Projection of Hot and Cold Extremes in the Amu River Basin of Central Asia using GCMs CMIP6

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Abstract
The extreme temperature has become more frequent and intense due to global warming, particularly in dry regions, causing devastating impacts on humans and ecosystems. The transboundary Amu river basin (ARB) is the most vulnerable region in Central Asia (CA) to extreme weather linked to climate change. This study aimed to project warm and cold extremes in ARB for four Shared Socioeconomic Pathways (SSP1-2.6, SSP2-4.5, SSP3-7.0 and SSP5-8.5) and two time-horizons, 2020–2059 and 2060–2099, using daily maximum (Tmax) and minimum temperature (Tmin) simulations of global climate models (GCMs) of Coupled Model Inter-comparison Project phase six (CMIP6). Results revealed that the basin’s west experiences more hot extremes and the east more cold extremes. Climate change would cause a significant increase in the annual mean of Tmax and Tmin. However, the increase in mean Tmin would be much higher (5.0°C) than the mean Tmax (4.6°C). It would cause an increase in the hot extremes and a decrease in the cold extremes in the basin. The higher increase in the hot extremes would be in the west, while the higher decrease in the cold extreme in the basin’s east. The number of days above 40°C would increase from 45 to 60 days in the basin’s west and northwest compared to the historical period. The number of days below −20°C would decrease up to 45 days in the basin’s east. Overall, the decrease in cold extremes would be much faster than the increase in hot extremes.

Keywords Temperature extreme · Thresholds · Climate change · Extreme indices

1 Introduction
Global warming-induced climate change caused a change in temperature extremes’ recurrence, intensity, duration, timing, and geographical variability (Islam et al. 2021b; Pérez et al. 2021). The changes in temperature extremes significantly affected human health, agricultural yield, economic activities, social conflicts and the biophysical environment (Li et al. 2019; Islam et al. 2021a; Pérez et al. 2021; Zhao et al. 2021a; Hamed et al. 2022a). Natural hazards like the frequency and severity of heat waves, cold spells, drought, aridity and forest fires have also been exacerbated by increasing temperature extremes (Ahmed et al. 2018; Khan et al. 2019; Ajjur and Al-Ghamdi 2021; Lotfi-rad et al. 2021a, b). The recurrence, duration and severity of temperature extremes have also increased in central Asia (CA) like many other regions (Feng et al. 2018; Zhang et al. 2019b; Peng et al. 2020). According to the Paris agreement, global warming would be further intensified in the forthcoming years even if the carbon emission reduction is possible (Zhao et al. 2021a; Du et al. 2022; Hamed et al. 2022c). Dry regions like CA are more vulnerable to temperature extremes for their friable ecosystem (Salman et al. 2017; Khan et al. 2019). Evaluation of possible changes in temperature extremes is vital for such regions for adaptation and mitigation planning.
Global climate models (GCMs) of CMIP5 and earlier versions have been widely used for the projection of climatic extremes in many regions of the globe (Li et al. 2019; Sharafat et al. 2020; Ying et al. 2020; Ajjur and Al-Ghamdi 2021; Almazroui et al. 2021; Bai et al. 2021; Seong et al. 2021; Zhao et al. 2021b; Deng et al. 2021). CMIP6 is the latest generation of CMIPs that integrated Radiative Concentration Pathways (RCPs) with Shared Socioeconomic Pathways (SSPs) that makes climate projection climate more reliable (Eyring et al. 2016). RCP represents the future atmospheric emission concentration affecting the radiative forcing, while SSP considers the possible socioeconomic development (e.g., change in population, economy and technology) along with radiative forcing (Van Vuuren et al. 2011; O’Neill et al. 2014). There are five high-priority SSPs scenarios: SSP1-2.6 reflects sustainable development, SSP2-4.5 represents the middle of the road, SSP3-7.0 considers regional rivalry, and SSP5-8.5 represents high fossil-fuel development throughout the 21st century. Besides, SSP 1-1.9 is another high priority scenario developed to follow the Paris Agreement’s 1.5 °C global warming restriction target (Meinshausen et al. 2020). The radiative forcing considered in SSP1-2.6, SSP2-4.5, SSP3-7.0 and SSP5-8.5 correspond to the RCP2.6, RCP4.5, RCP6.0 and RCP8.5, respectively. The CMIP6 GCMs have some advantages, including enhancement in model structure, spatial resolution, uncertainty, and representing synoptic progressions (Eyring et al. 2016; Scher and Messori 2019; Kamal et al. 2021; Su et al. 2021a; Hamed et al. 2022c). This emphasizes reassessing the changes in temperature extremes for new scenarios using CMIP6 to update the knowledge of climate change implications on temperature extremes and rationalize the adaptation strategies planned based on CMIP5 projections.

Uncertainties associated with GCMs hinder the reliable projection of extreme temperature (Pour et al. 2018; Shiru et al. 2019, 2020). Generally, projection uncertainties are minimized using GCMs ensemble, selected according to their ability to replicate the observed climate (Lutz et al. 2016; Salman et al. 2018; Ahmed et al. 2020; Hassan et al. 2020; Khan et al. 2020; Hamed et al. 2022b). Different methods, including statistical metrics, multi-objective linear programming and machine learning methods, have been used to assess GCM’s past performance and create an ensemble using best performing GCMs (Noor et al. 2019; Hassan et al. 2020; Nashwan and Shahid 2020; Shiru et al. 2020; Srivastava et al. 2020; Hamed et al. 2022b).

The extreme indices are commonly used to assess the changes in climatic extremes. The Expert Team on Climate Change Detection and Indices (ETCCDI) proposed 27 extreme climate indices, including 16 temperature extremes (Ying et al. 2020). These extremes are based on days with temperatures above or below specific physically-based thresholds or quantiles (Zhang et al. 2011). Therefore, they can provide different characteristics of both hot and cold extremes related to social impacts. This has made them widely used for assessing temperature extremes across the globe.

Amu river, the largest transboundary river and the primary source of CA’s freshwater, flows within five riparian’s countries (Jalilov et al. 2016; Dilshod et al. 2021). The livelihoods and economy of approximately 80 million people from these countries depend on water supplies by the Amu River (Saidnamatov et al. 2020; Hu et al. 2021). About 6 million hectares (ha) of lands in Uzbekistan in Turkmenistan, Afghanistan, Tajikistan and Kirgizstan are irrigated by the Amu River (Ahmad and Wasiq 2004). The basin’s hydrology has undergone tremendous change in the recent past due to human intervention in river flow (Khaydar et al. 2021). The increased temperature in the basin has worsened this situation and imposed further stresses on water resources and public health (White et al. 2014; Hoell et al. 2020; Hu et al. 2021; Su et al. 2021b; Xu et al. 2021) projected that increased temperature in the ARB would decrease river flow by 78.8–98.7% during 2021–2050. The faster glacier melting under a warmer climate would shift the peak flow from summer to spring. Su et al. (2021) projected to decline in the glacier extent in ARB by 71.9% for RCP8.5 over 2021–20100. This glacier decline would reduce future runoff and water availability, especially for irrigation in summer in crop season downstream of the river. Increased temperature extremes would worsen the situation. However, studies related to changes in temperature extremes in CA is very limited (Table 1). ARB was not the focus of any previous studies conducted in CA.

The present study aimed to assess the possible change in temperature extremes in ARB for different shared socioeconomic pathways. Daily maximum temperature (T \text{max}) and minimum temperature (T \text{min}) simulations of four CMIP6 GCMs for four SSPs were used to project the changes in twelve temperature extremes over ARB. Maps are prepared to show the geographical distribution of the changes in several temperature extremes for different future horizons to aid adaptation planning. Several studies have been conducted to project temperature extremes in CA, including ARB (Table 1). However, previous studies employed CMIP3 or CMIP5 GCMs to project temperature extremes for RCP or Special Report Emission Scenarios (SRES). This is the first attempt to evaluate extreme temperature changes over ARB for SSPs using CMIP6 models. This study is vital for apprising information on climate change impacts on temperature extremes in the ARB for new scenarios to streamline the existing adaptation measures derived for RCPs.
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stan, Kyrgyzstan, Afghanistan, Turkmenistan, Uzbekistan,
and ends at the Aral sea (Gao et al. 2021; Hu et al. 2021).
It mostly recharges by glaciers and snow melted water, espe-
cially by Vakhsh and Pyandj tributaries as headwaters in the
high mountain of the Pamir, Tien Shan and Hindukush in

2 Study Area and Data

2.1 Amu river basin

The Amu river is the main water resource in CA and a major
feeder of the Aral Sea (average discharge 78.5 km$^3$/year). It
flows 2,540 km within riparian countries, including Tajiki-
stan, Kyrgyzstan, Afghanistan, Turkmenistan, Uzbekistan,
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Table 1  Existing temperature extreme studies in CA

| Author         | Major Findings                                                                 |
|----------------|--------------------------------------------------------------------------------|
| Hu et al. (2016)| Increasing trend in $T_{\text{min}}$ and $T_{\text{max}}$ at annual and seasonal scales, except in winter $T_{\text{max}}$. Increase in warm nights and days and decrease in cold nights and days. |
| Feng et al. (2018)| Rise in both $T_{\text{max}}$ and $T_{\text{min}}$, but it was faster for $T_{\text{max}}$. Warm indices showed a substantial increase from Turkmenistan to China. |
| Zhang et al. (2019a)| Increase in $T_{\text{max}}$ and $T_{\text{min}}$ and extremes related to $T_{\text{min}}$. |
| Peng et al. (2020)| Increase in annual maximum of $T_{\text{max}}$ and minimum of $T_{\text{min}}$ for all RCPs |
| Zhu et al. (2020)| Increase in $T_{\text{max}}$ and $T_{\text{min}}$, and days having $T_{\text{min}} > 25$ °C, while a decrease in days having $T_{\text{min}} < 0$ °C for all RCPs. |
| Liu et al. (2020)| Increase in mean temperature in CA by 1.48 °C for 1.5 °C warming scenario. Increase in hot days and growing season length. |

RCP = Representative concentration pathways

Fig. 1  Topography of the Amu river basin and its location in Central Asia
Tajikistan and Afghanistan, which contribute 85% of river flow (Schlüter et al. 2013; Kattakulov et al. 2021). The

Fig. 2 (a) land use; and (b) population density maps of the study area
topography of the basin (Fig. 1) is complex, with 7,750 m elevation in the high upstream mountains to 200 m in the plains. The climate of the ARB is continental, with a yearly average temperature of 13.1 °C and total precipitation of 1015 mm in the upstream mountains and 100 mm in the low lands deserts (Gao et al. 2021; Salehie et al. 2021b, 2022). The maximum temperature reaches 35 °C in summer in the west, and the minimum temperature goes below –8 °C to –20 °C all over the basin in the winter (Behzod and Su-Chin 2013; Wang et al. 2016). The annual evaporation in ARB is nearly 2000 mm (Wang et al. 2021).

The land use and population density maps of the ARB are shown in Fig. 2(a) and (b), respectively. Agriculture is the major sector of livelihood of 43 million people and the national economy of the riparian countries (Erokhin et al. 2020). Nearly 30% of the population depends on agriculture for livelihood, which contributes to 20 to 35% of the gross domestic products of the riparian countries (Erokhin et al. 2020; Alam and Shrestha 2021). Agriculture mostly depends on ARB water. Population in the basin is higher in the central, particularly central north, where the major urban centers are located, and the croplands are more. A major portion of the domestic water supply in the populated region comes from ARB (Shi et al. 2021). The population density in most parts of the basin is increasing by 1.26 to 6.71 person/km². The increase is much higher in the central west region covered by Afghanistan and Tajikistan. Irrigated agriculture is expanding in proportion to population growth to produce food for the growing population, which in turn caused an increasing water demand in the basin. Climate change caused a large increase in temperature in ARB (Salehie et al. 2021a). Rising temperature caused an increase in evaporation and water demand. In contrast, the river flow of the basin has decreased by nearly 15.5% between 1951 and 2007 due to changes in precipitation patterns (Wang et al. 2016). Increasing water demand and decreasing water availability caused a gradual increase in water stress and affected the sustainable socioeconomic development of the basin (Xu et al. 2021).

2.2 Datasets

Daily \( T_{\text{max}} \) and \( T_{\text{min}} \) of four GCMs CMIP6 were used to project temperature extremes in ARB (Table 2). Salehie et al. (2021) evaluated the skill of 19 GCM-CMIP6 for the ARB and found these four GCMs as the best in simulating the observed climate of the basin. Therefore, these four GCMs were selected. The first model run (r1i1p1f1) was applied for a fair comparison. GCM’s simulations were obtained from: https://esgf-node.llnl.gov/search/cmip6/.

### 3 Methods

The procedure followed in this study to assess the extreme temperature for the historical (1975–2014) and projected periods, 2020–2059 (near future) and 2060–2099 (far future), is presented in Fig. 3. Twelve temperature extremes over the basin were evaluated and described in Table 3. ETCCDI proposed 16 indices for assessing temperature extremes. However, some of the indices are interrelated. Some do not provide additional information than that obtained from the indices selected in this study. For example, considering the glacial environment of the study area, days with a minimum temperature <0°C is not relevant when days with temperatures < -20°C is assessed. Therefore, these twelve temperature extreme indices were found adequate to understand the temperature extremes in the basin.

The indices were calculated using the matrixStats package of R software. The GCMs were interpolated to 1°×1° resolution, nearly to the mean resolution of all GCMs, using the bilinear interpolation method discussed in Hamed et al. (2021) to avoid inconsistency due to spatial resolutions (Nashwan and Shahid 2020). The raw GCM data was used to assess the changes in temperature extremes. It helped to preserve the original climate change signal without any distortion. Most of the previous studies 1°×1° resolution gridded CMIP6 GCMs for their performance evaluation and climate change projections in different regions of the globe (Rivera and Arnould 2020; Yazdandoost et al. 2021; Hamed et al. 2022c). The hot and cold extreme indices were assessed using \( T_{\text{max}} \) and \( T_{\text{min}} \) of CMIP6 for the historical and the two future periods at 73 grids over the ARB, and the changes were presented using maps.

| No | Model name       | Institution                                      | Country     | Resolution   |
|----|------------------|--------------------------------------------------|-------------|--------------|
| 1  | AWI-CM-1-1-MR    | Alfred Wegener Institute Climate Model            | Germany     | 0.9°×0.9°    |
| 2  | CMCC-ESM2        | Fondazione Euro-Mediterranean Center on Climate Change | Italy       | 0.9°×0.9°    |
| 3  | INM-CM4-8        | Institute for Numerical Mathematics              | Russia      | 1.5°×2.0°    |
| 4  | MPI-ESM1-2-LR    | Max Planck Institute Earth System Model           | Germany     | 1.875°×1.86° |
4.1 Hot Extreme

Figure 4 shows the spatial variability of $M_{xT_{\text{max}}}$ for the reference period and its changes in two future time horizons for four SSPs. The figure indicates that the annual maximum of $T_{\text{max}}$ is highest (47 °C) in the west and northwest of the basin. It gradually decreases towards the center (32 to 44 °C) and reaches a minimum, 23°C in the basin’s east. The geographical variability of projected change in the $M_{xT_{\text{max}}}$ was almost similar for all SSPs. SSP1-2.6 showed a similar increasing pattern in $M_{xT_{\text{max}}}$ in the two future periods, while SSP2-4.5 showed a greater increase in $M_{xT_{\text{max}}}$ during 2020–2059 than during 2060–2099. The highest increase in $M_{xT_{\text{max}}}$ (3–6 °C) was projected in the far future for higher SSPs. The lowest rise in $M_{xT_{\text{max}}}$ was projected in the basin’s center and north for all SSPs. However, the projected highest rise in $M_{xT_{\text{max}}}$ was different for different SSPs. For higher SSPs, a greater increase in $M_{xT_{\text{max}}}$ was projected in the east and central northwest of the basin.

The spatial distributions of $M_{\text{meanT}}$ for the reference period (22.5 °C) was in the west and northwest of the basin. It gradually decreases towards the center (7.5–20°C) and reaches in the range of 0–2.5 °C in the basin’s east. The $M_{\text{meanT}}$ was projected to increase more for higher SSPs. For example, SSP1-2.6 projected an increase in $M_{\text{meanT}}$ by 1.8 °C, while SSP5-8.5 by 2.2 °C in the near future. Greater changes were also projected in the late period. For example, the increases were between 2.2 and 2.6 °C in the near future for different SSPs, while those were between 4.2 and 4.6 °C in the far future.

Figure 6 presents the results obtained for $T_{\text{max}}$ above 95-th percentile ($p_{95T_{\text{max}}}$) in the ARB. The highest value of $p_{95T_{\text{max}}}$ (40 °C) was observed in the basin’s west and northwest and the lowest in the east (15 °C). The $p_{95T_{\text{max}}}$ was projected to increase gradually from lower to higher scenarios and from the early to the later period. The increase would be 1.5 °C in the near future for SSP1-2.6, and between 1.5 and 2.5 °C for SSP5-8.5. For the far future, it would be 1.5–3 °C for SSP1-2.6 and 5.5 °C for SSP5-8.5. Overall, a greater change in $p_{95T_{\text{max}}}$ over the whole basin was projected for SSP-7.0 (between 4 and 5 °C) followed by SSP2-4.5 (up to 3.5 °C).

Figure 7 showed the changes in $T_{\text{max}}$ above 99-th percentile ($p_{99T_{\text{max}}}$) in the ARB for two future periods and four SSPs. Different parts of the basin showed different patterns in $p_{99T_{\text{max}}}$. The highest $p_{99T_{\text{max}}}$ during the reference period was 45 °C in a small patch in the west. It was between 20 and 40 °C in the center, north, south and northwest, and only 15 °C in the basin’s east. The projected change showed a steady rise in $p_{99T_{\text{max}}}$ with time. SSP1-2.6 showed changes...
northwest and no change in the east. A gradual expansion in the area of increased D40T$_{\text{max}}$ was noticed with time. The results increase more hot days in the region where hot days are already very high. A similar increase in the days with a temperature higher than 45°C (D45T$_{\text{max}}$) was also noticed (Fig. 9). In other parts of the basin, it may seldomly reach above 45°C. The spatial distribution of D45T$_{\text{max}}$ for the reference period showed that it only occurs for up to 7 days in the basin’s west. The projection of D45 showed a possible increase by 5 to 45 days. But the increases would be concentrated only in the basin’s northwest. The increase will be much faster in the later period for all SSPs than in the earlier period. The projected increase in D45T$_{\text{max}}$ for SSP1-2.6 was 10 to 15 days for the far future. It indicates a nearly 100% increase in extremely hot days in the northwest of the basin, even if the global temperature can be restricted to below 2ºC according to the Paris agreement.

4.2 Cold Extreme

The spatial pattern of annual minimum temperature (MnT$_{\text{min}}$) for the base period and the projected changes in MnT$_{\text{min}}$ in ARB for two future time horizons for four SSPs are presented in Fig. 10. The basin experiences the lowest MnT$_{\text{min}}$ (-40 °C) in the east. It varies between −20 and −35 °C in the rest of the basin. This means all the basin experiences frosting temperatures during winter. The changes in MnT$_{\text{min}}$ were like other indices, greater changes in the later period than the early period and a higher increase for higher SSPs than lower SSPs. The highest increase in MnT$_{\text{min}}$ (13 °C) was projected in a small portion in the northwest for SSP5-8.5, followed by SSP3-7.0 (12 °C), SSP2-4.5 (10 °C) and SSP1-2.6 (8 °C). However, the change in MnT$_{\text{min}}$ across the whole basin was between 0 and 10 °C for SSP1-2.6 and SSP2-4.5, and between 2 and 13 °C for SSP3-7.0 and SSP5-8.5 in the far future. Overall, the results revealed a higher increase in MnT$_{\text{min}}$ compared to MxT$_{\text{max}}$. It indicates the extreme cold temperature is decreased faster than the increase in extremely hot temperature.

The spatial pattern of MeanT$_{\text{min}}$ and its projections are present in Fig. 11. The lowest MeanT$_{\text{min}}$ (-12 °C) was noticed in the basin’s east and the highest (12 °C) in the west and northwest. The MeanT$_{\text{min}}$ in the north, south and center of the basin was between 0 and 9 °C. The projected change in MeanT$_{\text{min}}$ showed a gradual increase from lower to higher SSPs and from the near to the far future. In the early period, the projected increase in MeanT$_{\text{min}}$ was between 1.4 and 1.8 °C for SSP1-2.6 and SSP5-8.5, respectively, while it was between 1.8 and 5 °C in the far future for the same SSPs. The highest increase in MeanT$_{\text{min}}$ was noticed in a narrow path in the basin’s north, south, east and northwest...
for the far future. In contrast, the spatial distribution of projected change in MeanT$_{\text{min}}$ was different for different SSPs in the near future. However, the projected increase was higher in the south for most SSPs.
The geographical distribution of $p05_{T_{\min}}$ and its projected changes are shown in Fig. 12. The basin’s east experiences the lower $p05_{T_{\min}}$ (-20 to -30 °C) than the other parts (-5 to -10 °C). Besides, a small patch in the basin’s south also
experiences a relatively high $p_{05T_{\text{min}}}$ (-15 and −20 °C. The geographical variability in $p_{05T_{\text{min}}}$ projection was similar for all SSPs in the near future (1 to 3 °C). It was projected to rise between 2.5 and 7.5 °C for the far future for all SSPs.
Overall, a higher increase in $p05T_{\text{min}}$ in the basin’s north and south was noticed. The highest increase (7 to 7.5 °C) was in the north, south and smaller area in the center and northwest for SSP5-8.5. Overall, a higher increase in $p05T_{\text{min}}$ in the basin’s north and south was noticed.
Figure 13 shows the spatial distribution of $p_{01T_{\text{min}}}$ and its projections for two future periods in ARB. The lowest $p_{01T_{\text{min}}}$ (-35 °C) was observed in the basin's east and the highest (-10 °C) in the rest of the basin. The $p_{01T_{\text{min}}}$ was
similar for all SSPs in the near future. They showed an increase in $p01_{T_{\text{min}}}$ in the range of 1 to 4°C. However, the geographical distribution of the change in $MnT_{\text{min}}$ was projected to increase from the early to the late period. The geographical distribution of the change in $p01T_{\text{min}}$ was similar for all SSPs in the near future. They showed an increase in $p01T_{\text{min}}$ in the range of 1 to 4°C. However, the
higher SSPs than only in the range of 1 to 5 °C for lowe
spatial pattern of the increase was different for the far future.
A large increase in p01T$_{\text{min}}$ (up to 8.5°C) was projected for higher SSPs than only in the range of 1 to 5 °C for lowe
SSPs. This indicates a very fast rate of increase in $p_{01}T_{min}$ in the later period for higher SSPs.
Figure 13 shows the spatial distribution of D-20$T_{\text{min}}$ for the reference period. The changes in D-20$T_{\text{min}}$ for two future periods and four SSPs are also presented. The D-20$T_{\text{min}}$ varies from 100 days in the river upstream of the basin to 10
days in the west. The D-20T_{min} was projected to decrease for the whole basin. However, the decrease would be more (25 to 45 days) in the cold regions (river upstream) than in the other parts (5 days). The results indicate cold days would decrease more where it is more frequent and less where it is less experienced. This would make the geographical variability of cold days more homogeneous over the basin.

The spatial distribution of D-30T_{min} for the reference period was similar to D-30T_{min} (Fig. 15). The D-30T_{min} occurs only in the eastern mountainous cold region. It seldomly occurs in other parts of the basin. The projected changes in D-30T_{min} showed decreases in its occurrence in the range of 5 to 25 days for different SSPs. The decrease would be much higher in the far future for higher SSPs. However, there would be a more or less similar decrease in D-30T_{min} for all scenarios in the near future. There was no significant difference in the projected changes in D-30T_{min} between the near and far future for SSP1-2.6. The results indicate a decrease in very cold days by 5 to 10 days in the near future, even for the mildest climate change scenario (SSP1-2.6).

5 Discussion

The changes in hot and cold extremes in the ARB for two future periods under four SSPs have been evaluated in this study. The results indicate increased frequency, intensity, spatial extent, and temporal variations in temperature extremes in CA’s arid and semiarid regions. Overall, the study revealed increases in hot extremes and decreases in cold extremes in the basin. However, decreases in cold extremes would be much faster than increases in hot extremes. No study previously assessed the changes in temperature extremes in ARB using CMIP6 models and SSPs. However, the study’s findings collaborate with those obtained using CMIP5 models and RCP scenarios. Zhu et al. (2020) reported a temperature rise between 2.0 and 5.0 °C and the consequent decrease in the annual freezing days over CA for RCP4.5 and 8.5. Hu et al. (2016) also showed that the warmer days would increase and cold days would decrease over CA.

The present study revealed greater changes in temperature extremes for higher SSPs and the far future. However, some indices showed similar changes for all SSPs in the near future. For example, the geographical variability of projected change in the MxTmax was almost similar for all SSPs in the near future. However, a large change was noticed between the near and far future for most indices for higher SSPs. For example, the projected decrease in MeanT_{min} for SSP5-8.5 was between 1.4 and 2.2 °C in the early period; however, it was between 4.2 and 5.0 °C in the far future for the same SSP. Similar significant shifts were also noticed for almost all hot and cold extremes. This indicates a sharp change in some temperature extreme in the latter part of the century for higher SSPs in the ARB.

The present study showed that the changes in mean temperature define the changes in temperature extremes in ARB. An increase in mean T_{max} caused an increase in hot temperature extremes, while a reduction in T_{min} caused a decrease in cold temperature extremes. The higher SSPs projected a higher increase (decrease) of mean T_{max} (T_{min}), and thus, a higher increase (decrease) of hot (cold) extremes. The present study also showed that the rise in hot extremes from early to late would be faster for higher SSPs than the lower SSPs. This indicates a sharp rise in hot extremes with time for higher SSPs. The shift in temperature regime in the
Some temperature extremes showed considerable change even for the mildest climate change scenario (SSP1-2.6). The positive direction would also cause a sharp decrease in cold extreme from early to late for higher SSPs.

**Fig. 15** Same as Fig. 14, the days with a minimum temperature of less than –30°C (D-30Tmin)
6 Conclusions

This study attempted to assess characteristics of hot and cold extremes over ARB using twelve indices. Results revealed that the number of hot days would increase especially in the far future. In contrast, the number of cold days would likely decrease. The increase in the number of hot extremes would be higher in the basin’s west to northwest, while the decrease in cold extremes would be only in the east, which generally experiences a long cold period. These extreme temperature changes reflect a noticeable impact of climate change in the ARB. The information generated in this study can be useful for researchers. It can also serve as a good base for developing mitigation strategies and decision-making planning. The maps and data generated in this research can be used for other climate applications. This study employed CMIP6 GCMs selected from the available pool of GCMs during the study period. In future, the study can be repeated with all CMIP6 GCMs when they are available. Future work should also consider other indices like heat and cold waves. In addition, a comparative study using CMIP5 and CMIP6 models can be conducted to quantify the changes needed in adaptation planning that was derived using CMIP5 models.

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Authors 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; the initial draft of the paper was prepared by Obaidullah Salehie and Mohd Khairel Idlan Muhammad; the article was repeatedly revised to generate the final version by Tarmizi bin Ismail and Shamsuddin Shahid.

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Availability of data All the data are available in the public domain at the links provided in the texts.

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

Declarations

Conflict of interest The authors declare no conflict of interest.
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