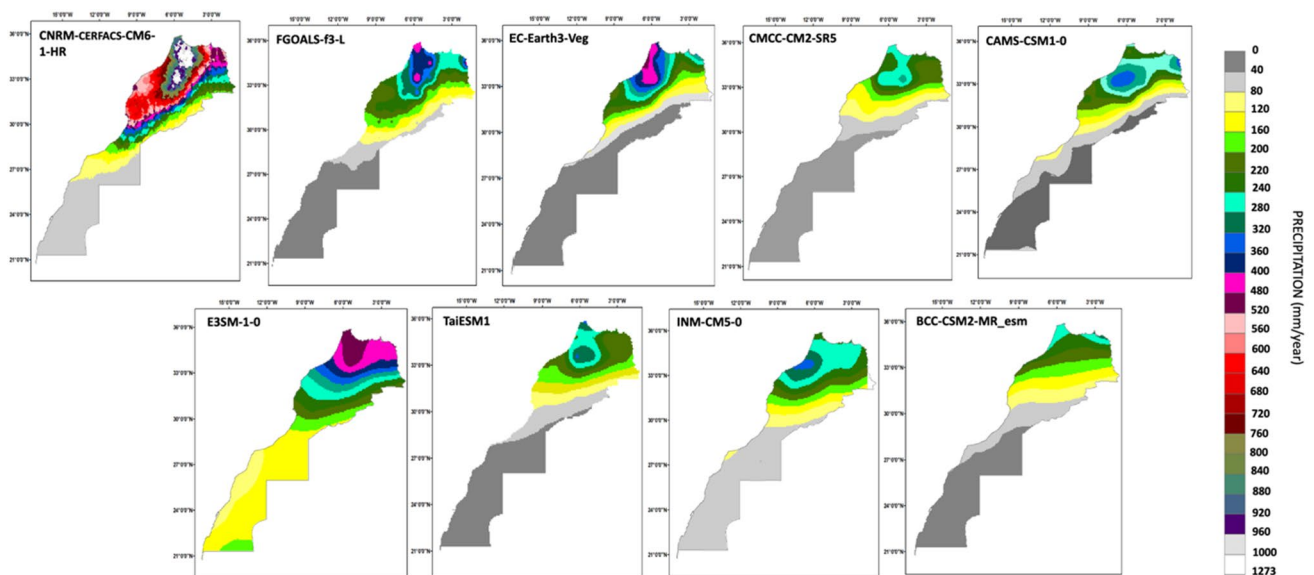

Fig. 3 Spatial distribution of mean annual precipitation from the GCMs over the study area (1981–2014)

Table 2 Summary of GCMs performance for monthly precipitation against CHIRPS data over Morocco during 1981–2014

	MBB			STD DEV	PCC
	Mean	Max	Min		
CNRM-CERFACS-CM6-1-	2.23	8.12	− 37.80	3.80	0.87
FGOALS-f3-L	− 7.38	6.77	− 128.28	10.09	0.78
CMCC-CM2-SR5	− 18.83	7.18	235.98	18.61	0.79
E3SM-1-0	1.92	7.99	− 25.06	4.38	0.80
CAMS-CSM1-0	− 8.52	8.08	− 208.88	17.50	0.78
EC-Earth3-Veg	− 30.40	6.94	− 373.48	36.09	0.79
TaiESM1	− 11	6.38	− 123.06	13.25	0.81
INM-CM5-0	− 3.06	7.87	− 62.48	7.41	0.78
BCC-CSM2-MR_esm	− 11.06	7.50	− 88.77	10.03	0.78

a minimal variability compared to the CHIRPS observation. Furthermore, all models have a correlation ratio between 0.55 and 0.73. The CNRM-CERFACS-CM6-1-HR model has the lowest correlation ($r = 0.55$), and the TaiESM1 model has the highest ($r = 0.73$). In terms of centered RMSE, GCMs BCC-CSM2-MR_esm, CMCC-CM2-SR5, EC-Earth3-Veg, and TaiESM1 showed good performance, which is reflected in a low centered RMSE value of less than 600. The correlation coefficients obtained were satisfactory, but the standard deviation and RMSE values were farther apart for the GCMs than for the CHIRPS observations. Also, a higher standard

deviation reflects high extreme precipitation events (Atto-gouinon et al. 2020; Kamruzzaman et al. 2021).

Indeed, the evaluation of the spatial simulation of annual precipitation showed poor performance for all models (Fig. 7), with five models showing negative linear correlations, suggesting that when precipitation increases, these models simulate a reduction (Gadain and Libanda 2023). The positive correlation decreases to values between 0.01 and 0.25 for the CAMS-CSM1-0, INM-CM5-0, TaiESM1, and EC-Earth3-Veg GCMs and varies from 0.1 to 0.3 negatively for the FGOALS-f3-L, CNRM-CERFACS-CM6-1-HR, E3SM1-0, CMCC-CM2-SR5, BCC-CSM2-MR_esm GCMs. The spatial simulation refers to how well the model captures the observed spatial patterns of precipitation, such as the location and intensity of rainfall or snowfall across different regions. These results on the spatial simulation performance of GCMs at an annual scale are comparable to those obtained by Ongoma et al. (2019) in a study of 22 CMIP5 GCMs with the observed CRU data over equatorial East Africa from 1951 to 2005. Indeed, the Ongoma et al. (2019) study revealed that the correlation obtained between GCMs simulated monthly precipitation is positive and satisfactory, while the interannual spatial correlation is low, ranging from 0.01 to 0.24, with 10 GCMs showing negative correlations.

To assess the ability of each model to reproduce the spatial patterns of annual precipitation, we used the robust KGE spatial assessment measure. The power of KGE is due to its multiple components, expressed by Eq. (6). Figure 8 shows the heatmap of KGE results for each GCM for each year. For
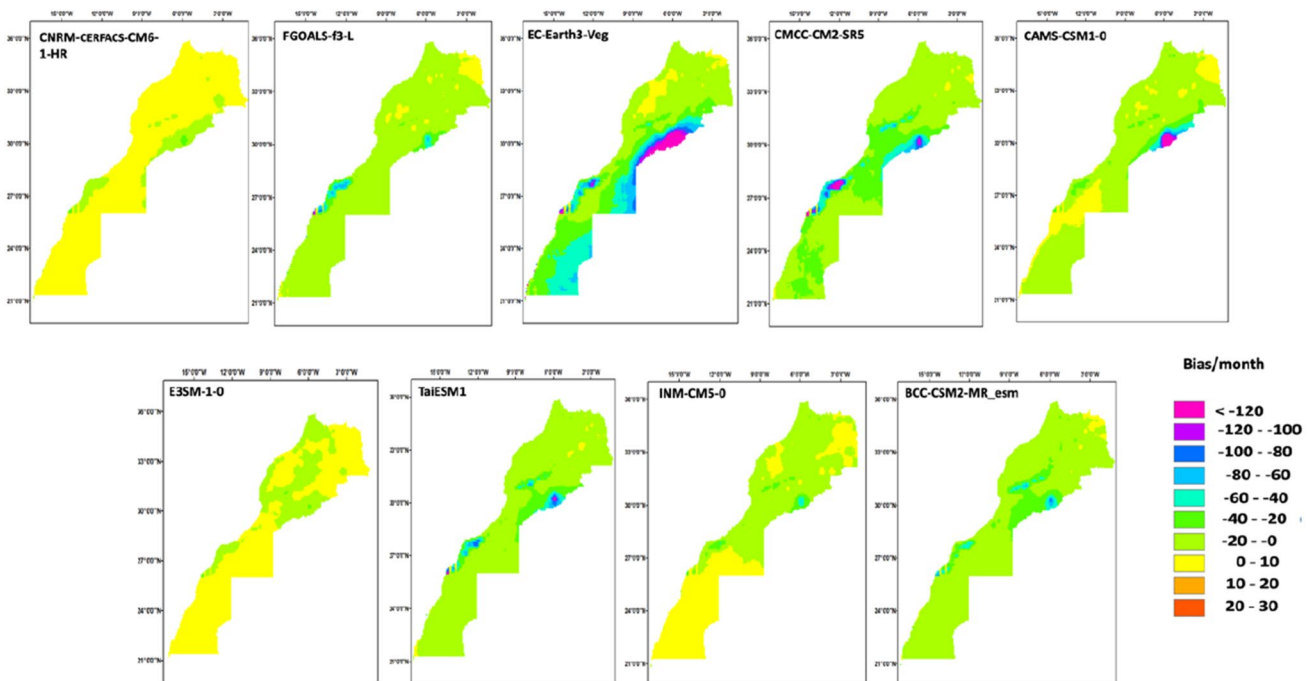
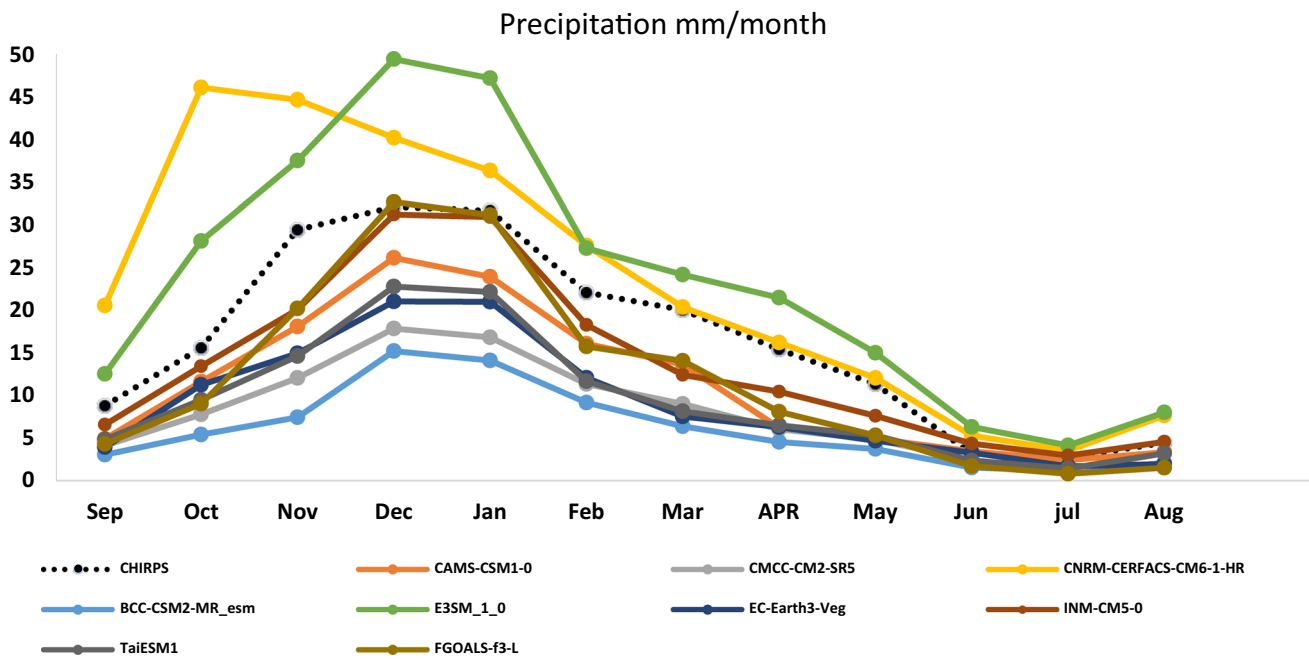**Fig. 4** Spatial distribution of monthly bias over the study area (1981–2014)

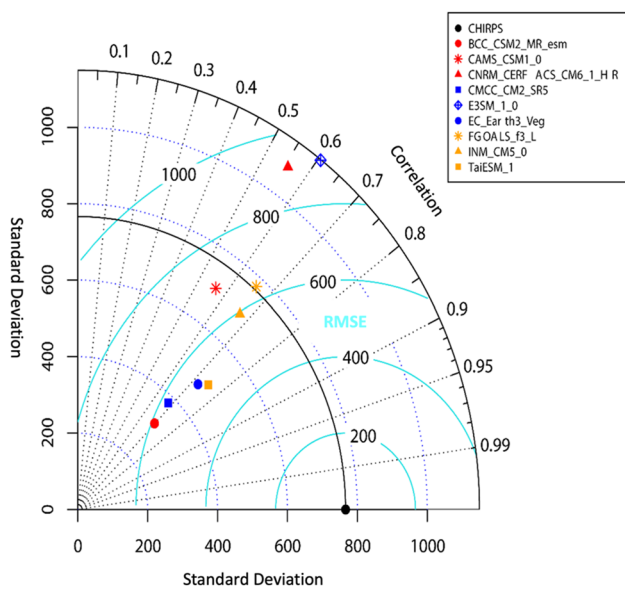**Fig. 5** Annual cycle of monthly precipitation for the period 1981–2014 over the study region

Fig. 6 Taylor diagram of monthly precipitation (1981–2014) over the study area

classes. The algorithm classifies GCMs based on two objectives: the variance of KGE within a class is the lowest, and the variance of mean KGE of different classes is the maximum. The JO classifies data into relatively few categories and allows easy selection of the GCMs subset (Hamza et al. 2019).

Their performance was acceptable, with a high average KGE varying between 0.45 and 0.023, as shown in Table 3. The results showed that the obtained KGE values range between 0.023 and 0.45. The highest KGE of 0.45 is recorded by the INM_CM5_0 model, followed by the FGOALS_f3_L with an average KGE of about 0.41, E3SM1-0 presented the lowest KGE of 0.023. These results align with the findings of Magdy et al. (2021), who estimated the KGE of CMIP6 models between 0.48 and 0.6 for Southeast Asia. Similarly, our results are consistent with those of Nashwan and Shahid (2022), who obtained mean KGEs for annual precipitation, winter, and summer precipitation of 0.21, 0.34, and -6.73, respectively. According to Moon et al. (2018), the poor performance of the models in estimating monthly and annual scale precipitation may be due to the drizzle problem that exists in all climate models as well as in the CMIP6 and CMIP5 GCMs, which produces a significant bias in arid environments.

The analysis of the spatio-temporal trends of annual and monthly precipitation over Morocco showed that the CNRM-CERFACS-CM6-1-HR and the E3SM-1-0 are the most performant with minimal bias, while spatial trends remain a challenge at the annual scale with average correlations. Some GCMs, such as INM_CM5_0, FGOALS_f3_L, and TAIESM, can track and reproduce the spatial trends observed from KGE
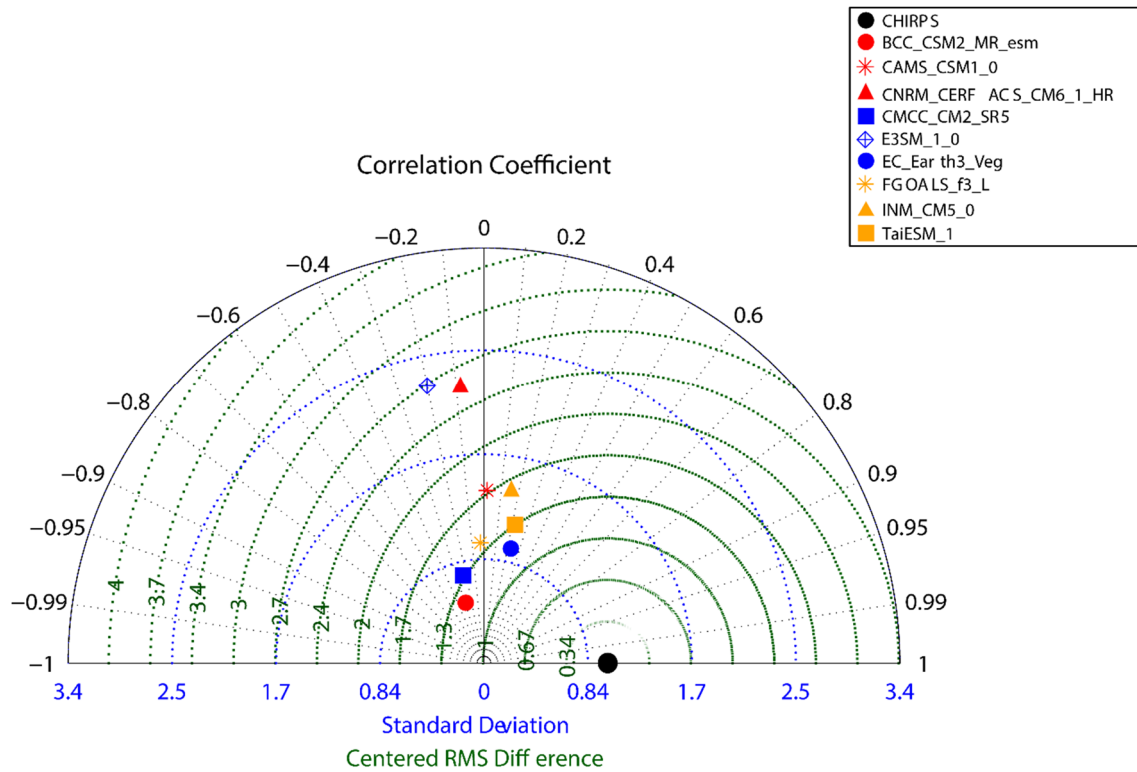
all GCMs, the KGE values vary from − 3 to 1. The Jenks optimization (JO) algorithm was used to rank the GCMs according to the KGE values (Jenks 1967). Jenks optimization is a statistical technique used for data classification and visualization. It aims to find the optimal arrangement of data values into distinct classes or groups based on minimizing the variance within each class and maximizing the variance between

Fig. 7 Taylor diagram of annual precipitation (1981–2014) over the study area

values. Several studies have shown that the INM_CM5_0 and FGOALS_f3 GCMs have good spatial representation of observations in arid climates, e.g., the studies conducted in Egypt (Magdy et al. 2021), Nigeria (Shiru and Chung 2021), and Asia's arid areas (Yazdandoost et al. 2021; Guo et al. 2021). In a recent study conducted in Morocco by Gumus et al. (2023), minimum and maximum temperature and precipitation data from 27 observation stations were compared with the outputs of 15 GCMs of CMIP6 for the period 1980–2014. Among these GCMs, only four models were present in both studies: CNRM-CERFACS-CM6-1, FGOALS-f3-L, EC-Earth3-Veg, and INM-CM5-0. Gumus et al. (2023) utilized the Comprehensive Rating Index (CRI) method developed by Jiang et al. (2015) to determine the best-represented GCMs. The results of the study indicate that no single model can be considered robust for most stations. However, the MIROC6, CanESM5-CanOE, IPSL-CM6A-LR, INM-CM5-0, and NESM3 models demonstrated high success rates. The findings above suggest that the INM-CM5-0 GCM has demonstrated proficiency in reproducing precipitation patterns in Morocco, as indicated by two distinct evaluation metrics.

This implies that different models may have strengths and weaknesses in capturing precipitation patterns. The reliability of these simulations needs to be studied and evaluated to identify uncertainties and correct any underlying biases. Currently, GCMs are becoming increasingly available, and their simulation is essential for initiating climate research and assessment studies (Eyring et al. 2016). Precipitation is the most difficult model variable to predict both in short-term prediction and long-term climate simulation. Along with temperature, precipitation is a fundamental model output that carries the most important surface climate signature and has the largest socio-economic impact. Our study region is semi-arid, and a change in future precipitation regimes may alter its economy, relying largely on agriculture, which requires timely rainfall for crop growth and sustenance. Therefore, it is of first-order importance to evaluate and sort climate models' performance in simulating precipitation in semi-arid regions, where every drop counts. The ability to predict precipitation offers a lifeline for communities striving to adapt to the challenges of a variable climate and ensure the sustainable use of scarce water resources.

The simulations of nine GCMs were evaluated against the CHIRPS data. Examination of all results indicated that the overall performance of the CMIP6 models varies considerably in time and space. Although no model can be considered ideal, some models performed relatively well for spatio-temporal simulation but did not perform well for spatial simulation. The spatio-temporal simulation considers spatial and temporal dimensions, capturing the dynamics and
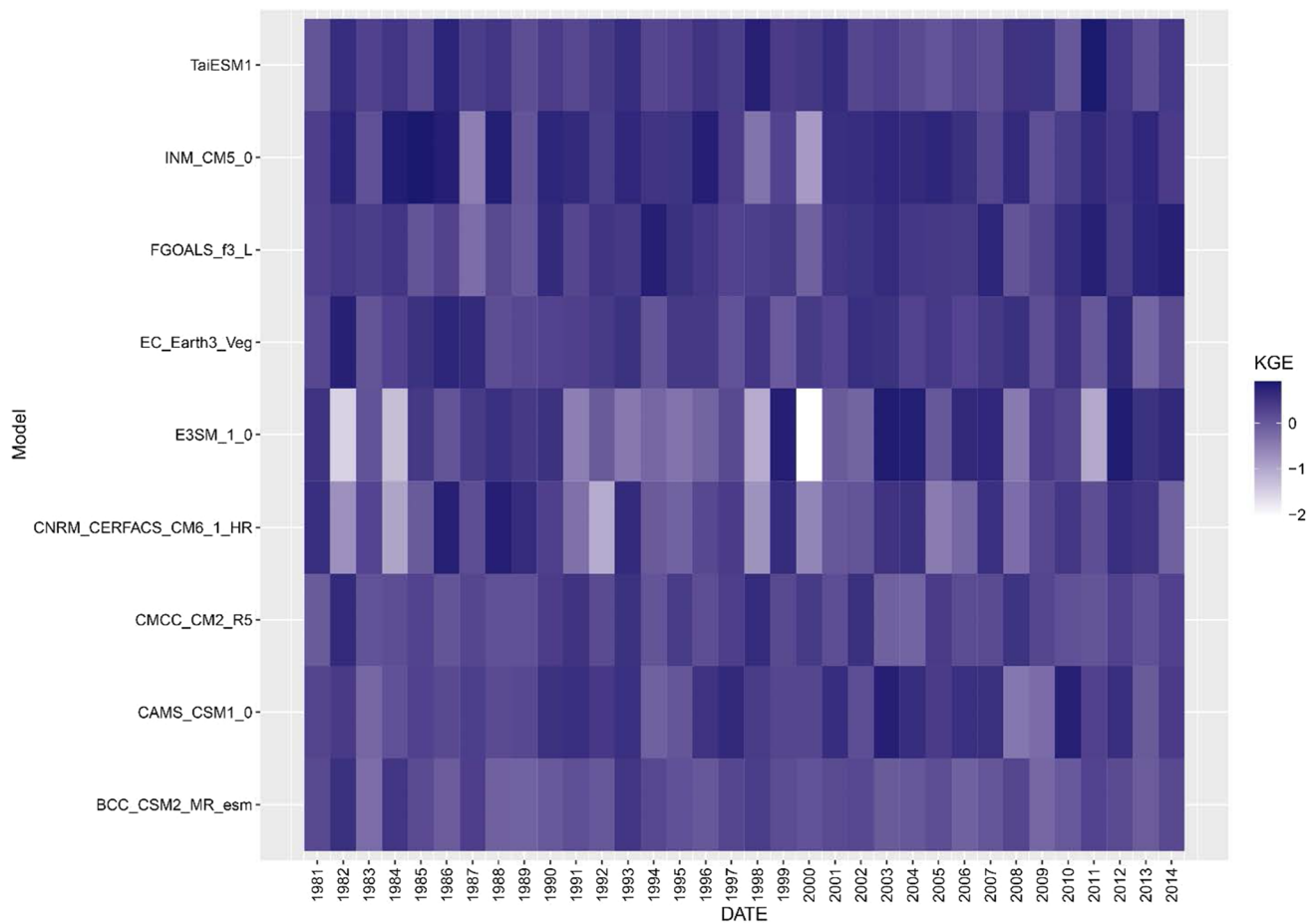
Fig. 8 The past spatial performance evaluation results of different GCMs runs on an annual scale from 1981–2014

interactions over time and space. Spatial simulation, on the other hand, focuses solely on the spatial aspects, analyzing the patterns and relationships within a given spatial context without explicitly considering temporal changes.

Other complexities also appear in different studies. For example, some GCMs would rank higher for reproducing

maximum and minimum temperatures but may be among the lowest for reproducing precipitation (Magdy et al. 2021). To minimize the uncertainties of GCMs, many scientists advocate selecting a multi-model ensemble set of efficient GCMs. However, there is no optimal reference number of GCMs for the multi-model ensemble generation (Ahmed et al. 2019a). All studies that have used a multi-model ensemble of GCMs have shown that the simulation of a multi-model ensemble outperforms the best single model (Salman et al. 2020; Guo et al. 2021; Iqbal et al. 2021).

Evaluating the performance of GCMs in reproducing precipitation patterns in Morocco is significant for future studies and has several contributions. First, understanding the accuracy of GCMs in simulating precipitation in a specific region like Morocco helps improve our understanding of regional climate dynamics. This knowledge can be used to assess the potential impacts of climate change on precipitation patterns, water resources, and ecosystems in Morocco. The findings of such research contribute to climate modeling advancements. By choosing the best GCMs outputs, researchers lead to enhanced climate

Table 3 The KGE of the GCMs and their classification using Jenks optimization

Model	Mean of KGE
BCC_CSM2_MR_esm	0.128050856
CAMS_CSM1_0	0.332046511
CMCC_CM2_R5	0.251031466
CNRM_CERFACS_CM6_1_HR	0.109154062
E3SM_1_0	0.023304636
EC_Earth3_Veg	0.357696599
FGOALS_f3_L	0.415279939
INM_CM5_0	0.455026604
TaiESM1	0.385766988

projections, predictions, and downscaling, which are crucial for informing local adaptation and mitigation strategies in the face of climate change. In addition, by evaluating GCMs' ability to reproduce precipitation, policymakers, farmers, and water resource managers can make informed decisions regarding water allocation and crop development. This is paramount in a semi-arid region, where sustained drought conditions affect water availability, irrigation, and various socio-economic activities.

Assessing GCMs' performance is time-consuming and requires human and material resources. Therefore, this research is essential for future studies on climate change and its impacts on various ecosystems and for studies dealing with sustainable development.

The present study is preliminary and has certain limitations. However, it can be considered as a possible starting point for future research into the new era of high-resolution climate models. First, this study was limited to only nine GCMs. Thus, an evaluation of more CMIP6 models still needs to be carried out. Second, the study only focused on climate models' historical data from 1981 to 2014, and researchers may investigate a more extended period in the future. Finally, the study relied mainly on a single source of observed data, which could present some inaccuracies. The use of multiple sources and advanced methods may provide better estimates. Further research into model intercomparison is strongly recommended to better understand changes within climate models and the climate characteristics in Morocco.

4 Conclusion

This study evaluated the performance of nine CMIP6 GCMs in reproducing the properties of mean monthly and annual precipitation using several statistical metrics and by comparing the GCMs output with CHIRPS data over the entire domain. Through this study, we shared the first statistical evaluation of the most recent global climate models (CMIP6) in the rainfall simulation in Morocco. Considering annual precipitation, the bulk of models showed an underestimated pattern, except for the CNRM-CERFACS-CM6-1-HR model, which overestimated the simulated precipitation. All GCMs could show the dependence of precipitation on geographical location and account for both wet, high northern latitudes, and dry regions, such as Moroccan deserts, with simulated precipitation increasing from south to north. The results showed that the GCMs satisfactorily reproduced the mean monthly precipitation of the dry and wet months with a slight over/underestimation of the dry and/or wet months, and most of the models simulated December as the wettest month. The analysis of the spatio-temporal performance

of annual and monthly precipitation over Morocco showed that the CNRM-CERFACS-CM6-1-HR model is the most performant. The spatial performance of GCMs according to the KGE indicator ranked the INM_CM5_0 GCM in first place with the highest KGE value (0.45), followed by the FGOALS_f3_L GCM with an average KGE of about 0.41. The findings of this study may have practical implications for assessing climatic patterns at the regional level.

Declarations

Conflict of interest The authors have no financial or non-financial interests to disclose.

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