Researches in Earth Sciences

Journal homepage: https://esrj.sbu.ac.ir

Research Article

Evaluation of the accuracy of CMIP6 models based on Taylor diagram for simulating precipitation in the southern part of the Aras river basin

Bromand Salahi[1*], Ali Shahi[1]

1-Department of Physical Geography, Faculty of Social Sciences, University of Mohaghegh Ardabili, Ardabil, Iran

Received: 02 May 2025 Accepted: 15 Jul 2025

Abstract

This study was aimed at evaluating the accuracy of selected models at 7 synoptic meteorological stations based on Taylor's diagram to simulate precipitation in the southern part of the Aras river basin (Iran) over the past three decades. This study, by examining the the CMIP6 series models with high horizontal resolution, intends to introduce the superior model in the region for predicting precipitation so that the water resources situation in the studied region can be managed. For this purpose, data from 4 AOGCM (MPI-ASM1-2-HR, CMCC-CM2-SR5, BCC-CSM2-MR and EC-Earth3-CC) were used by the CMIP6 series models. The historical period of 1985-2014 was considered. The raw output of the models downscaled by CMhyd software. To select the appropriate downscaling method, three methods were used: Linear Scaling, Power transformation, and Taylor diagram distribution mapping. The performance of the models at each station was evaluated by Taylor's chart. The calculations showed that the top model in all selected stations in the study area is the BCC model and the weakest model for simulation of the southern part of the Aras river basin, the MPI model. The results showed that the raw output of the models had a lot of error and could not be used directly. The results also showed that the Linear Scaling downscaling method has a good ability to optimize the output of GCM models in the study area. Based on the study, the BCC model is reliable for predicting precipitation in the study area.

Keywords: CMhyd, CMIP6, Aras river basin, Precipitation, Simulation.

Citation: Salahi, B. and Shahi, A., 2025. Evaluation of the accuracy of CMIP6 models based on Taylor diagram, *Res. Earth. Sci:* 16(Special Issue), (52-61) DOI: 10.48308/esrj.2025.239764.1274

* Corresponding author E-mail address: salahi@uma.ac.ir

Introduction

Increasing surface temperature and change in precipitation patterns are the dominant phenomena in climate change and affect all parts of the water cycle (Ahmadabadi and Sedighifar, 2018). Precipitation is directly affected by the increase in global temperature, which increases the evapotranspiration rate, resulting in the concentration of water vapor in the atmosphere. The variety of different properties of precipitation, namely, intensity, frequency and temporal distribution in different areas is expected (Nasidi et al, 2021). Studies in Iran indicate a decrease in precipitation, increased temperature and water resources reduction under climate change (Zarrin and Dadashi Roudbari, 2020). In order to illustrate climate change in future periods, 3D paired AOGCM (Atmospheric and Oceanic General Circulation Models) are the most prestigious tools. Given the dependence of climate change on the results of climatic models (Chen et al, 2015), it is mostly possible to achieve more reliable illustrations in the future using the climatic models presented in the new 6th report (Stouffer et al, 2017). The CMIP6 (Coupled Model Intercomparison Project Phase 6) continues the pattern of evolution and previous phases of the CMIP and includes new organized scenarios of global climatic modeling designed to identify different weather mechanisms (Eyring et al, 2016). Compared to the CMIP5, the models in CMIP6 have generally improved better clarity and physical processes (Stouffer et al, 2017). Using a single AOGCM model to estimate temperature and precipitation changes in different parts of the world is a common approach. Research has shown that using a single model in this field may cause error and uncertainty in climate change forecasts (Zareian et al, 2015). The reason for using higher -ranking models in terms of simulation skills is that models have different skills in different areas and courses (Bağçaci et al, 2021). Uncertainty and bias vary from model to model and for specific variables. Therefore, direct use of model outputs is not recommended as it may lead to incorrect results. Therefore, the use of downscaling methods or bias correction for using climate data from GCM models is considered a necessary step (Zhao et al, 2017). Nilawar and Waikar (2019) examined the impacts of climate change on the flow of the Purna River in India using RCP scenarios. The results showed that temperature and precipitation would rise in the coming period. Wehner et al. (2020) comparatively studied precipitation data and the extreme temperatures of the Earth during the historical periods of CMIP5 and CMIP6 reports. The results showed that the historic CMIP6 output was able to better simulate precipitation and limit temperatures as corresponding to the CMIP5 data. Majdi et al. (2022) used the average of 2 GCM models and two SSP scenarios to preview temperature and precipitation changes in the Middle East and North Africa. The results indicate an increase in temperature and a decrease in precipitation in most parts of the study area Tiku et al. (2025) simulated and evaluated precipitation with CMIP6 models in the Amhara region of Ethiopia. They used 16 GCM models. Statistical measures such as coefficient of determination (R^2), Root Mean Square Error (RMSE), Mean Bias (MB), Taylor plot, and T-Test were used to evaluate the performance of the models over the period 1985–2014. The results showed that the models performed better in the eastern part of Amhara than in the western part. Sharifan et al. (2025) used CMIP6 models to assess the impact of climate change on future precipitation in the Siminehrood River Basin (Iran). For this purpose, the performance of 26 climate models used to predict precipitation in the base period (1988-2018) was evaluated and the models were ranked and weighted. Then, the precipitation change trend during 2031-2050 was examined under the SSP1-2.6, SSP2-4.5 and SSP5-8.5 scenarios and the LARS-WG 7.0 model was implemented to downscale the precipitation data of the GCM models. The results showed that annual precipitation will decrease under all three scenarios compared to the base period. Li et al. (2025) assessed and predicted heavy rainfall in the Yangtze and Yellow River regions based on the optimized CMIP6 models using statistical downscaling. The results showed systematic overestimations, especially in the eastern parts of the region, with deviations reaching 304.8% for winter. Gulakhmadov et al. (2025) modeled historical and future changes in temperature and precipitation in the Panj River basin in Central Asia under the CMIP5 RCP and CMIP6 SSP scenarios. Uncertainty analysis showed that the

CMIP6 precipitation deviation bands were significantly improved, leading to a more accurate picture of different climatic regions than CMIP5. Malkian et al. (2019) studied the effects of climate change on some hydrological characteristics of water resources in Ardabil province. The results from simulations using the Bilan model indicate insignificant changes in total surface runoff in the future period in the studied basins compared to the reference period. Aghabeigi et al. (2020) evaluated the effects of climate change on runoff in some watersheds of Ardabil province using the IHACRES hydrological model. For this purpose, the climate parameters of maximum temperature, minimum temperature, and precipitation over the coming decades (2011-2030) were investigated using the LARS-WG exponential downscaling model and the output of the HadCM3 model. The results showed that the amount of precipitation over the coming decades will fluctuate and overall, for the period 2011-2030, the amount of precipitation has decreased by 3.68%. Khajeh Amiri et al. (2022) evaluated the accuracy of CMIP6 climate models on the Makran coast using the NSE (Nash–Sutcliffe efficiency) coefficient, RMSE (Root Mean Square Error), and, KGE (Kling-Gupta Efficiency). To this end, they used four global circulation models in the historical period 1-4. According to the surveys, six models of FGOALS, MPI-ASM1, CaneSM5, MRI-ASM2, EC-Earth3, IPSL-CM6A, Access-ASM were selected as the best model. Then, two ensemble models were introduced, the arithmetic mean and the Independence Weighted Mean (IWM) methods, and the weighted mean model showed better results. Abdolalizadeh et al. (2023) projected and evaluated climatic variables of Lake Urmia temperature and precipitation using CMIP6 models under two SSP1-2.6 and SSP5-8.5 scenarios in 2031-2055 and 2071-2095 periods. The accuracy of the models for the base period (1990-2014) was evaluated after downscaling using the Taylor graph and the RMSE and the NRMSE (Normalized Root Mean Square Error) indexes. Among the models, the MRI-AM2-0 model was selected for temperature and the Inm-CM5-0 model for precipitation by SSPLIN downscaling for the future climate. The results showed that the average annual temperature of the Lake Urmia catchment will increase under all scenarios and the average annual precipitation in all scenarios would decrease. Based on the spatial distribution of temperature and precipitation changes in the coming period, the highest increase in temperature and the highest decrease in precipitation in the northern areas of Lake Urmia will occur. Asadi (2024) preview the trend of climatic parameters affecting almond product growth at the Birjand Station for 2021 to 2100 using IPSL-CM5A-LR and GFDL-ASM2M models related to CMIP5 and GFDL-ASM4 and IPSL-CM6A-LR models related to the CMIP6 report.

The results of the Mann-Kendall test indicated that the average, maximum, and minimum temperatures had an increasing trend of more than 3 degrees Celsius, and the amount of precipitation also had a decreasing trend. CMIP6 models predicted temperature and precipitation in the study area with a lower average error than CMIP5 models. The Aras basin has good conditions for agriculture and since agriculture requires water, and many dams have been built in the area that are the source of electricity generation in many areas, with climate change, precipitation patterns have changed and threaten the agriculture and water plant in the region. According to the above mentioned, it is important to study the precipitation of the Aras basin in future period. This study is innovative in terms of downscaling with CMhyd software, using models with high horizontal resolution, and using four coupled 3D atmospheric and oceanic general circulation models to evaluate precipitation.

Materials and Methods

Study Area

Figure 1 shows the geographical location of the study area. The Aras river basin is the longest river in Iran and is part of the western sub-basin of the Caspian Sea. The southern part of this basin is located in the northwest of Iran on the connecting axis of the Middle East with Central Asia in a region with a special and sensitive location that includes the northern parts of Ardabil, East Azerbaijan, and West Azerbaijan provinces. The Aras river basin in Iran is located between the geographical coordinates 44º 01´ 42´´ - 48º 42´ 33´´ east longitude and 37º 46´ 10´´ - 39º 47´ 07´´ north latitude (Kiani Sefidan Jadid, 2005). This basin is of great importance due to its large size and climatic diversity and its location in three provinces (Hafezparast et al, 2015). The southern part of this river belongs to Iran, and the highest point in this part is Sabalan Peak, which is located at an altitude of 4811 meters above sea level. Its lowest point is located at the outlet of the Aras River on the border of Iran and the Republic of Azerbaijan. A major part of the basin area is located in mountainous and foothill areas. The Sabalan, Baghrou, Qara-Dagh, Ghoshe-Dagh, Mishudagh, Kiamki-Dagh, and Orin mountains are among the high mountains of this basin. This watershed, located in northwest Iran, is bounded by the Aras border river to the north, Turkey to the west, Lake Urmia and Sefidrud watersheds to the south and southeast, and Talesho and Anzali Marsh watershed to the east (Ministry of Energy of Iran, 2011).

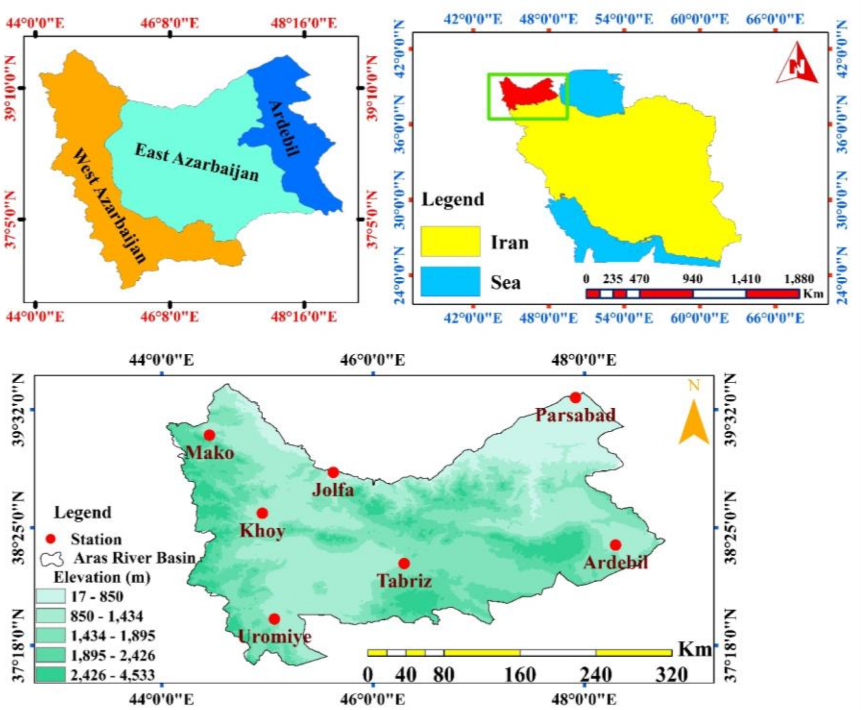

Fig. 1: Geographical Location of the Study Area

In this study, two groups of observational and model data were used daily for 3 decades. Daily precipitation data from 7 synoptic stations located in northwest Iran were obtained from the Iran Meteorological Organization (www.irimo.ir). The output of the CMIP6 was extracted from the https://esgf-node.llnl.gov/projects/cmip6/ for the time period 1985-2014 (historical period). Table 1 shows the models used in this study. In this study, initially, among the CMIP6 series models, those models that had data with common historical periods and high horizontal spatial resolution were selected.

Table 1: Specifications of the CMIP6 models analyzed in the study

Row	Model	Developer Organization	Country	Spatial Resolution
1	MPI-ESM1-2-HR	German Regional Data Center	Germany	100 km
2	CMCC-CM2-SR5	European Mediterranean Center	Italy	100 km
3	BCC-CSM2-MR	Beijing Climate Center	China	100 km
4	EC-EARTH3-CC	Consortium of Several Commercial Firms	European Union (2 countries)	100 km

After extracting the output of the 4 selected models, in order to reduce the uncertainty, 3 methods (Linear Scaling), Power Transformation and Distribution Mapping) were used for downscaling in the CMhyd (Climate Model data for hydrologic modeling) software environment. The efficiency of each of the 3 downscaling methods was determined by drawing the Taylor diagram. The Taylor diagram simultaneously considers the skewness, standard deviation and root mean square indices (Taylor, 2001).

Taylor diagram was drawn in the R software environment. In this diagram, the observed data is specified as a reference point on the horizontal axis and the angular dimension indicates the correlation between the observed and simulated values. The standard deviation values are plotted as concentric circles with respect to the center of the circle and the RMSE values are plotted as concentric circles with respect to the reference point.

Downscaling by CMhyd

The output of GCM models cannot be used directly due to their large scale. To overcome the problem of low spatial resolution, downscaling methods are used (Fallah Ghalhori, 2019). The CMhyd software was used to downscale the output of general circulation models.

This software was developed for hydrological modeling by Rathjens et al. 2016 at Purdue University, USA, in the Python environment. The CMhyd uses eight bias correction methods in a separate process for precipitation and temperature. Out of the eight methods, five methods are specific to precipitation. Fast execution and the ability to select different options are the advantages of this software (Babaeian et al, 2023).

This software requires three types of data, including observation data, historical climate model data, and scenario data (future) climate models. The downscaling process is performed in five steps, which are: entering observation variables (in text form), selecting a bias correction method, entering model data in the historical and scenario periods (in text form or NetCdf), processing (including checking data and performing downscaling), and outputting results in both numerical and graphical forms (Babaeian et al, 2021).

Model Performance Evaluation Criteria

Historical simulations are useful for assessing the accuracy of models. Historical model periods are an important tool for determining the consistency and sensitivity of climate models to observational data and controlling the uncertainty of these models (Eyring et al, 2016). To determine the accuracy of each of the 4 models in this study at 7 stations in northwest Iran, after removing bias, Taylor plots were used. After determining the best models for each station, the raw and downscaled output of the best models for each station was verified with the Kling-Gupta Efficiency (KGE) statistical index (Equation 1). The KGE index is a composite index that is able to combine several statistical indices such as mean, standard deviation, and data correlation with each other and increase the accuracy of model selection based on their ability to simulate the historical period. In other words, when several statistical indicators are used separately in this field, it will be difficult to make a final decision without using the KGE index (Knoben et al, 2019).

Eq. 1)

$$KGE = 1 - \sqrt{(r-1)^2 + \left(\frac{\sigma_s}{\sigma_o} - 1\right)^2 + \left(\frac{\mu_s}{\mu_o} - 1\right)^2}$$

In this relation, O_i and S_i are the values of the observed and simulated precipitation data, respectively. μ is the mean, σ is the standard deviation and r is the Pearson correlation coefficient (Zareian, 2022).

Results and Discussion

Figure 2 shows the Taylor diagrams of Jolfa station for 4 models in the base period, based on the output of 3 methods: Linear Scaling, Power Transformation, and Distribution Mapping. This figure proves that the Linear Scaling method has high accuracy and less error than the other two methods. The Taylor diagram of Jolfa station for 3 models in the base period, based on the output of 3 methods: Linear Scaling, Power Transformation, and Distribution Mapping, showed that the Linear Scaling method has high accuracy and less error than the other two methods. According to Figure 2, the standard deviation and root mean square error values in the Linear Scaling downscaling method are 0.25 and 1, respectively. The standard deviation and RMSE values in other downscaling methods (Power Transformation and Distribution Mapping) are about 0.5 and greater than 1, respectively. In the case of low values of the correlation coefficient, it is necessary to note that with a complex and volatile precipitation variable, it is not possible to expect a high value of the correlation coefficient; while the correlation coefficient in temperature studies shows high values.

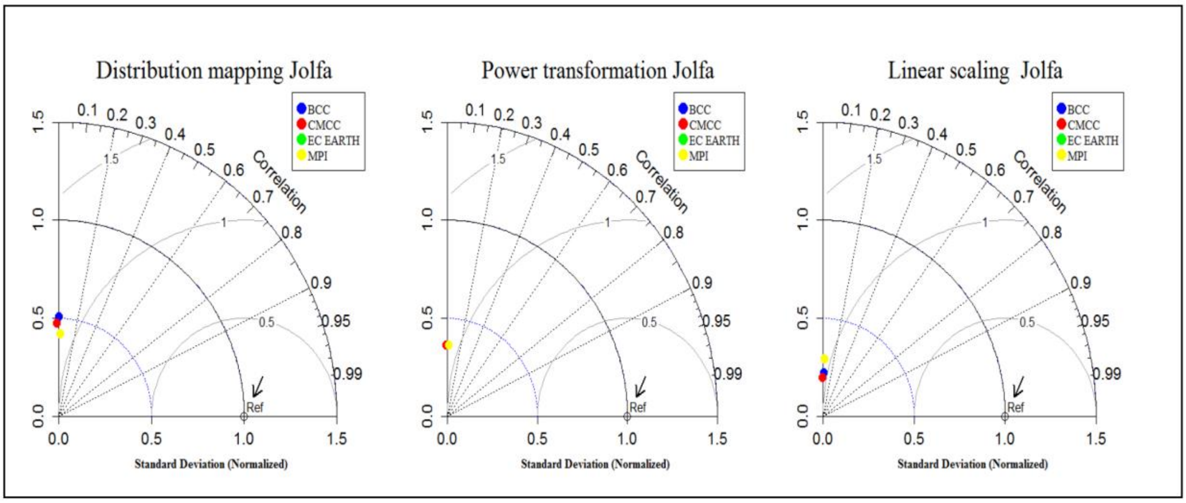

Fig. 2: Taylor diagram for the Three Bias Correction Methods at Jolfa Station over the 30-Year Baseline Period

Based on the evaluation performed by the Taylor diagram (Figure 2), among the three bias correction methods, the Linear Scaling method was selected (Table 2) and the downscaling of the raw output of the models in this study was performed using the above method in the CMhyd software.

Table 2: Formulas used in downscaling methods of CMhyd software

Method Name	Description of the Downscaling Method	Source
Linear Scaling	The ratio of the monthly mean observed values to the model's historical period values is applied to the future simulated time series. This method is preferably used for the downscaling of precipitation, vapor pressure, and radiation.	Mendez et al, 2020

After downscaling, the precipitation output of the 7 synoptic meteorological stations selected in this study in the historical period (1985-2014) was verified by 4 models with Taylor diagrams. According to the Taylor diagram drawn at each synoptic meteorological station, the BCC model had the best output at all stations in the study area with small values of standard deviation and also root mean square error, of course, at Jolfa station, the first place belongs to the CMCC model by a small difference. Regarding small values for correlation, it should be noted that the uncertainty of the precipitation variable is much higher than the temperature variable and the correlation coefficient cannot be expected to have significant values. According to the Taylor diagrams drawn in Figure (3), the standard deviation is in the range of 0.5 to 1 and the RMSE is in the range of 1 to 1.5 and the Pearson correlation coefficient is in the range of 0 to 0.1 at all stations. The best performance of the models with standard deviation and RMSE 0.25 and 1 belongs to Jolfa station, and the weakest performance of the models with standard deviation and RMSE 0.7 and 1.25 belongs to Urmia station.

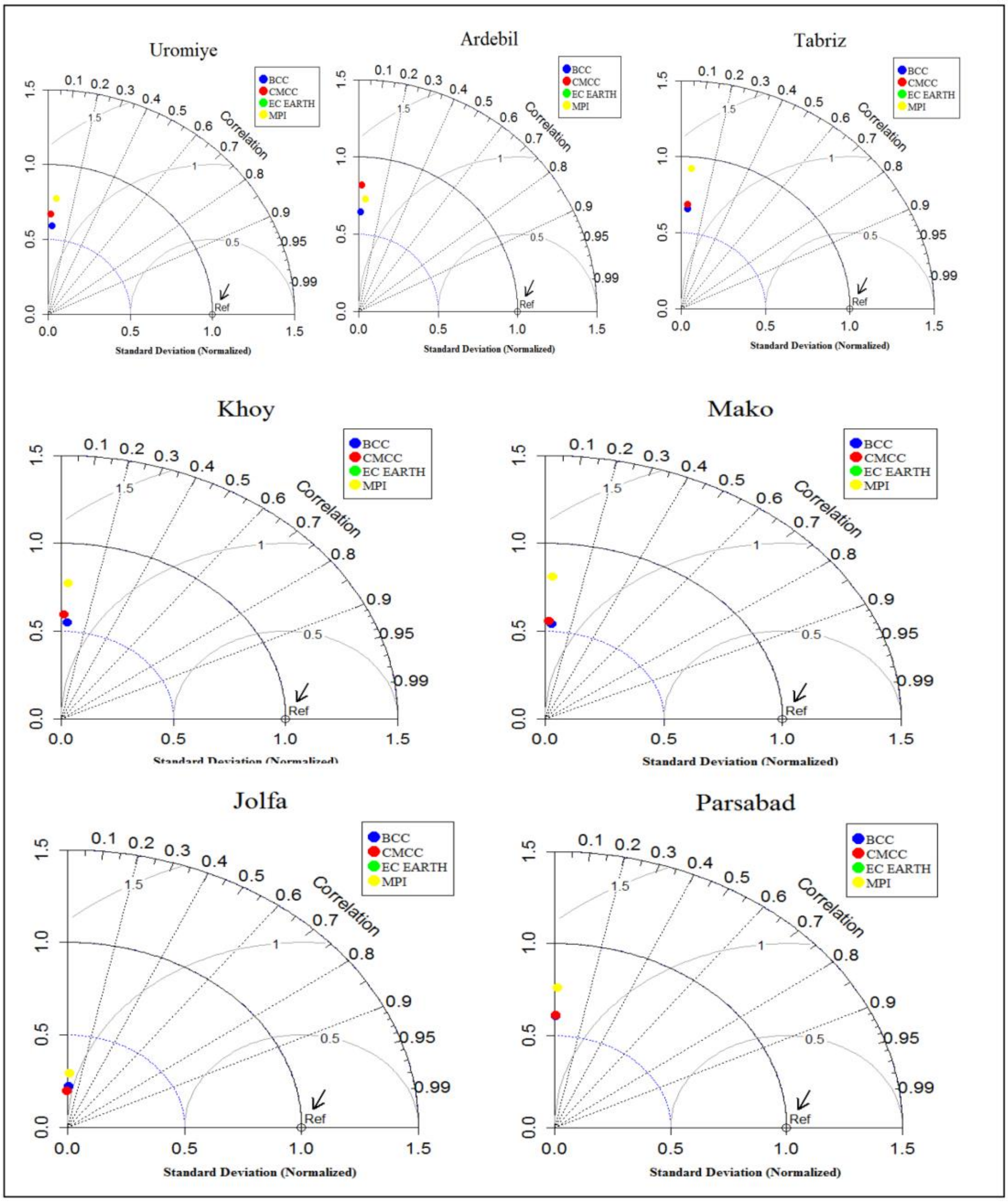

Fig. 3: Taylor diagram for each station in the study area during the historical period (1985-2014)

After validating the 4 models used in this study using Taylor diagrams, the best models were identified by synoptic station in the southern part of the Aras basin. Based on table 3, in all selected stations except Jolfa station, the best model among the 4 models was the BCC model.

Table 3: Best model for each synoptic station in the study area

Station	Best Model
Ardabil	BCC
Parsabad	BCC
Jolfa	CMCC
Tabriz	BCC
Uromiye	BCC
Khoy	BCC
Mako	BCC

Table 4 shows the results of the validation of the top 7 stations' models before and after downscaling with the KGE metric. According to the calculations, the downscaling performed by the Linear Scaling method has appropriately optimized the output of the models in all stations of the study area and reduced their errors. According to Table 4, the maximum and minimum differences in KGE index values (before and after downscaling) were observed at Jolfa and Urmia stations, respectively.

Table 4: Comparison of the accuracy of the best model for 7 selected stations before and after downscaling in the study area

Station	KGE	
	After downscaling	**Before downscaling**
Ardabil	-0.04	-0.43
Parsabad	-0.06	-0.35
Jolfa	-0.7	-47
Tabriz	0	-0.4
Uromiye	-0.04	-0.17
Khoy	-0.05	-0.43
Mako	-0.05	-0.5

Conclusion

Precipitation plays the most important role in human life, to the point that many atmospheric scientists consider it the most important atmospheric element. This study aimed to evaluate the accuracy of selected models at 7 synoptic stations based on the Taylor diagram for simulating precipitation in the southern part of the Aras river basin (Iran) over the past three decades. Research on precipitation is very prominent due to climate change, and in the field of predicting future precipitation, it is necessary to use models with better resolution and compatible with the studied environment. Given the high uncertainty in studying climate change, especially precipitation, single or small models cannot be used. As a result, validating a number of general atmospheric circulation models with appropriate metrics is the best solution to identify better models for predicting precipitation in different regions. The results of the study evaluating the accuracy of the IPCC6 Report models for simulating precipitation based on the Taylor diagram in the southern part of the Aras river basin in the historical period (1985-2014) using 4 GCM models presented in the IPCC Report 6 at 7 synoptic meteorological stations based on statistical downscaling with CMhyd software with the Linear Scaling method showed that the superior model in the study area for simulating precipitation is the BCC model and the weakest model in evaluating precipitation in the study area is the MPI model.

The results of the present study are consistent with the results of research conducted by Zarrin and Dadashi Roudbari (2020) and Abdolalizadeh et al. (2023) on the low accuracy of GCM model outputs and the need for downscaling and bias correction of model outputs. On the other hand, the results indicated that the Linear Scaling fine-tuning method had better capabilities based on the verification test conducted among the other 2 downscaling methods of this study (Power transformation and Distribution mapping). The evaluation results with the KGE measure for raw and downscaled output values of all stations indicate the appropriate performance of the Linear Scaling fine-tuning method. The results also showed that based on the outputs of the Taylor diagram and the KGE index in the field of evaluating the models used in the study area, the most accurate performance was at the Jolfa station and the weakest performance was at the Urmia station; in other words, the performance of the models in the northern part of the Aras river basin was better than its southern part. It is suggested that researchers in their studies evaluate the performance of CMIP6 models in simulating temperature variables for the southern part of the Aras river basin in the past three decades based on the KGE index and the Taylor diagram.

Acknowledgment

There has been no support from any organization to carry out this project.

References

Abdolalizadeh, F., Mohammad Khorshiddoust, A. and Jahanbakhsh, S., 2023. Projection of the future outlook of temperature and precipitation in Urmia Lake basin by the CMIP6 models. Physical Geography Research, v. 55(1), p. 95-112. Doi: 10.22059/jphgr.2023.352727.1007737 (In Persian).

Aghabeigi, N., Esmali Ouri, A., Mostafazade, R. and Golshan, M., 2019. The Effects of Climate Change on Runoff Using IHACRES Hydrologic Model in Some of Watersheds, Ardabil Province. Irrigation and Water Engineering, v. 10(2), p. 178-189. Doi: 10.22125/iwe.2019.100750 (In Persian).

Ahmadabadi, A. and Sedighifar, Z., 2018. Prediction of Climate Change Induced Hydrogeomorphology by using SDSM in CAN Watershed. Jgs, v. 18(51), p. 103-114. http://dx.doi.org/10.29252/jgs.18.51.103 (In Persian).

Asadi, M., 2024. Comparison of the outcomes of the CMIP5 and CMIP6 reports on the trends of climatic parameters affecting almond growth: A case study in Birjand County. Journal of Geography and Planning, Doi: 10.22034/gp.2024.61686.3262 (In Persian).

Babaeian, I., Modirian, R., Khazanedari, L., Kouhi, M., Kouzegaran, S., Falamrazi, Y., Karimian, M. and Malbusi, Sh., 2021. Precipitation forecasting in Iran using downscaled statistical methods based on CMIP6 model outputs. Internal Project of the Climatology Research Institute, Mashhad (In Persian).

Babaeian, I., Modirian, R., Khazanedari, L., Karimian, M., Kouzegaran, S., Kouhi, M., Falamarzi, Y. and Malbusi, S., 2023. Projection of Iran's precipitation in 21st Century using downscaling of selected CMIP6 models by CMhyd. Journal of the Earth and Space Physics, v. 49(2), p. 431-449. Doi: 10.22059/jesphys.2023.332410.1007436 (In Persian).

Bağçaci, S.Ç., Yucel, I., Duzenli, E. and Yilmaz, M.T., 2021. Intercomparison of the expected change in the temperature and the precipitation retrieved from CMIP6 and CMIP5 climate projections: A Mediterranean hot spot case, Turkey. Atmospheric Research, v. 256, p. 105576. https://doi.org/10.1016/j.atmosres.2021.105576

Chen, H., Zhao, Y., Feng, H., Li, H. and Sun, B., 2015. Assessment of climate change impacts on soil organic carbon and crop yield based on long-term fertilization applications in Loess Plateau, China. Plant and Soil, v. 390, p. 401-417. https://doi.org/10.1007/s11104-014-2332-1

Eyring, V., Bony, S., Meehl, G.A., Senior, C.A., Stevens, B., Stouffer, R.J. and Taylor, K.E., 2016. Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization. Geoscientific Model Development, v. 9(5), p. 1937-1958. https://doi.org/10.5194/gmd-9-1937-2016, 2016.

Fallah Ghalhori, G.A., Yousefi, H., Hosseinzadeh, A., Alimardani, M. and Reyhani, E., 2019. Assessment of Climate Change in Bojnourd Station in 2016-2050 using Downscaling Models LARS WG and SDSM. Iranian journal of Ecohydrology, v. 6(1), p. 99-109. https://doi.org/10.22059/ije.2018.265918.952

Gulakhmadov, A., Chen, X., Gulahmadov, N., Rizwan, M., Gulakhmadov, M., Nadeem, M.U. and Liu, T., 2025. Modeling of historical and future changes in temperature and precipitation in the Panj River Basin in Central Asia under the CMIP5 RCP and CMIP6 SSP scenarios. Scientific Reports, v. 15(1), p. 3037. https://doi.org/10.1038/s41598-025-86366-4

Hafezparast, M., Araghinejad, Sh. and Sharif Azari, S., 2015. Sustainability Criteria in Assessment of Integrated Water Resources Management In The Aras Basin Based on DPSIR Approach. Journal of Water and Soil Conservation, v. 22(2), p. 61-77. https://dor.isc.ac/dor/20.1001.1.23222069.1394.22.2.4.8 (In Persian).

Li, R., Wu, J. and Xu, Y., 2025. Evaluation and Projection of Precipitation and Precipitation Extremes in the Source Region of the Yangtze and Yellow Rivers Based on CMIP6 Model Optimization and Statistical Downscaling. Atmospheric Science Letters, v. 26(6), p. e1305. https://doi.org/10.1002/asl.1305

Khajeh Amiri, C., Khosravi, M., Tavousi, T., Hamidianpour, M. and kiani moghadam, M., 2022. An analysis of the output performance of CMIP6 climate models in comparison with the observational data of Makran coast. Journal of Meteorology and Atmospheric Science, v. 5(1), p. 22-41. Doi: 10.22034/jmas.2023.379448.1193 (In Persian).

Knoben, W.J., Freer, J.E. and Woods, R.A., 2019. Inherent benchmark or not? Comparing Nash–Sutcliffe and Kling–Gupta efficiency scores. Hydrology and Earth System Sciences, v. 23(10), p. 4323-4331. https://doi.org/10.5194/hess-23-4323-2019.

Kiani Sefidan Jadid, T., 2005. Synoptic analysis of convective rainfall in the southern Aras Basin (Master's thesis, University of Tabriz, Faculty of Humanities and Social Sciences, Department of Geography). Supervisor: B. Sarisarraf (In Persian).

Malkian, A., mirdashtvan, M. and Ghadimi, M., 2019. Investigating the impacts of climate change on some hydrological characteristics of water resources in Ardebil province. Journal of Ecohydrology, v. 6(3), p. 695-705. Doi: 10.22059/ije.2019.282033.1120 (In Persian).

Majdi, F., Hosseini, S.A., Karbalaee, A., Kaseri, M. and Marjanian, S., 2022. Future projection of precipitation and temperature changes in the Middle East and North Africa (MENA) region based on CMIP6. Theoretical and Applied Climatology, https://doi.org/10.1007/s00704-021-03916-2.

Mendez, M., Maathuis, B., Hein-Griggs, D. and Alvarado-Gamboa, L.F., 2020. Performance evaluation of bias correction methods for climate change monthly precipitation projections over Costa Rica. Water, v. 12(2), p. 482. https://doi.org/10.3390/w12020482.

Ministry of Energy of Iran., 2011. Classification and coding of watersheds and study regions across the country (Revised in 2010–2011). Iran Water Resources Management Company, Deputy for Watershed Coordination, Office of Basic Water Resources Studies.

Nasidi, N.M., Wayayok, A., Abdullah, A.F. and Mohd Kassim, M.S., 2021. Dynamics of potential precipitation under climate change scenarios at Cameron Highlands, Malaysia. SN Applied Sciences, v. 3(3), p. 1-17. https://doi.org/10.1007/s42452-021-04332-x

Nilawar, A.P. and Waikar, M.L., 2019. Impacts of climate change on streamflow and sediment concentration under RCP 4.5 and 8.5: A case study in Purna river basin, India. Science of the Total Environment, v. 2, p. 2685-2696. http://dx.doi.org/10.1016/j.scitotenv.2018.09.334.

Rathjens, H., Bieger, K., Srinivasan, R., Chaubey, I. and Arnold, J.G., 2016. CMhyd User Manual: Documentation for preparing simulated climate change data for hydrologic impact studies. Texas: SWAT.

Sharifan, F., Ramezani, Y., Amirabadizadeh, M. and De Michele, C., 2025. Evaluating the impact of climate change on precipitation in the future period using CMIP6 models (case study: Siminehrood River Basin, Iran). Acta Geophysica, p. 1-16. https://doi.org/10.1007/s11600-025-01612-7.

Stouffer, R.J., Eyring, V., Meehl, G.A., Bony, S., Senior, C., Stevens, B. and Taylor, K.E., 2017. CMIP5 scientific gaps and recommendations for CMIP6. Bulletin of the American Meteorological Society, v. 98(1), p. 95-105. https://doi.org/10.1175/BAMS-D-15-00013.1

Taylor, K.E., 2001. Summarizing multiple aspects of model performance in a single diagram. Journal of geophysical research: atmospheres, v. 106(D7), p. 7183-7192. https://doi.org/10.1029/2000JD900719

Tiku, T.W., Tarekegn, G.B., Sahlu, D., Teshebo, G.B., Enyew, F.B., Umer, Y. and Debele, S.E., 2025. Evaluating CMIP6 Precipitation Simulations Across Different Rainfall Regimes in the Amhara Region, Ethiopia. Natural Hazards Research. https://doi.org/10.1016/j.nhres.2025.03.002

Wehner, M., Gleckler, P. and Lee, J., 2020. Characterization of long period return values of extreme daily temperature and precipitation in the CMIP6 models: Part 1, model evaluation. Weather and Climate Extremes, v. 30, p. 100283. https://doi.org/10.1016/j.wace.2020.100283

Www.irimo.ir

Zarrin, A. and Dadashi Roudbari, A.A., 2020. Projection the Long-Term Outlook Iran Future Temperature Based on the Output of The coupled model intercomparison project phase 6 (CMIP6). Journal of the Earth and Space Physics, v. 46(3), p. 583-602. Doi: 10.22059/jesphys.2020.304870.1007226 (In Persian).

Zareian, M.J., Eslamian, S. and Safavi, H.R., 2015. A modified regionalization weighting approach for climate change impact assessment at watershed scale. Theoretical and Applied Climatology, v. 122(3), p. 497-516. https://doi.org/10.1007/s00704-014-1307-8 (in Persian).

Zareian, M., 2022. Effects of Climate Change on Temperature and Precipitation in Yazd Province Based on Combined Output of CMIP6 Models. Jwss, v. 26 (2), p. 91-105. http://dx.doi.org/10.47176/jwss.26.2.31501 (In Persian).

Zhao, T., Bennett, J.C., Wang, Q.J., Schepen, A., Wood, A.W., Robertson, D.E. and Ramos, M.H., 2017. How suitable is quantile mapping for postprocessing GCM precipitation forecasts?. Journal of Climate, v. 30(9), p. 3185-3196. https://doi.org/10.1175/JCLI-D-16-0652.1.