Selection of CMIP6 GCM with projection of climate over the Amu Darya River Basin

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Abstract
The most practical methods to predict climate change are global climate models (GCMs). This research set out to evaluate the ability of 19 GCMs from the Coupled Model Intercomparison Project 6 (CMIP6) to reproduce the historical precipitation, maximum, and minimum temperature (Pr, Tmx, and Tmn) of climate prediction center data for the Amu Darya river basin (ADRB), as well as to project the climate of the basin using the chosen GCMs. The Kling-Gupta efficiency (KGE) metric was used to assess the effectiveness of GCMs to simulate the annual geographic variability of Pr, Tmx, and Tmn. A multi-criteria decision-making approach (MCDMA) was used to integrate the KGE values to rank GCMs. The findings showed that AWI-CM-1–1-MR, CMCC-ESM2, INM-CM4-8, and MPI-ESM1-2-LR best replicate observed Pr, Tmx, and Tmn in ADRB. Projection of climate employing the selected GCMs indicated an increase in precipitation (9.9–12.4%), Tmx (1.3–4.9 °C), and Tmn (1.3–5.5 °C) in the basin for all the shared socioeconomic pathways (SSPs), particularly for the far future (2060–2099). A significant variation can be seen in Tmx and Tmn over the different climatic zone. However, the intercomparison of selected GCM projected revealed high uncertainty in the projected climate. The projection uncertainty is noticed highest for Tmx. The uncertainty is also noticed higher in the far future and higher SSPs compared to the near future and lower SSPs.

1 Introduction
Climate change is a worldwide phenomenon that affects almost all aspects of life. The frequency and intensity of climatic hazards have increased globally, which disrupted agricultural livelihoods, water resources, food security, socioeconomic development, and human health in many regions (Li et al. 2020a; Pour et al. 2020; Shiru et al. 2020; Wang et al. 2019). However, the impacts of climate change are not consistent throughout the globe. Arid and semi-arid regions are relatively more sensitive than other climate zones due to their vulnerable ecosystem (Ahmed et al. 2019c; Pour et al. 2020). Therefore, due to its arid to semi-arid environment, Central Asia (CA) is one of the most exposed areas to climate change (Yadav et al. 2019).

Climate change is generally perceived by studying precipitation and temperature variables (Sheffield and Wood 2008). Global climate models (GCMs) are considered the most feasible tools for simulating the past climate and projection of future climate based on emission scenarios (Li et al. 2020a). Over the years, many GCMs have been developed, and the structure of Coupled Model Intercomparison Project (CMIPs) has been revised from CMIP1 to the newly designed CMIP6 (Meehl et al. 2014; Pascoe et al. 2019; Scher and Messori 2019). CMIP6 is a set of GCMs and the latest released stage of the CMIP series (Eyring et al. 2016). In addition to the DECK (Diagnostic, Evaluation and Characterization of Klima experiments) and the CMIP6 historical replication, 21 individual MIPs have been endorsed by the CMIP panel for inclusion in CMIP6 (Eyring et al. 2015). The CMIP6 historical...
simulations consider anthropogenic and geogenic forcing for 1850–2014 (Srivastava et al. 2020). The number of GCMs has increased with each generation of MIPs, reaching 55 in CMIP6 (Eyring et al. 2016). In comparison to CMIP5, CMIP6 has numerous advantages, including combined radiative concentration pathways (RCPs) with shared socioeconomic pathways (SSPs), improvements in the models and additional experiments, higher spatial resolution, lower biases, and better representation of synoptic processes (Kamal et al. 2021; Su et al. 2021a).

To reduce the uncertainty of the GCMs and produce results that are in line with local conditions, researchers typically employ mean multi-model ensembles (MMEs) (Ahmed et al. 2019a; Wang et al. 2018). In developing countries where both human and computing resources are scarce, selecting an appropriate collection of GCM is crucial for better water resource management and impact assessment in the face of climate change (Hassan et al. 2020; Lin and Tung 2017). This is due to the fact that GCMs are prone to biases in both directions, causing them to either under- or overestimate climate change (Srivastava et al. 2020). Choose GCMs that can accurately reproduce the observed climate’s spatial and temporal variability (Nashwan and Shahid 2020). For the most part, the envelope approach and historical performance are used to determine which group of GCMs is the most reliable (Hassan et al. 2020; Salman et al. 2018). The past performance method examines GCMs’ capability to mimic the past climate without considering the future projection (Raju and Kumar 2014, 2015). The envelope approach selects a set of GCMs models based on probable future climate projections without concerning a GCMs’ performance to replicate the historical climate (Warszawski et al. 2014). However, most GCM ensemble member selection is done based on historical performance since it is assumed that models that can successfully reproduce the observed climate of a region can more accurately predict its future climate (Khan et al. 2020; Nashwan and Shahid 2020). In literature, different approaches have been offered for GCM selection and ensemble preparation (Hassan et al. 2020; Salman et al. 2018; Shiru et al. 2020).

Several studies assessed the climate in CA at the basin, country, or regional scale. Duulatov et al. (2019) used four GCMs of CMIP5 to assess precipitation changes over CA models for RCPs 2.6 and 8.5. Gulakhmadov et al. (2020) used 5 GCMs of CMIP5 to project precipitation (Pr), maximum temperature (Tmx), and minimum temperature (Tmn) in the Vakhsh River Basin of CA for RCP4.5 and RCP8.5. Ta et al. (2018) evaluated the performance of 37 GCMs of CMIP5 to mimic historical Pr over CA. Huang et al. (2014) estimated the ability of 28 GCMs of CMIP5 to project changes in annual Pr over CA for RCPs 2.6 and 8.5. Xiong et al. (2021) assessed the skill of 24 CMIP5 models against the climate research unit (CRU) historical temperature in CA. Zhao et al. (2018) used 25 CMIP5 to simulate the subtropical westerly jet and its impact on projected RCP8.5 summer precipitation over CA. Recently, CMIP6 GCMs are also used for climate projections in different parts of CA. Jiang et al. (2020) used 15 CMIP6 models to assess changes in Pr in CA for four shared socioeconomic pathways (SSPs). Li et al. (2020b) used four CMIP6 models to evaluate total column water vapor changes in the atmosphere over CA for different SSPs. Guo et al. (2021) assessed the ability of CMIP6 to simulate Pr over CA. Li et al. (2021) used four models of CMIP5 and CMIP6 to project future changes in biodiversity in CA for different RCPs and SSPs.

The Amu Darya River (ADR) is the primary supply of fresh water in CA, and it flows through five countries: Kyrgyzstan, Tajikistan, Afghanistan, Turkmenistan, and Uzbekistan (Jalilov et al. 2016). The region’s livelihood and national economy depend heavily on water supplies in the ADR basin (Saidmamatov et al. 2020). The basin is highly vulnerable to climate owing to its arid to semiarid climate and fragile environment. However, only a fewer studies evaluated climate change over the ADR basin. Hagg et al. (2013) used 6 CMIP3 GCMs to project annual and seasonal glacier changes and runoff in the upper ADR basin. White et al. (2014) assessed the ability of fourteen CMIP3 GCMs precipitation and temperature against CRU to project future water supply in the ADR basin. Lutz et al. (2013) evaluated all available CMIP3 and CMIP5 mean MME against the Asian Precipitation–Highly-Resolved Observational Data Integration Toward Evaluation (APHRODITE) and Princeton’s Global Meteorological Forcing Data (PGMFD) datasets to assess the impact of climate change on the future glacier extent in the ADR and Syr Darya river basins. Su et al. (2021b) developed an integrated multi-GCM Bayesian-neural-network hydrological study using GCM simulated climate to assess the influence of climate change on runoff in the ADR basin. Different studies in the basin and other CA regions used different sets of GCMs, which produced contradictory climate projections. This has also made decision-making based on the previous studies impossible. It is very important to recommend a suitable ensemble for climate projection in the ADR basin. Besides, reliable projection of basin’s climate with the selected GCMs for SSPs is vital to aid climate mitigation policymaking.

This study aims to assess CMIP6 GCMs’ ability to replicate observed climate in the ADR basin to recommend an appropriate ensemble for the basin’s climate projections. Besides, the study projected the basin’s climate with associated uncertainty using the selected GCMs to provide vital information for climate change adaptation planning.
2 Study area and data

2.1 Amu Darya River

The Amu Darya River (Fig. 1) is the longest river and primary source of fresh water in CA. The river length is 2540 km, with an annual mean flow of about 79 km$^3$ (Awan et al. 2011; Leng et al. 2021; Schlüter and Herrfahrdt-Pähle 2011; Wegerich 2008; Xu et al. 2021). It originated in the high glaciers and snow-covered Hindukush and Pamir mountains in Tajikistan, Kyrgyzstan, and Afghanistan, and passed through the deserts and the arid plain in Uzbekistan and Turkmenistan before reaching the Aral Sea (Schlüter and Herrfahrdt-Pähle 2011; Wang et al. 2021). The average annual precipitation of the basin is 400 mm (Salehie et al. 2021). The Aral Sea is fed by a delta in the ADR basin, which stretches from a height of 7748 m in the upstream highlands to a height of roughly 300 m in the downstream northwest plains. Some locations in the upstream study area receive precipitation amounts of nearly 2000 mm, while only 100 mm in the downstream (Behzod and Su-Chin 2013).

2.2 Gridded data

In this study, the Climate Prediction Center (CPC) data of Pr, Tmx, and Tmn for the time horizon of 1979–2014 were used as a reference to estimate the performance of GCMs. CPC is a gridded dataset based on gauges that was developed by the NOAA Climate Prediction Center (Xie et al. 2007). From 1979 to the present, you can access this dataset at https://psl.noaa.gov/data/gridded/ with a spatial resolution of 0.5°×0.5°.

Salehie et al. (2021) assessed the ability of seven gridded precipitation datasets against 55 station data over the Amu Darya basin. They found that CPC is the best dataset to replicate the observed precipitation. Salehie et al. (2022) also showed CPC’s ability to replicate observed temperature in the basin. Therefore, the CPC dataset was considered the reference dataset used in this study to assess GCMs’ performance in simulating Pr, Tmx, and Tmn.

2.3 CMIP6 GCMs simulations and scenarios

Nineteen CMIP6 GCMs monthly Pr, Tmx, and Tmn simulations were used to select the best GCMs to
replicate the Pr, Tmx, and Tmn in the study area. Several international research organizations collaborated to produce these GCMs, as presented in Table S-1. The GCMs were selected because they provide monthly historical simulations and future estimates for four SSPs, namely SSPs (1–2.6, 2–4.5, 3–7.0, and 5–8.5) at the time of the study. For a fair comparison of various GCMs model, historical single run r1i1p1f1 (e.g., ensemble members [r1], initialization states [i1], physical parameterizations

Fig. 2 Average annual precipitation of GCMs and CPC for the period of 1979–2014
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[p1], and forcing index [f1]) were considered for all cases. GCMs’ historical (1979–2014) and projection (2015–2100) data can be downloaded from this website: http://cmip-pcmdi.llnl.gov/cmip6/.

3 Methodology
The reference dataset (CPC) and GCMs have various spatial resolutions. Hence, CPC, historical, and future projection
GCMs were interpolated to 73 grid points having the common $1^\circ \times 1^\circ$ resolution for all variables (Pr, Tmx, and Tmn). This resolution was chosen as it was almost close to the mean of all GCMs. The inverse distance weighting approach was used to interpolate the four closest grid points to each grid point, as discussed in (Hamed et al. 2021). GCMs were re-gridding to prevent bias from different spatial resolutions during performance evaluation (Nashwan and Shahid 2020). The procedures for the selection of GCMs are defined below:

1. Compare the monthly historical variables of 19 GCMs and the reference dataset (CPC) using the KGE metric at each grid point.

2. Rank each variable based on KGE, then select the GCM subset using the multi-criteria decision analysis (MCDMA) method.

3. Create an MME using the top four GCMs results from the ranking process.

4. Use the MME to project all climate variables in the near and far future.

### 3.1 Performance evaluation using KGE

In this study, Kling-Gupta efficiency (KGE) was used to evaluate the performance of the historical GCMs in

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Fig. 4 Annual average of daily minimum temperature estimated by GCMs and CPC for the period of 1979–2014

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Fig. 5 Performance evaluation of GCMs precipitation, maximum, and minimum temperature using KGE.
Table 1 KGE ranking of GCMs and the final rank using MCDMA

| GCMs               | Rank (Pr) | Rank (Tmn) | Rank (Tmn) | Average Sum | MCDMA |
|--------------------|-----------|------------|------------|-------------|-------|
| ACCESS-CM2         | 7         | 12         | 7          | 8.67        | 6     |
| ACCESS-ESM1-5      | 19        | 6          | 1          | 8.67        | 7     |
| AWI-CM-1-1-MR      | 4         | 8          | 12         | 8           | 4     |
| BCC-CSM2-MR        | 14        | 7          | 17         | 12.67       | 16    |
| CanESM5            | 11        | 9          | 9          | 9.67        | 10    |
| CMCC-CM2-SR5       | 8         | 17         | 6          | 10.33       | 11    |
| CMCC-ESM2          | 9         | 5          | 4          | 6           | 2     |
| EC-Earth3          | 3         | 13         | 19         | 11.67       | 15    |
| EC-Earth3-Veg      | 1         | 15         | 15         | 10.33       | 12    |
| EC-Earth3-Veg-LR   | 2         | 16         | 16         | 11.33       | 14    |
| FGOALS-g3          | 16        | 19         | 8          | 14.33       | 17    |
| GFDL-ESM4          | 13        | 14         | 18         | 15          | 18    |
| INM-CM4-8          | 5         | 1          | 14         | 6.67        | 3     |
| INM-CM5-0          | 12        | 2          | 11         | 8.33        | 5     |
| IPSL-CM6a-LR       | 18        | 18         | 10         | 15.33       | 19    |
| MIROC6             | 15        | 10         | 3          | 9.33        | 9     |
| MPI-ESM1-2-HR      | 10        | 4          | 13         | 9           | 8     |
| MPI-ESM1-2-LR      | 6         | 3          | 2          | 3.67        | 1     |
| MRI-ESM2-0         | 17        | 11         | 5          | 11          | 13    |

Bold presents the top 4 GCMs

Fig. 6 Historical (1979–2014) and future (2015–2099) simulations of precipitation of a the selected GCMs and b three lowest performing GCMs with the selected GCMs for SSP1–2.6, SSP2–4.5, SSP3–7.0, and SSP5–8.5

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replicating the observed dataset in three different variables (Pr, Tmx, and Tmn). KGE is a statistical index incorporating correlation, bias, and variability to find the association and biases in the mean and the changes of measured and predicted climate variables (Nashwan and Shahid 2020). KGE was presented by Gupta et al. (2009) and then modified by Kling et al. (2012), which defined as:

\[ KGE = 1 - \sqrt{(r - 1)^2 + (\beta - 1)^2 + (\gamma - 1)^2} \]  

where \( r \) is the linear correlation between observed and grid-ded data; \( \beta \) represents the bias obtained by the ratio of mean simulated and mean observed, and \( \gamma \) is the variability component that can be calculated by the percentage of the simulated (GCMs) and observed (CPC) coefficients of variation:

\[ \beta = \frac{\mu_s}{\mu_0} \quad \text{and} \quad \gamma = \frac{\sigma_s/\mu_s}{\sigma_o/\mu_0} \]  

where \( \mu \) and \( \sigma \) are the distribution mean and standard deviation, respectively, while the subscripts \( s \) and \( o \) reflect simulated and observed data, respectively. KGE can range between \(-\infty\) to 1, where 1 is the optimal value, while values greater than 0.4 indicates a fair performance.

### 3.2 Ranking of GCMs

Multi-criteria decision-making analysis (MCDMA) is a recall for evaluating an alternative from multi-objective complex problems and uncertain information of physical and social issues when no method is found to undertake (Wang et al. 2009). The MCDMA approach integrates statistically and numerically obtained outcomes to rank the best option of different choices (Salehie et al. 2021). Salehie et al. (2021) used MCDMA to rank the precipitation gridded dataset. In
In this study, the GCMs are ranked using the KGE metric in a different variable based on their performance. The higher weight of a GCM is provided as a higher frequency of occurrence; therefore, the model is top-ranked. For example, if the model ranked first at most grids from the total number of grid points for each variable, it shall be ranked first among all GCMs. The output rank from each variable was merged using the average method, as shown in Eq. (3). Finally, the average sum was ranked to describe the best GCMs among the set.

$$\text{Average Sum} = \frac{Pr_{\text{rank}} + Tmx_{\text{rank}} + Tmn_{\text{rank}}}{3}$$

### 3.3 Ensemble projections

The top four GCMs were used to create an ensemble mean for climate projection. The advantages of MME are increasing the accuracy of projection and reducing uncertainty in the individual model (Ahmed et al. 2020; Salman et al. 2018; Shiru et al. 2020). Different techniques are used to generate MME, but the weighted average method is the most commonly used (Sachindra et al. 2014; Shiru et al. 2020). This technique was also adopted in the current study. The MME was used to project the ADR basin’s climate change for two periods; the near
future (2020–2059) and the far future (2060–2099). Spatial distribution maps were created to show the change in the basin for precipitation (%) and temperature (°C). Also, each variable’s change in each climate zone was presented.

4 Results

4.1 Mean annual precipitation spatial distribution

The mean annual precipitation climatology of CPC and 19 GCMs of CMIP6 for the period of 1979–2014 are presented in Fig. 2, while the mean Tmx and Tmn are shown in Fig. 3 and Fig. 4 in the supplementary. CPC showed that the mean annual precipitation for the study area ranged between 50 and 350 mm. The highest precipitation occurs in the center part, while the lowest is in the basin’s northwest. The precipitation decreases gradually from the south of Tajikistan and north of Afghanistan until it reaches the basin’s northwest. It was observed from the figure that some GCMs, such as EC-Earth3-Veg and EC-Earth3-Veg-LR showed a similar spatial pattern to observed precipitation. Many GCMs like ACCESS-CM2, ACCESS-ESM1-5, and BCC-CSM2-MR showed high precipitation in the center and east part of the
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4.2 Performance evaluation of GCMs

The GCM’s performance was evaluated against CPC Pr, Tmx, and Tmn data for the period 1979–2014 using the KGE metric. The results are presented using a level plot in Fig. 5. Annual Pr, Tmx, and Tmn had median KGE of −0.03, 0.51, and −1.37, respectively, for all GCMs. Many GCMs had negative KGE for both Pr and Tmn, whereas the Tmx of most GCMs was quite good at mimicking the CPC Tmx. The results showed the highest KGE value (0.85) for INM-CM4-8 in Tmx and the lowest, 0.11, for EC-Earth3-Veg for Pr.

4.3 Ranking of GCMs

We ranked the GCMs for each variable from best to worst based on their KGE values. The higher value of KGE for a GCM indicates its better skill in replicating historical observations. The average rank of all three variables was obtained using Eq. (3), as shown in Table 1. Finally, the lowest average rank was taken as the best GCM in reproducing the CPC dataset. The top four findings were MPI-ESM1-2-LR, CMCC-ESM2, INM-CM4-8, and AWI-CM-1–1-MR, respectively. The rest of the GCMs showed weak performance in replicating the observations. The top four GCMs were used to estimate the ensemble mean. The KGE of the MME mean was 0.04, 0.75, and 0.13 for rainfall, Tmx, and Tmn, respectively.

The selection of GCMs based on past performance does not guarantee consistency in future projections due to the non-linear response and the general complexity of the climate system. Therefore, Pr simulations of the four selected GCMs (Fig. 6a) and Pr simulations of the four worst-performing models with the selected models (Fig. 6b) were compared to justify selection. GCM simulations for both historical and future periods (1975–2099) are presented in the figure. The result showed high consistency in the future projections of the selected GCMs (MPI-ESM1-2-LR, CMCC-ESM2, INM-CM4-8, and AWI-CM-1–1-MR), while a large inconsistency in projections of worst-performing models (FGOALS-g3, IPSL-CM6A-LR, and GFDL-ESM4) compared to the selected models. Similar results were observed for Tmx and Tmn. The results justify the selection of GCMs in the study area based on their past performance.

4.4 Climate projection

The top selected GCMs were merged to create the mean MME. The MME was used to project the changes in annual Pr, Tmx, and Tmn for four SSPs in the near future (2020–2059) and the far future (2060–2099) over different climate zones of the basin. The map of climate zones is presented in Fig. 7, which was adapted from the Köppen-Geiger climate classification global map (Peel et al. 2007). The following sections summarize the projected fluctuations in annual Pr, Tmx and Tmn.

4.4.1 Precipitation projection

The changes for Pr in the ADR basin projected by MME of the selected GCMs are presented in Fig. 8. Results indicate that projected change in the far future is greater (3.3–12.5%) than in the near future for all SSPs. The percentage of change in Pr in the near future for SSP1–2.6 to SSP5–8.5 were in the range of −12.4 to 3.1%, −7.3 to 10.5%, −6.4 to 7.0%, and −10.3 to 4.2%. The projected change in Pr for the far futures for those SSPs were −8.3 to 3.3%, 1.6 to 9.1%, −4.2 to 12.2%, and −4.3 to 10.8%. Most GCMs projected higher Pr over a small patch in the northwest cold desert climate region. For example, one of the selected GCMs (INM-CM4) is presented in Figure S1 in the supplementary documents. It shows similar variability to MME projections. The precipitation change is negative in most parts of the basin, with harsh change in the center to the south in the near future for SSP1–2.6. However, it showed a negative change in the far future over the basin but relatively less compared to the near future.

4.4.2 Temperature projection

The annual Tmx changes were presented as the absolute difference between the future projection and the historical simulation. The absolute changes for Tmx and Tmn using INM-CM4 are presented in Figures S2 and S3, respectively. Figure 9 depicts the geographic distribution of annual Tmx changes using MME. The figure indicates a gradual increase in Tmx from SSP1–2.6 to 5–8.5 across the basin in both future periods. However, all GCMs showed a larger growth for the far future relative to the near future. Only SSP3–7.0 showed a homogeneous spatial distribution of Tmx over the whole basin. The lower projected change in Tmx in the near future was from 1.3 to 1.6 °C, while the far future ranged between 1.6 and 4.9 °C. The highest increase (4.9 °C) was for far future SSP5–8.5.

The changes in annual Tmn were very similar to Tmx. The spatial patterns of the projected change in Tmn are presented in Fig. 10. Compared to Tmx, the projected change in Tmn was greater. There was a variation in change for different GCMs, except for SSP5–8.5 in the near future, which showed a more homogenous spatial pattern in change for all GCMs. Like Tmx, a gradual
increase in Tmn was noticed from SSP1–2.6 to 5–8.5 across the basin for both future scenarios. Long-term projections indicated a greater temperature rise, between 2.3 and 5.5 °C. The highest increase in Tmn (5.5 °C) was for SSP5–8.5 in the far future, while the lowest change (1.3 °C) was for near future SSP1–2.6.

### 4.5 Uncertainty in projected climate change

The uncertainty in the projected climate was estimated from the lower and upper band values of projections by different GCMs for individual SSP. The uncertainty in the projected precipitation projected changes (%) in different climatic zones of the Amu Darya basin for two future periods for different SSPs is shown in Fig. 11. It shows a higher uncertainty in projection in the far future (2060–2100) compared to the near future (2020–2059). The uncertainty in projection was also higher for higher SSPs. For example, the highest upper band value (32%) was observed for far future SSP5–8.5. This agrees with what has been found by the vast majority of research estimating uncertainty in GCM estimates. Pour et al. (2018) showed an increase in uncertainty with time and emission scenarios for rainfall. Alamgir et al. (2019) also projected higher uncertainty in temperature projections in the late period for higher emission scenarios.

Uncertainties associated with Tmx are presented in Fig. 12. Uncertainty in Tmx was less compared to Tmn. This is due to the higher variability of precipitation than temperature. Hamed et al. (2022) showed a higher uncertainty in projected precipitation than temperature. The variation in projection was in the range of 3.0 to 7.0 °C or 4.0 °C for climate zone 4 (Warm Dry Summer Continental Climate). Similarly, the uncertainty in the projected Tmn (Fig. 13) was less. The highest uncertainty in Tmn was 3.8 °C for SSP5–8.5 during 2060–2099 for climate zone 1 (Cold Desert Climate). However, like Pr, the uncertainty for both Tmx and Tmn was higher for the far future and higher SSPs.

### 5 Discussion

A range of uncertainty exists across different global climate models (Khan et al. 2020; Lutz et al. 2016). So as to reduce the uncertainty in climate projections, it is necessary to choose GCMs depending on their performance in modeling the climate of a certain region (Ahmed et al. 2019b; Salman et al. 2018). MMEs are usually suggested to decrease the uncertainties related to GCMs simulations or projections (Ahmed et al. 2020). In this research, we employed a model-based uncertainty reduction technique to choose a subset of GCMs (MME) based on their historical performance.

A few analyses have been performed in the ADR basin, which is different from our work in terms of method and data availability. A recent study (Guo et al. 2021) used CMIP6 to simulate precipitation over CA and found that the performance of GCMs varies from region to region with a consistent annual cycle shape in western CA. They showed limited models performance in simulating the observations. White et al. (2014) used mean MME special reports on emission scenarios (SRA2) precipitation annual temperature anomalies for 2070–2099 over the ADR basin. They showed a mean annual rise in temperature ranged between 4 and 4.6 °C through the basin by 2070–2099 under a high-emission scenario and downward precipitation trend, ranging between – 5.3% in Nukus city Uzbekistan and – 13.6% in Mary city in the Kara-kum desert Turkmenistan. Xu et al. (2021) projected streamflow in ADR for climate change scenarios. The multi-scenario ensemble streamflow forecast showed that during 2021–050, the mean annual precipitation and the mean temperature should increase. However, the average annual streamflow would decline, which climate change donates 78.8 to 98.7% of streamflow change in each scenario.

This study utilized the past performance approach to select a subset of GCMs from 19 GCMs. Secondly, the KGE metric was used to evaluate the association between all GCMs and the CPC (Pr, Tmx, and Tmn) at each of the 73 grid points of 1° × 1° resolution. Thirdly, an MCDMA was used to rank the inconsistent results obtained using KGE for three variables (Pr, Tmx, and Tmn). The results of MCDMA revealed that MPI-ESM1-2-LR, CMCC-ESM2, INM-CM4-8, and AWI-CM-1–1-MR are the best in replicating observed climate in ADRB.

Results obtained using future MMEs showed an increase in Pr ranging between 3.3 and 12.5% in the far future (2060–2099) when all SSPs were considered. The four SSPs’ spatial pattern of projected change showed a higher increase in Pr in the east and northwest of the basin and less in the basin’s center. This result contradicts Agal’tseva et al. (2010) findings, which showed a 5–12% reduction in precipitation during 2070–2099. This increase in Pr could be due to the effect of atmospheric circulation of the Caspian Sea caused by increased temperature (Farley Nicholls and Toumi 2014). It could also be because of the Aral Sea surrounding the ADR basin delta. The highest precipitation in the east of the basin may be due to the increased intensity of the Siberian monsoon that causes rain and snow in the area in the winter and spring (Wang et al. 2020).

The absolute change in temperature between the historical and future projection MME were used to
present the change in Tmx and Tmn. The results indicated a gradual increase in Tmx and Tmn in the basin. The results were almost in agreement with previous studies (Agal’tseva et al. 2010; Gulakhmadov et al. 2020; White et al. 2014; Xu et al. 2021) in the region.

6 Conclusions

The performance of 19 GCM-CMIP6 in replicating the historical precipitation and temperature in the ADR basin was assessed to recommend an appropriate set of GCMs for climate studies. Besides, the study employed the selected
GCMs for the projection of the climate of the basin for different SSPs with associated uncertainty. The results showed that MPI-ESM1-2-LR, CMCC-ESM2, INM-CM4-8, and AWI-CM-1–1-MR best replicate observed Pr, Tmx, and Tmn in the ADR basin. Climate projection using the selected GCMs revealed a rise in Pr, Tmx, and Tmn in the basin for all SSPs, especially for 2060–2099. Both precipitation and temperature were predicted to increase, with the former more so at higher SSPs and further in the future than closer to the present. The uncertainty in projected climate showed more uncertainty in precipitation projections compared to temperature. The uncertainty was also noticed higher for
higher SSPs and in the far future compared to the near future. This is the first attempt to evaluate CMIP6 GCMs’ performance in the ADR basin to select the GCM ensemble and climate projections using the selected ensemble. The results of the study can be used for climate change studies and decision-making processes. In the future, GCMs’ skills can be evaluated according to their ability to replicate climatic extremes in the basin. Besides, the selected GCMs can be used to evaluate future changes in climate extremes, like floods and droughts in the basin. In addition, the impact of future change in the nearby Syr Darya River can be assessed with the Amu Darya River.

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Author contribution All the authors contributed to conceptualizing and designing the study. Obaidullah Salehie and Tarmizi bin Ismail gathered data; the programming code was written by Shamsuddin Shahid and Mohammed Magdy Hamed; the initial draft of the paper was prepared by Obaidullah Salehie and Tze Huey Tam; the article was repeatedly revised to generate the final version by Tarmizi bin Ismail and Shamsuddin Shahid.

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Data availability All the data are available in the public domain at the links provided in the texts.

Code availability The codes used for the processing of data can be provided on request to the corresponding author.

Declarations

Ethics approval Not applicable.

Consent to participate Not applicable.

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