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Research Article

Keywords: Droughts, Climate change, CMIP6, SSPs, SPEI, Amu Darya basin

Posted Date: December 15th, 2021

DOI: <https://doi.org/10.21203/rs.3.rs-1088081/v1>

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Abstract

Droughts significantly affect socioeconomic and the environment primarily by decreasing the water availability of a region. This study aims to assess the changes in drought characteristics in Central Asia's transboundary Amu Darya river basin for four shared socioeconomic pathways (SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5). The precipitation, maximum and minimum temperature (Pr, Tmx and Tmn) simulations of 19 global climate models (GCMs) of the coupled model intercomparison project phase 6 (CMIP6) were used to select the best models to prepare the multimodel ensemble (MME). The standard precipitation evapotranspiration index (SPEI) was used to estimate droughts for multiple timescales from Pr and potential evapotranspiration (PET) derived from Tmx and Tmn. The changes in the frequency and spatial distribution of droughts for different severities and timescales were evaluated for the two future periods, 2020–2059 and 2060-2099, compared to the base period of 1975-2014. The study revealed four GCMs, AWI-CM-1-1-MR, CMCC-ESM2, INM-CM4-8 and MPI-ESM1-2-LR, as most suitable for projections of droughts in the study area. The multimodel ensemble (MME) mean of the selected GCMs showed a decrease in Pr by -3 to 12% in the near future and a change in the range of 3 to -9% in the far future in most parts of the basin for different SSPs. The PET showed almost no change in most parts of the basin in the near future and an increase in the range of 10 to 70% in the far future. The change (%) in projected drought occurrence showed to noticeably decrease in the near future, particularly for moderate droughts by up to $\leq -50\%$ for SSP5-8.5 and an increase in the far future by up to $\geq 30\%$ for SSP3-7.0. The increase in all severities of droughts was projected mostly in the center and northwest of the basin. Overall, the results showed a drought shift from the east to the northwest of the basin in the future.

Key words: Droughts, Climate change, CMIP6, SSPs, SPEI, Amu Darya basin

1. Introduction

Drought is a recurrent, slow-moving, relative longer duration natural phenomenon with serious economic, social and environmental impacts (Kala, 2017; Marumbwa et al., 2021). It occurs on a local to regional scale and for periods varying from weeks to decades (Ojeda et al., 2021), unlike other natural hazards, which are generally local and affect society for a shorter period (Kala, 2017; Wilhite, 2000). Therefore, drought is ranked top among all-natural hazards based on its economic damage (Wilhite, 2000; Alamgir et al., 2020). The duration, severity and impacts of drought have been aggravated in recent years due to climate change, especially in arid and semiarid regions, leading to water stress for economic development (Ahmed et al., 2016; Qutbudin et al., 2019; Ukkola et al., 2020; Pour et al., 2020b). Like many other parts of the globe, Central Asia (CA) frequently suffers from drought due to its arid to semiarid climate conditions with low Pr and high evaporation (Barlow et al., 2016; Lioubimtseva and Henebry, 2009; Schiemann et al., 2008; Pour et al., 2020b). However, the severity and impacts of droughts in CA are much higher than in many other parts of the globe due to large rainfall variability and high dependency on irrigated agriculture. For example, about 97% of cropland in Turkmenistan is irrigated. Therefore, nearly 80% of agriculture in the country was damaged during 2000-2001 drought (Lipton, 2019). A recent study suggested that changes in Pr and vegetation patterns and gradual warming in mountain regions, the sources of major rivers, caused increased water scarcity for irrigation and pasture in the region (Yang et al., 2020a). The recently released AR6 of IPCC identified CA as one of the drought hotspots due to climate change.

Amu Darya is one of CA's biggest transboundary river basins (Dilshod et al., 2021). Approximately 80 million people living in five countries, Afghanistan, Kyrgyzstan, Tajikistan, Turkmenistan, and Uzbekistan, depend on the Amu Darya river water (Hu et al., 2021b). Amu Darya river provides water for irrigation of 2.3 million hectares (ha) area in Uzbekistan, 1.7 million ha in Turkmenistan, 1.16 million ha Afghanistan, 0.5 million ha in Tajikistan and 0.1 million ha in Kirgizstan (Ahmad and Wasiq, 2004). Drought is the most devastating and recurrent natural disaster in the basin. Recent droughts in 2018 in the basin caused a large decline in food production, and thus, food scarcity in some parts of the basin (Hoell et al., 2020). In recent years, the basin's hydrology has undergone tremendous change due to human intervention in river flow (Khaydar et al., 2021). Climate change, particularly the rise in temperature and changes in Pr patterns, has worsened the situation (Hu et al., 2021b; Salehie et al., 2021b). These caused severe damage to the ecology and water balance

of the basin. The temperature rise caused an increase in evapotranspiration and water demand, and thus, water stress in the basin (Hu et al., 2021b; White et al., 2014). The climate of the basin is changing in the line of global climate change. The continuous rise in temperature and consequent Pr changes would certainly change drought patterns in the basin (Hoell et al., 2020; Kattakulov et al., 2021; Yang et al., 2020b). Due to the arid nature and complexity of the hydrological regime of the basin, climate change may extremely affect the hydrological process (Immerzeel et al., 2012; Xu et al., 2021). The river flow in the basin has decreased by 15.5% between 1951 and 2007 due to the decrease in Pr (Wang et al., 2016). This reduced the river flow to reach downstream, especially in Uzbekistan's deserts and the Aral Sea and caused many environmental impacts (Schlüter and Herrfahrdt-Pähle, 2011; Xu et al., 2021). Understanding possible changes in droughts are very important for climate adaptation planning and ensuring food security and sustainable development of the nation's sharing the basin's water.

Global climate models (GCMs) estimate possible changes in climate for different greenhouse gas emission (GHG) pathways. The GCMs of the latest phase Coupled Model Intercomparison Project (CMIP6) provides future climate projections for different shared socioeconomic pathways (SSPs). The strengths of CMIP6 are additional models, improvement in the models and experiments, higher spatial resolution, integration of RCPs combined with SSPs, less biases and well representation of synoptic processes (Eyring et al., 2016; Kamal et al., 2021; Su et al., 2021). These models can well simulate temperature and rainfall and their interannual variability over China and nearby region (Jiang et al., 2020; Xin et al., 2020). Projection of climate and droughts for SSPs are required to update the information obtained through CMIP5 radiative concentration pathways (RCPs) and restructure adaptation measures based on SSPs. Therefore, CMIP6 GCMs have been widely used to update the drought projections in different parts of the globe (Shiru et al., 2020; Cook et al., 2020; Eyring et al., 2016; Hamed et al., 2021a; Kamal et al., 2021; Kim et al., 2021; Mondal et al., 2021; Sharma et al., 2021; Shrestha et al., 2020; Song et al., 2021; Su et al., 2021; Ukkola et al., 2020; Wang et al., 2021c).

Conventionally, meteorological drought is estimated using observed climatic variables such as rainfall and evapotranspiration (Shiru et al., 2019). Many methods have been developed for this purpose, including run approach, drought indices, frequency analysis, and Markov chain (Alamgir et al., 2015; Thompson, 2017). Among them, drought indices are most popular because of their accuracy in reconstructing droughts. Nearly 150 drought indices have been developed to quantify droughts (Niemeyer, 2008), including

Reconnaissance Drought Index (RDI) (Tsakiris et al., 2007), Standardized Runoff Index (SRI) (Shukla and Wood, 2008), National Rainfall Index (NRI) (Gommes and Petrassi, 1996), Agricultural Drought intensity Index ADI (Lu et al., 2017), Surface Water Supply Index (SWSI) (Shafer and Dezman, 1982), Effective Drought Index (EDI) (Byun and Wilhite, 1999), Palmer Drought Severity Index PDS (Palmer, 1965), Standardized Precipitation Index (SPI) (McKee et al., 1993) and standard precipitation evapotranspiration Index (SPEI) (Vicente-Serrano et al., 2010). Among them, SPEI has been most widely used for drought characterization and projection of droughts (Jiang et al., 2021). SPEI uses rainfall and evapotranspiration variables to estimate droughts for different time steps (Shiru et al., 2018; Dikshit et al., 2021). Therefore, it is considered more reliable for estimating droughts in any climatic region.

Literature review suggests several studies have been conducted to assess the drought hazards in different CA's countries (Feng et al., 2021; Guo et al., 2018; Jiang and Zhou, 2021; Li et al., 2017; Peng, 2021; Tian et al., 2021; Wang et al., 2021b; Xu et al., 2016; Zhang et al., 2021). However, studies related to droughts is very limited in the Amu Darya River basin. Only two studies attempted to project drought in the study area (Hoell et al., 2020; Yang et al., 2020b). However, the results presented by Yang et al. (2020b) are highly uncertain due to unreliable data. The droughts projected by Hoell et al. (2020) is incomplete due to the use of only RCP5-8.5. It is required to project droughts for SSPs to streamline the existing mitigation measures adopted based on RCPs. Existing studies related to droughts in CA and the Amu Darya basin are briefly presented in Table 1.

The objective of the present study is to assess the changes in drought characteristics in Central Asia's transboundary Amu Darya River basin for four shared socioeconomic pathways (SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5). The Pr and temperature simulations of four GCMs of CMIP6, identified as the most reliable for simulating observed climatology of the basin, were used to estimate droughts using SPEI. The estimated SPEI were used to estimate the changes in two drought characteristics, frequency and spatial distribution of different severities of droughts, for the two future periods, 2020–2059 and 2060-2099, compared to the based period of 1975-2014.

Table 1. Existing drought studies in Amu Darya basin and Central Asian countries

Reference	Study area	Data	Method	Major Finding
Yang et al. (2020b)	Amu Darya Basin	Precipitation from https://gis.ncd	MCMC-MEC and HDI	At 95% confidence level with ≥ 10.0 months, drought risk would be 1%-

				c.noaa.gov/maps/; Runoff from Global Runoff Data Centre		2% and severity ≥ 10.6 .
Hoell et al. (2020)	Amu Darya Basin	GCM CMIP5	Climate Model Ensembles			Longest drought last in 8 years to as many as 4 decades in every 100 years in the upper and lower regions. 50% of droughts last in these regions for less than 6 and 9 months.
Yang et al. (2020a)	CA	GRACE combined with CPC precipitation and GLDAS	Combined Climatological Deviation Index (CCDI) align with SPI, SPEI and PDSI			The impact of precipitation is not significant; severe drought happened in 2012, 2014, and 2017.
Zhang et al. (2021)	CA	CRU	DII and DEI			DII and DEI are strongly correlated with the tropical Niño 4 sea surface temperature and extratropical atmospheric teleconnections with seasonal differences in degree of impact.
Jiang and Zhou (2021)	CA	CRU, GPCC, APHRODITE, HadEX3 and CMIP6	Moisture budget analysis; Mann-Kendall and Student's t test			Drying trend is dominated by anthropogenic change of the subtropical westerly jet (SWJ).
Li et al. (2017)	CA	CRU, GLDAS and Runoff data	PDSI			Drying 42% and wetting 58% of the land area with a wetting trend of 0.0036/year.
Wang et al. (2021b)	CA	CRU, Tree-ring data	PDSI			Main impact on tree growth was humidity from previous years and the present growing season.
Peng (2021)	CA	Last Millennium Climate Reanalysis Project Version 2.0	-			Six severe decadal droughts occurred in ACA during the last 530 years.
Xu et al. (2016)	CA	MODIS' temperature and precipitation data from http://gis.ncdc.noaa.gov/	SPEI			Wide vegetation degradation was related to summer water deficit due to decrease in precipitation and increase potential evapotranspiration
Guo et al. (2018)	CA	CUR	Run theory, SPEI and Modified Mann-Kendall			A significant drying pattern is detected in most CA; The drought changes in CA highly associated

				with ENSO and NAO; eastern Central Asia is affected by the Siberian High
Ta et al. (2018)	CA	SPEI from http://spei.csic.es/	SPEI, Mann-Kendall Test	No clear drying trends in spring and summer. Autumn and winter showed a wet trend; geographically, drought frequency is 42.87% over the entire CA from 1930 to 2014.
Zhang et al. (2020)	CA	CRU	Run Theory, SPEI	The severity of drought is larger in the west than in the east in CA; the return period was assessed to be likely 80% in around 2 years.
Zou et al. (2020)	CA	MODIS	Mann–Kendall, TVDI, WUE	Mean ecosystem WUE of CA varied with various drought levels, regions, and vegetation categories.
Chen et al. (2019)	CA	PDSI; tree-ring chronology, NCEP climate data	PDSI; ST, CE and RE	PDSI well captured drought and the regional dry/wet times.
Aitekeyeva et al. (2020)	CA	MODIS Time-Series Data	VHI, VCI and TCI	Some of croplands of Kazakhstan showed less resistant to annual drought than other cropland regions
Zhang et al. (2019)	CA	CMIP5 under RCP2.6 and RCP4.5 scenarios	Thornthwaite (TH) formula for calculation of PDSI	The spatial pattern of dry and wet regions is likely to change greatly in the future; the frequency of drought and drylands were higher in 1.5 °C scenario.

CCDI=Climatological Deviation Index; GRACE= Gravity Recovery and Climate Experiment; GLDAS= Global Land Data Assimilation System; CPC= Climate Prediction Center; DII= drought intensity index; DEI= drought extent index; CCRU= Climate Research Unit; GPCC=Global Precipitation Climatology Center; APHRODITE= Asian Precipitation Highly Resolved Observational Data Integration Toward Evaluation of Water Resources; HadEX3=Hadley Center Global Climate Extremes Index 3; MODIS= Moderate Resolution Imaging Spectroradiometer; NCEP=National Center for Environmental Prediction; VHI=Vegetation health index; VCI= vegetation condition index; TCI=temperature condition index; ENSO=El Nino-Southern Oscillation; NAO=The North Atlantic Oscillation; MCMC-MEC= MCMC-based maximum entropy copula; HDI=Hydrological drought index; TVDI=Temperature vegetation dryness index; WUE=Ecosystem water use efficiency; ST=Sign test; CE=Coefficient of efficiency; RE=Reduction of error.

2. Study Area and Data

2.1 Study Area

The Amu Darya (Figure 1) is the longest transboundary river in Central Asia, traversing the countries of Afghanistan, Kyrgyzstan, Tajikistan, Turkmenistan and Uzbekistan (Mergili et al., 2013; White et al., 2014). The river is 2,540 km long, with an annual average flow of about 79 km³ (Hu et al., 2021a; Leng et al., 2021; Xu et al., 2021). Vahsh, Pandj and Zeravshan are the main tributaries to the Amu River (Normatov and Normatov, 2018). Initiated from high glaciers and snow-covered mountains in Tajikistan, Kyrgyzstan, the north of Hindu Kush and from Whakhan in Afghanistan, it flows through the deserts in Uzbekistan and Turkmenistan before ending to the Aral Sea (Kumar et al., 2019; Wang et al., 2021a). The topography of the basin is complex, which is divided into three uneven features: (1) an upstream with high mountain terrain of up to 7,750 m elevation; (2) a mid-zone with several patches of large irrigated oases, and (3) a downstream area to the northwest with a delta and discharging to the Aral Sea. The upstream (Eastern Pamir) of the Amu Darya receives precipitation of 2000 mm (average annual of 464 mm), while the downstream receive only less than 100 mm (Behzod and Su-Chin, 2013). Pr mostly during November to May (Gaybullaev and Chen, 2013; Wang et al., 2016). The basin's climate is continental with cold winter, hot summer, low Pr, less relative humidity, and a mean annual temperature of 13.0 °C (Jalilov et al., 2013; Sun et al., 2019).

Figure 1. The topography of the Amu Darya river basin and its location in Central Asia.

3.1 Datasets

In this study, GCMs' performance was evaluated against Climate Prediction Center (CPC) data of Pr, Tmx and Tmn for the period (1979-2014). CPC is a gauge-based gridded dataset provided by the NOAA Climate Prediction Center, National Centers for Environmental Prediction (Xie et al., 2007). This dataset can be obtained with a resolution of $0.5^\circ \times 0.5^\circ$ from <https://psl.noaa.gov/data/gridded/>.

Salehie et al. (2021a) assessed the ability of seven gridded Pr datasets' ability to estimate precipitation at 55 stations across the Amu Darya basin. They showed CPC as the best in replicating the observed Pr. Salehie et al. (2021b) also found CPC's capability to better replicate in-situ temperature in the basin. Therefore, the CPC product was used as reference data to assess GCMs' performance in simulating Pr, Tmx and Tmn.

The skill of 19 CMIP6 GCMs was evaluated in this study in simulating monthly Pr, Tmx and Tmn, as listed in Table S-1. The GCMs were selected based on the availability of monthly historical simulation and future projections for four SSPs scenarios (1-2.6, 2-4.5, 3-7.0 and 5-8.5). The simulations based on historical single run r1i1p1f1 (e.g., ensemble members [r1], initialization states [i1], physical parameterizations [p1] and forcing index [f1]) was used for a fair comparison. GCMs' historical (1979-2014) and SSPs scenarios (2015-2100) data were downloaded from: <https://esgf-node.llnl.gov/search/cmip6/>.

3. Methods

The procedure followed in this study to evaluate the performance of GCMs and estimate the changes in droughts due to global warming is outlined below:

1. CPC and GCMs were interpolated to $1^{\circ} \times 1^{\circ}$ resolution (close to the mean resolution of all GCMs) using the inverse distance weighting (Hamed et al., 2021b) method to prevent inconsistency and bias in estimation due to variation in spatial resolution (Nashwan and Shahid, 2020).
2. The Kling-Gupta Efficiency (KGE) metric was used to assess the performance of the GCMs in replicating Pr, Tmx and Tmn, compared to the reference product (CPC) at each grid point (73 grids covering the study area).
3. The GCMs were ranked based on average KGE for all three variables (Pr, Tmx and Tmn), and the best GCMs were selected for drought assessment.
4. The PET was calculated using the Thornthwaite approach at all GCM grid points.
5. The change in rainfall and PET were calculated for the multimodel ensemble (MME) of selected GCMs for two future periods, the near future (2020–2059) and the far future (2060–2099), against the historical period (1975–2014).
6. The SPEI was used to estimate the occurrence frequencies of different severities for 3-, 6-, 9- and 12-month droughts for the historical and future periods for different SSPs scenarios.
7. MME mean historical and future projected drought occurrence frequency was prepared by averaging the drought occurrence frequency estimated by the selected GCMs.

8. The MME mean of drought occurrence frequency was used to show the percentage of change in drought occurrence frequency in two future periods, the near future (2020–2059) and the far future (2060–2099), against the historical period (1975–2014).

3.1 Evaluation of GCM CMIP6 Models using KGE

The KGE is a statistical metric that integrates correlation, bias, and variability to detect the association and biases in the mean and the changes of observed and simulated climate variables (Nashwan and Shahid, 2020). KGE is primarily introduced by Gupta et al. (2009) and then modified by Kling et al. (2012), expressed as;

$$KGE = 1 - \sqrt{(r - 1)^2 + (\beta - 1)^2 + (\gamma - 1)^2} \quad \text{Equation 1}$$

where r is the linear correlation between measured and GCMs data; β represents the bias obtained by the ratio of mean simulated and mean observed and γ is the variability component can be obtained by the percentage of the simulated (GCMs) and observed (CPC) coefficients of variation:

$$\beta = \frac{\mu_s}{\mu_o} \quad \text{and} \quad \gamma = \frac{\sigma_s/\mu_s}{\sigma_o/\mu_o} \quad \text{Equation 2}$$

where μ and σ are the distribution mean and standard deviation, respectively, while the subscripts s and o reflect simulated and measured data, respectively. KGE can range between $-\infty$ to 1, where 1 is the optimal value.

3.2 Drought Metrics

The SPEI (Vicente-Serrano et al., 2010) is calculated based on the difference between Pr and PET . The SPEI values are not sensitive to PET estimation method (Stagge et al., 2014). Thus, any approach based on data availability can be used to compute PET (Mohsenipour et al., 2018). In this study, the Thornthwaite method was used to calculate PET from the monthly temperature data (Thornthwaite, 1948), as follows:

$$PET = 16K \left(\frac{10T_{mm}}{I} \right)^m \quad \text{Equation 3}$$

where T_{mm} is the monthly average of daily mean temperature $^{\circ}C$; I is the heat index which could be computed from the monthly temperature over the year; m is a coefficient depending

on I ; and K is a coefficient which is calculated as a function of the latitude of the region and the month the year.

The accumulated water balance is obtained as the difference (D) between precipitation (P) and PET for the i month using the following formula:

$$D_{n=1}^k = \sum_{i=1}^{k-1} (P_{n-1} - PET_{n-1}), \quad n \geq k \quad \text{Equation 4}$$

where k is the time scale (month), and n indicates the calculation frequency. As D parameter can get a negative value and hence the three-parameter distributions are required to fit it. The probability distribution function of D can be calculated using a three-parameter log-logistic distribution as follows:

$$F(D) = \left[1 + \left(\frac{\alpha}{x - \gamma} \right)^\beta \right]^{-1} \quad \text{Equation 5}$$

where α , β and γ are scale, shape and origin parameters, respectively. The SPEI then can be obtained as the standardized value of probability distribution function $F(D)$.

The distribution function parameters were estimated for the historical and future periods separately. This method identifies the dryness or wetness in a region in the future against historical periods. The classification for the SPEI for the dry conditions is presented in Table 3. In this study, SPEI for four-time scales were estimated, SPEI-3, 6, 9 and SPEI-12. SPEI-3 indicates at least three consecutive months for a drought event, and SPEI-12 is considering utmost twelve consecutive months for a drought event. For hydrological and meteorological drought, 12 months' timescale is suitable, as the SPEI values increase with timescale (Zhai et al., 2020).

Table 3. Classification of the dry conditions of the SPEI indicator

Category	Index range
Near normal	$-1 < SPEI < 0$
Moderately dry	$-1.5 < SPEI \leq -1$
Severely dry	$-1.99 < SPEI \leq -1.5$
Extreme dry	$SPEI \leq -2$

4. Results

The skill of the GCMs in replicating the CPC Pr, Tmx and Tmn climatology over the basin for the reference period (1975–2014) was estimated using KGE. All GCMs were then ranked for each variable in ascending order from the highest KGE value (best performance) to the lowest (Table 4). The average rank of all three variables was then estimated to find the highest ranked GCMs. The results revealed MPI-ESM1-2-LR, CMCC-ESM2, INM-CM4-8 and AWI-CM-1-1-MR ranked 1st, 2nd, 3rd, and 4th, respectively. The rest of the GCMs presented weak ability in replicating the observed data. Therefore, those four GCMs were selected for drought projection.

Table 4. Ranking of GCMs using KGE metric and average sum

GCMs	KGE (Pr)	Rank (Pr)	KGE (Tmx)	Rank (Tmx)	KGE (Tmn)	Rank (Tmn)	Average Sum
ACCESS-CM2	-0.02	7	0.5	12	0.24	7	8.67
ACCESS-ESM1-5	-0.26	19	0.64	6	0.83	1	8.67
AWI-CM-1-1-MR	0.02	4	0.55	8	-1.7	12	8
BCC-CSM2-MR	-0.12	14	0.63	7	-16	17	12.67
CanESM5	-0.04	11	0.53	9	-1.17	9	9.67
CMCC-CM2-SR5	-0.02	8	0.19	17	0.34	6	10.33
CMCC-ESM2	-0.03	9	0.65	5	0.42	4	6
EC-Earth3	0.06	3	0.5	13	-114.58	19	11.67
EC-Earth3-Veg	0.11	1	0.43	15	-7.68	15	10.33
EC-Earth3-Veg-LR	0.08	2	0.38	16	-10.24	16	11.33
FGOALS-g3	-0.17	16	-0.36	19	-0.39	8	14.33
GFDL-ESM4	-0.08	13	0.45	14	-72.41	18	15
INM-CM4-8	0.02	5	0.85	1	-2.55	14	6.67
INM-CM5-0	-0.06	12	0.83	2	-1.59	11	8.33
IPSL-CM6A-LR	-0.19	18	0.13	18	-1.37	10	15.33
MIROC6	-0.16	15	0.51	10	0.49	3	9.33
MPI-ESM1-2-HR	-0.03	10	0.7	4	-1.76	13	9
MPI-ESM1-2-LR	0	6	0.78	3	0.53	2	3.67
MRI-ESM2-0	-0.17	17	0.51	11	0.35	5	11

The bold font indicates GCMs with higher rank

4.1 Precipitation and PET Climatology

The geographical distributions of average annual Pr and PET were estimated for 1975-2014 using four selected CMIP6 GCMs and presented in Figure 2. The highest Pr occurs upstream of the basin covers the territory of Afghanistan and Tajikistan (300 to 1200 mm) and the lowest in the plain deserts of Uzbekistan and Turkmenistan (≤ 200 mm). AWI-CM-1-1-MR showed higher rainfall upstream (400 to >1200 mm) than the other models. CMCC-ESM2 showed a higher Pr in the basin's east, followed by MPI-ESM1-2-LR and INM-CM4-8. In contrast, all models provided similar spatial distribution of Pr in the west and northwest of the basin.

Figure 2 (right panel) shows the spatial patterns of PET over the basin. All models showed more or less similar spatial variability of PET. The maximum PET (>1400 mm) was in the deserts, downstream part of the basin with low Pr. In contrast, PET was relatively less (≤ 400 mm) in the cold region of the basin's east, which receives more Pr, but mostly as snow. AWI-CM-1-1-MR showed greater PET in the west and northwest of the basin (1000 to >1400 mm), followed by CMCC-ESM2, MPI-ESM1-2-LR and INM-CM4-8.

Figure 2. The geographical distribution of mean annual precipitation (left side) and average annual potential evapotranspiration (right side) over the Amu Darya river basin, estimated using four CMIP6 models.

4.2 Temperature Climatology

The spatial pattern of mean annual daily Tmx and Tmn over the basin are presented in Figure 2. The results reveal that all models provided an almost similar spatial pattern of Tmx and Tmn over the basin. The deserts areas in the west and northwest showed a higher Tmx ($>30^{\circ}\text{C}$), while the eastern mountainous regions showed lower Tmx ($<5^{\circ}\text{C}$). However, there was a slight difference in this distribution among the models. AWI-CM-1-1-MR showed the highest Tmx ($>30^{\circ}\text{C}$) in the west and northwest, while the lower Tmx in the east. In contrast, Tmn was relatively higher (5 to 15°C) in the west and northwest and less (-5 to -20°C) in the

upstream snow-dominated areas. AWI-CM-1-1-MR showed the highest value of Tmx in the basin's west and northwest, followed by CMCC-ESM2.

Figure 3. Spatial distribution of the annual average of daily maximum and minimum temperature over the Amu Darya river basin, estimated using four CMIP6 models.

4.3 Drought Frequency

The geographical distribution of occurrence frequencies of different severities of 3, 6, 9 and 12-month droughts was calculated for the historical (1975-2014). Figure 4 shows the spatial

distribution of the frequency for different drought severities for the historical period, obtained using the AWI-CM-1-1-MR model. Figure 4 indicates that the higher drought frequency (>80) was for the 3-month moderate drought. The drought occurrence frequency showed a decrease with the increase in time scale. Therefore, the lowest frequency was for 12 months droughts. The highest occurrence of the drought was noticed in the basin's east, south, and northwest. Compared to moderate droughts, severe and extreme droughts showed lower frequency for all time scales with a minimum value ≤ 10 for the extreme case. The average drought frequency estimated using CMCC-ESM2, INM-CM4-8 and MPI-ESM1-2-LR were more or less similar to the AWI-CM-1-1-MR. Those are provided in the supplementary.

Figure 4. Occurrence frequency of different severities of 3-, 6-, 9- and 12-months drought in the study area during the reference period (1975 – 2014) estimated from AWI-CM-1-1-MR.

The MME mean of occurrence frequency of different severities for 3, 6, 9 and 12-month droughts was estimated using the average drought frequency of the four GCMs (1975-2014), as shown in Figure 5. The results were nearly similar to that obtained using individual GCMs, indicating that higher frequency in 3 months' time scale moderate drought and gradually decrease for higher timescales and severities. However, the distributions were not

the same for different parts of the basin. The east of the basin showed relatively a higher occurrence of droughts than the rest of the basin.

Figure 5. MME mean occurrence frequency of different severities of 3-, 6-, 9- and 12-month droughts during the reference period (1975 – 2014).

4.4 Precipitation and PET projection

The percentage of changes in mean annual MME Pr for four SSPs and two future periods over the Amu Darya basin is presented in Figure 6. Considerable changes in the annual Pr were noticed for different SSPs. An increase in Pr (0-12%) was projected in the eastern and northwest of the basin for all SSPs and future periods. SSP2-4.5 projected the increase over a larger area in the far future. Conversely, a decrease in Pr was projected (up to -12%) in the center, south and most areas in the northwest of the basin. SSP1-2.6 projected a higher decrease in Pr for the near future (-6 to >-12%) followed by SSP5.8.5 (-9 to -12%), SSP3-7.0 (-3 to -9%) and SSP2-4.5 (0 to -9%). Overall, a decrease in Pr was projected in most of the basin for all SSPs and periods, except for SSP2-4.5 in the far future.

Figure 6. Projected changes in mean annual MME precipitation for SSP1-2.6, 2-4.5, 3-7.0 and 5-8.5 for the two future periods (2020–2059 and 2060–2099) against the historical period (1975-2014) over the Amu Darya basin.

The projected changes in the average annual MME PET across the Amu Darya basin is presented in Figure 7. The PET showed an increase in all future periods for all SSPs. The increase was higher for higher SSPs and the far future. SSP1-2.6 showed an increase of less than 10% in the near future in the east and in the range of 10-20% in the west. It showed an increase (10 to 20%) over most of the basin in the far future. A similar increase in PET was

noticed in the far future compared to the near future for all SSPs. The highest increase was projected for SSP5-8.5 in the far future in the range of 40-50% in the east and 50-70% in the west. The results revealed a greater influence of PET compared to precipitation in determining future atmospheric water balance in the study area.

Figure 7. Projected changes in the mean annual MME PET for SSP1-2.6, 2-4.5, 3-7.0 and 5-8.5 and two future periods (2020–2059 and 2060–2099) against the historical period (1975–2014) over the Amu Darya basin.

4.5 Historical and Future Drought Frequency

The total number of different severities of drought events (moderate, severe and extreme drought) over the Amu Darya for the historical and two future periods are presented using box plot in Figure 8. The centerline in the box represents the mean value (or 50-th percentile) of drought occurrence, while the upper and lower lines indicate 75-th and 25-th percentile values, respectively. A higher median indicates more drought events.

The figure shows a drastic decrease in the median value of drought events in the near future compared to the reference period. The decrease was more for higher SSPs. In contrast, the drought events were projected to increase in the far future compared to the reference period for all SSPs. The increase was higher for moderate and severe droughts for higher SSPs but more for extreme droughts for lower SSPs. A sharp rise in PET in the far future is the cause of the increased occurrence of droughts in the late future.

Figure 8. Drought events frequency under different periods (rows) for moderate, severe, and extreme (columns) drought conditions [Hist=Historical; N=Near Future; F=Far Future]

4.6 Projected Changes in Droughts

Figure 9 shows changes in the spatial distribution of the drought frequency for SSP1-2.6 in two future periods, 2020–2059 and 2060–2099, compared with reference periods. The change in drought frequency in the figure is expressed as a percentage. The high percentage of change represents more recurrent droughts in the future. Figure 9 indicates a decrease in the frequency of different severities of droughts decreases in the near future and an increase in the far future compared to the reference period. The changes were more pronounced for the moderate droughts and less for severe and extreme droughts of almost all time scales. The

higher decrease in the near future and increase in the far future of all severities were observed in the basin's west and northwest. In contrast, the basin's east would experience less change in drought frequency. For example, the moderate drought occurrence was projected to decrease in the west in the range of -5 to -15% in the near future, while an increase by 5 to 25% in the far future. In contrast, a change in moderate drought occurrence in the east was projected in the range of -5 to 5% in the near future and by 0 to 15% in the far future. Some parts of the basin's east would experience decreased droughts for both futures for SSP1-2.6. Historically, droughts occur more in the east (Figure 5). A gradual decrease in different severities of droughts in the east and an increase in the west and northwest would cause a shift in high drought-prone areas in the basin in the future for SSP1-2.6.

The spatial distribution of the drought frequency changes for SSP2-4.5, 3-7.0 and 5-8.5 in two future periods, 2020–2059 and 2060–2099, compared to the reference period, are presented in Figures 10 to 12. All the scenarios showed a similar pattern of changes in the frequency of different severities and timescales of droughts. All the scenarios showed a decrease in drought occurrence in the near future and an increase in the far future. However, the decrease in the near future and increase in the far future would be more for higher SSPs. Besides, the decrease in drought occurrence would be more in the near future and increase in the far future in the west compared to the east. The increase would be more for moderate droughts, followed by severe and extreme droughts. For example, the decrease in moderate droughts in the west for the near future was projected in the range of -20 to -30% and increase in the far future in the range of 10 to 25% for SSP2-4.5. In the case of SSP5-8.5, the decrease in moderate droughts in the west for the near future was projected in the range of -40 to -50% and increase in the far future in the range of 10 to 30%. The results indicate a rapid increase in the occurrence of all severities and timescales of droughts from the near to the far future. However, the increase would be faster for higher SSPs.

Figure 9. Changes in drought frequency in the near (2020-2059) and the far (2060-2099) future, estimated using MME of GCMs for SSP1-2.6.

Figure 10. Changes in drought frequency in the near (2020-2059) and the far (2060-2099) future, estimated using MME of GCMs for SSP2-4.5.

Figure 11. Changes in drought frequency in the near (2020-2059) and the far (2060-2099) future, estimated using MME of GCMs for SSP3-7.0.

Figure 12. Changes in drought frequency in the near (2020-2059) and the far (2060-2099) future, estimated using MME of GCMs for SSP5-8.5.

5. Discussion

Like many other parts of the globe, the arid and semiarid Amu river basin have been affected by drought resulting from global warming-induced climate change. The resiliency and stability of the ecosystem in CA are very low to climate change and drought (Qin et al., 2021). The droughts in 2000 and 2001 had severe implications on water availability for irrigation, reservoirs and other water users in CA, especially in Uzbekistan and Aral Sea in the down reach of Amu Darya basin (Wegerich, 2002). The present study showed a gradual increase occurrence of different severities of droughts from the near future to the far future. The increase would be fast for higher emission scenarios. However, even if it is possible to keep global warming below 2°C at the end of the century (SSP1-2.6), there would be large increase in droughts from the near to the far future. For example, the moderate drought occurrence was projected to decrease in the west in the range of -5 to -15% in the near future, while an increase by 5 to 25% in the far future. It means the occurrence of moderate droughts of different timescales would increase from the near to the far future by 10 to 40% for SSP1-2.6. This would make the basin highly vulnerable to water resources.

Historically, droughts in the basin occur more in the east and less in the west. The present study revealed a higher increase in droughts in the west than in the east for all scenarios. It would make the spatial distribution of droughts more homogeneous in the basin or a shift from the east to the west. This indicates that drought-prone area, which was mostly concentrated in the east, would be extended to other regions in the future. The increase in the spatial extents of drought would affect more population and agriculture in the future compared to the present. The increase in the spatial extent would be higher for moderate droughts, followed by severe and extreme droughts.

Changes in precipitation and temperature are responsible for the changes in droughts of a region. The previous study by Hoell et al. (2020) indicated the probability of drought onset and demise during wet season mainly derived by the seasonal cycle of Pr in the upper and lower Amu Darya basin, while the role of temperature is less. In contrast, Aralova et al. (2016) remarked that the increase in drought anomalies in CA is closely linked to evapotranspiration rise in the plain and foothill areas. The finding of the present study collaborates more with Aralova et al. (2016). Both PET and Pr were projected to increase significantly in the basin in the far future for different scenarios. However, the increase of PET was more than Pr. A large increase in PET might be the cause of increased drought

occurrence in the far future. However, it should be noted that changes in drought frequency depends on the changes in variability of Pr and PET, not in the change of mean Pr and PET. The present study indicated an increased variability of Pr and PET with the increase of their mean in the future. This would cause an increase in droughts in the basin.

The change in drought frequency in the future will pose many implications on water resources availability, agricultural production, devastating ecosystems, loss of biodiversity and extinction of rare species and economic cost and social issues. The maps and data generated in this study will provide useful information for the basin's future drought mitigation and adaptation measures strategies.

6. Conclusion

This study was conducted to assess the drought frequencies and severities for the historical and two future periods in the Amu Darya basin using GCMs-CMIP6 datasets and SPEI methods. The study revealed a decrease in drought frequency in the near future and a large increase in the far future compared to the reference period for the whole basin. However, the increase in the far future was projected more in the west compared to the east. This indicates an expansion of the spatial extent of drought hotspots in the east to the west. Therefore, more population and economy would be affected by droughts in the basin in the future due to climate change. The study revealed a large increase in drought occurrence from the near to the far future. For the mildest scenarios, the increase in moderate drought over the basin would be 10 to 40%. The results indicate a large impact of climate change on droughts in the Amu Darya river basin. The basin needs long-term planning for mitigating the impacts of increasing droughts. The outcomes of this study can be utilized for mitigation planning and decision making. In addition, the maps and data produced in this study will be useful for other climate studies. It is recommended that future drought assessment should consider other drought indexes or integration of indices. Moreover, it is suggested that future work should use SSPs and the representative concentration pathways (RCPs) to assess relative change and propose a modification of the existing mitigation plans derived for RCPs.

Acknowledgement

The authors are grateful to Universiti Teknologi Malaysia (UTM) for providing financial support to conduct this research through grant No Q.J130000.2451.09G07. The authors are thankful to the World Climate Research Program (WCRP) for providing CMIP6 climate simulation data through the web portal. The authors are also grateful to the National Center for Atmospheric Research (NCAR) for providing Climate Prediction Center (CPC) climate data through their website.

Declarations

Funding

Not Applicable

Conflict of interest

The authors declare no conflict of interest.

Availability of data:

All data used in the study are available in the public domain. Those are also available for sharing on request to the corresponding author.

Availability of code

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

Authors contribution

All the authors contributed to conceptualizing and designing the study. Data were gathered by Obaidullah Salehie; the modelling was done by Obaidullah Salehie and Mohammed Magdy Hamed; the results were prepared by Mohammed Magdy Hamed and Tarmizi bin Ismail; an initial draft of the paper was prepared by Obaidullah Salehie and Shamsuddin Shahid; the article was repeatedly revised to generate the final version by Tarmizi bin Ismail and Shamsuddin Shahid.

Consent for publication

All the authors consented to publish the paper

Ethics approval

Not Applicable

Consent to participate

Not Applicable

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