Evaluation of CMIP6 Climate Models for Climate Change Impact Assessments in Upper Awash Basin, Ethiopia

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Evaluation of CMIP6 climate models for climate change impact assessments in Upper Awash Basin, Ethiopia

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Abstract

Identifying GCMs that represent the climate of a specific area is crucial for climate change studies. However, the uncertainties in GCMs caused by computational constraints, such as coarser resolution, physical parameterizations, initializations, and model structures, make it imperative to identify a representative individual or group of GCM for a climate impact study. An advanced envelope-based multi-criteria selection approach was used to identify a subset of the most appropriate future GCMs in the Upper Awash Basin. The skill accounting is based on (1) the range of projected mean changes of climate variables, (2) range of variability in climate extremes and, (3) model run performance to represent historical climate data. Statistical downscaling and bias correction were made for the selected model runs. The downscaled and bias-corrected monthly values for precipitation are expected to increase from 0.42% to 2.82% in mid-century and 0.15% to 3.79% by the end century considering the SSP4.5 scenario. For SSP8.5, it increases from 1.45% to 5.51% and 2.57% to 9.78% in the respective periods. Likewise, under the SSP4.5 forcing scenario, the monthly average air temperature projected to be warmer, which increased from 0.68 °C to 1.55 °C during mid-century and 0.09 °C to 1.92 °C end-of-century. Meanwhile, for SSP8.5, the projection indicates an increment of 0.19 °C to 1.98 °C under mid-century and 2.37 °C to 7.00 °C end-century. The projected change of future precipitation and temperature in the study basin increases the precipitation intensities, wet days and dry spells due to high-temperature increment.

1 Introduction

Climate change is altering environmental and hydrological systems at global and regional scales. Assessing the spatial and temporal variability of climate data is one of the basic requirements for solving hydrological and water management problems. A significant change in air temperature and precipitation can affect the hydrological system, which can cause disasters like floods and drought (Aich et al. 2014) by altering and hastening the hydrological cycle (Peterson and Halofsky 2018; Reshmidevi et al. 2018). Severe climate extremes such as El Niño may frequently occur in the coming decades, resulting in a significant loss of livestock, crop failure, and serious economic impacts. The increase in climate extremes that highly influence climate variability could increase regions susceptibility to droughts. Ethiopia experienced severe drought in the past decades and most droughts were El Niño induced. The Upper Awash Basin (UAB) is the most utilized and most developed basin in Ethiopia. It is one of the primary water source for urban, industry, hydropower and agriculture in central Ethiopia, including the capital of the country. This is an important basin in the country due to its location in a diverse climatic region. For sustainable water management, it is important to assess the future climate trends and its vulnerability.

General circulation models (GCMs) are numerical models which represent numerous developments in the land surface, oceans and atmosphere. GCMs are the primary input sources for future climate change impact studies and climate patterns assessment. Over the past years, the number of GCMs available for possible future changes has significantly increased. Phase 3 of the Coupled Model Intercomparison Project (CMIP3) (Annan and Hargreaves 2010), which was used for the Intergovernmental Panel on Climate Changes (IPCC) Fourth Assessment Report (AR4), contains climate data output of 25 GCMs, while CMIP5, which was used for AR5, contains climate data of 61 different GCMs (Lutz et al. 2016). The most recent GCM, which is from the CMIP6 (Eyring et al. 2016), have demonstrated qualitative and quantitative improvements over earlier generations of CMIP phases such as CMIP5 (Stocker et al. 2014; Taylor et al. 2012) and CMIP3 (Solomon et al. 2007), both in the representation of physical processes and the simulated fields as well as higher spatial resolution. The four sets of greenhouse gas emission scenarios called representative concentration pathways (RCPs) of RCP2.6,4.5,6.0 and RCP8.5 of the CMIP5 (Maloney et al. 2014) have been upgraded to shared socio-economic pathways (SSPs) SSP1-2.6, 2-4.5, SSP4-6.0, and SSP5-8.5, respectively. Uncertainty and bias remain large in the GCMs, limiting their applicability in impact studies, and it increases with an increasing number of climate models. Therefore, selecting climate models is vital for regional impact studies. From the large set of existing GCMs with high capability to represent future climate for a particular area is vital for climate impacts studies. Therefore, selection of climate models capable of representing future climate from the large set of existing GCMs is vital for climate impacts studies for a particular area. Therefore, the wide-ranging assessment of climate model performance is essential for the appropriate interpretation of the simulated results. The criteria to be considered on which climate variables are included depends on the impact study goals. For example, a study about the possibility of flood and drought occurrence will most likely consider changes of extremely high and dry rainfall events. In contrast, an assessment of evaporation due to climate change impact will be more concerned with temperature and related data.

The relevance and applicability of climate models at a local-scale for the study of climate change are limited because the raw GCM output is not capable of representing climate variables of particular regions (S.H Gebrechorkos et al. 2019; Joetzer et al. 2013; Knutti and Sedláček 2013; Lutz et al. 2013). This is due to their coarser spatial resolution (>100 km), inappropriate climate model selection approaches, emission scenarios, inaccurate representations of the complex natural interconnections, downscaling approaches, biases and uncertainties of model structures (Legates 2002; Mandal et al. 2019). The spatial resolutions of the raw GCM outputs are very coarse, which makes their direct usage in hydrological models not always recommended (S. H Gebrechorkos et al. 2019). Therefore, to improve the spatial resolution, climate models should be downscaled (Bader et al. 2008) by applying either statistical (Tavakol-Davani et al. 2013) or dynamical downscaling techniques (Chen et al. 2010). Also, bias correction must be performed using appropriate methods to minimize biases (Dixon et al. 2016) before applying the GCM outputs into hydrological models for impact assessment study (Dessu and Melesse 2013; Khan and Koch 2018) and other purposes. Finally, the downscaled climate model outputs will be used as input for the hydrological model to evaluate climate change impact on the hydrological system, especially for the likely change in streamflow, runoff, and other related water balance components.

Uncertainties arise in selecting climate models for impact studies due to large number of climate models. This uncertainty originating from a projected climate model is the primary cause of uncertainty in climate impact studies (Finger et al. 2012). It is more significant than model parameter uncertainty and structural uncertainties of hydrological models (Minville et al. 2008). Therefore, the selection of representative GCM needs strong attention when accompanying a climate change impact study. Different approaches can be used to evaluate the capability and skill of climate models for a specific location and purpose. Model selection can follow a single or multiple criteria approach. Selection of representative climate models can be made mainly based on different approaches: 1) projected changes in mean air temperature and total annual precipitation (Immerzeel et al. 2013; Warszawski et al. 2014) and projected changes in climatic extremes. 2) simulating historical climate performance (Ongoma et al. 2019) for either the means or extremes (Biemans et al. 2013; Pierce et al. 2009; Seager et al. 2007) 3) a combination of the above two approaches, which is called the envelope-based approach (Kaini et al. 2020; Lutz et al. 2016; Sa'adi et al. 2020) 4) taking average outcomes of all available GCM runs (Seager et al. 2007). In general, selecting an appropriate GCM runs highly depends on the purpose and specific location. Identifying an appropriate method for climate model selection is essential. Nevertheless, the aforementioned approaches have benefits and drawbacks that need to be considered during the selection process.

Previous multi-criteria studies conducted on climate model selection for different river basins and regions could not ingest all available ensemble models in the specific repositories during their selection process (Fu et al. 2013; Kaini et al. 2020; Lutz et al. 2016; Sa'adi et al. 2020). For example, Khan and Koch (2018) and Shiru et al. (2021) considered ensemble members who shared the same initial condition from each available GCM, typically the first ensemble member (r1i1p1 of CMIP5) and (r1i1i1f1 of CMIP6), respectively. Researchers in Ethiopia has implemented climate models to conduct climate change impact in the Awash Basin. Many focused on specific sub-basins such as Upper Awash and other watersheds of the basin. However, there is a lack of capacity for consistent projection models and multiple criteria on their procedure to select climate models for a particular purpose. For

example, Taye et al. (2018) revealed that among 24 GCMs obtained from CMIP5, three GCMs were selected based on performance in capturing historical climate variables. However, models representing the past climate variability of the study area may not describe the future climate projection. This uncertainty of using historical climate models fails to address future Green House Gases (GHG) emissions and different SSPs. The approach inherently assumes that the historical climate remains constant and valid in future projections. Such unguaranteed assumptions may lead to biases in the estimation of future climate and hydrological components. Daba and You (2020) take ensemble means of two climate models selected based on their spatial resolution for the atmospheric variable. The main drawback of applying the average of included GCM runs is that both high-performing and low-performing models are equally weighted. Bekele et al. (2019); Getahun et al. (2020); Tadese et al. (2020) and Tessema et al. (2020) randomly selected GCMs and RCMs from the pool of available climate models. None of the studies considered the mean trend of future projection and the seasonal variability.

This paper attempts to evaluate the CMIP6 GCMs by considering a combination of the two comprehensive approaches, the envelope approach (Kharin et al. 2013; Klein Tank et al. 2009; Min et al. 2009; Min et al. 2011; Park and Min 2019; Seneviratne et al. 2012; Zhang et al. 2011), and the past-performance approach (Biemans et al. 2013) to sort out the most appropriate climate model runs over the UAB. This method consists of three consecutive steps: a) range of projected changes in monthly mean. b) full possible range of projected changes in daily climatic extremes, and c) skill in reproducing past climate. We used 200 climate model runs for SSP4.5 and SSP8.5 for this study. This climate model selection approach is not straightforward; there are different step-wise approaches and handling of several GCMs. Such combined procedures are essential for discovering the incidence and severity of climate extremes and offering a more inclusive valuation than individual assessment criteria. This research comprehensively represents all the projected possible futures, which is essential to address the expected full potential range of climate models under investigation. Besides, GCM selection from the newly released CMIP6 climate models was not conducted over UAB; most future projections and selections were based on CMIP5 models. Therefore, it is necessary to improve the GCM selection and possible climate projection for UAB by adopting the GCMs from CMIP6 under SSP scenarios. Furthermore, we address the limitations of the previous studies by handling several GCM runs and a systematic approach of combined methodology with a narrow uncertainty range, which is a new insight for the study area.

This paper will be the preliminary work to select representative climate models using the advanced envelope-based method in the particular study area. This study aims to: (1) select representative climate model runs for UAB and (2) develop a full future range of climate scenarios based on downscaled and bias-corrected GCM data on UAB.

2 Study area and data

2.1 Study area

The representative climate model selection and the downscaling process was carried on the UAB, covering an area of 11,575 km^2 , located in the central part of Ethiopia, which lies within latitudes 8° 16' and 9° 18' N and longitudes 37° 57' and 39° 17' E. UAB is a very important sub-basin of the Awash Basin regarding water resources management as it is the head of the Awash Basin and representative of different climates. The highest and lowest elevation of the

basin is about 3500 and 1500 m a.s.l., respectively. The annual precipitation and average air temperature are about 1019 mm and 17.65 °C, respectively.

Fig. 1 Study area, the Upper Awash Basin

2.2 Data

Daily precipitation, maximum and minimum temperature, were downloaded from the CMIP6 archive (<https://esgf-node.llnl.gov/projects/cmip6>). The climate data unavailable on the Earth System Grid Federation website were downloaded from the climate impact archive (<https://climate4impact.eu>). To fully represent all models from the CMIP6 repository, we download the entire existing ensemble members (symbolized with different realizations) with available monthly and daily data, ensemble members with the two forcing scenarios (SSP4.5 and SSP8.5) for all the variables of interest must have historical and future output extending to 2100. A total of two hundred model runs from the initial pool of GCM runs were included when this simulation was undertaken (October 2020), which is processed in Climate Data Operators (CDO) (Schulzweida et al. 2012) software, developed by Max-Planck Institute for Meteorology (<https://code.mpimet.mpg.de/>). CDO is a standard climate data processing tool that contains more than 600 command lines. The NCEP-DOE (Kanamitsu et al. 2002) reference data derived based on observed stations were

used for the base period. The analysis was carried out using 30 years for the historical time frame of (1981-2010), the near future (2031-2060), and the end of the century (2061-2090) period.

3 Research methods and approach

The advanced envelope method was adopted in this paper to identify the suitable GCM models for the UAB. This method consists of three interconnected steps, (1) preliminary selection based on a projected range of annual mean temperature and total precipitation sum, (2) changes in climate extremes of daily average precipitation and temperature using the Expert Team on Climate Change Detection and Indices (ETCCDI) and (3) final selection based on models performance to simulate historical climate. This approach covers the skill of a large pool of climate model runs with respect to the NCEP-DOE reference data set. Each independent model run applies directly in the first, second, and third steps rather than average these climate models to produce an ensemble result. A single climate model is insufficient to characterize the complex climatic features. The future projections may vary immensely from wet to drier or hot to cooler future climates. Therefore GCMs are categorized to represent Dry-Cold, Dry-Warm, Wet-Warm, and Wet-Cold corners of the full spectrum. The complete range of likely future climatic circumstances needs to be covered to evaluate the full range of probable climate impact.

3.1 Initial shortlisting based on changes in mean air temperature and annual precipitation

As the first step, after resampling all available GCM runs to a common spatial resolution of $1.0^\circ \times 1.0^\circ$ grid (~100 km $\times$ 100 km) using bilinear remapping technique, monthly area-averaged mean air temperature and precipitation are calculated across the UAB. Changes in annual mean temperature (ΔT) and annual percentile mean of annual precipitation ($\Delta P\%$) were calculated with respect to the reference period. The 10th and 90th percentile values of ΔP and ΔT were calculated, representing the four corners of the seasonal projection of the study area as indicated in Table 1. The models closest to a corner of the spectrum represent the skilled model. Each model distance to the closest corner of the spectrum is calculated using the equation adopted from Lutz et al. (2016). Equation 1 calculates the distance (D) of each model to the closest corner of the spectrum, and the models are then ranked based on the value of D . Finally, five ensemble model runs with the lowest value of (D), are selected from each corner of the spectrum and qualify for the next step of the process.

$$D_{p_j^P, p_j^T} = \sqrt{(P_i^P - P_j^P)^2 + (P_i^T - P_j^T)^2} \quad (1)$$

where $D_{p_j^P, p_j^T}$ is the distance of models (j)'s ΔT and ΔP (P_j^P and P_j^T , respectively) to the corner (i)'s 10th and/or 90th a percentile score of ΔT and ΔP for the whole ensemble (P_j^P and P_j^T), respectively.

Table 1 Seasonal projection representing the four corners of climate extremes

ΔT	$\Delta P\%$	Seasonal Projection
10 th	90 th	Cold-Wet (C-W)

90 th	10 th	Warm-Dry (W-D)
10 th	10 th	Cold-Dry (C-D)
90 th	90 th	Warm-Wet (W-W)

3.2 Selection based on changes in climate extremes

For the qualified models, we evaluated their changes based on climate extremes in this step. The models are subjected to changes in climate extremes relating to temperature and precipitation. The calculations were computed using CDO software for the CMIP6 data sets covering UAB using the same procedure as Sillmann et al. (2013a). Table 2 shows the two climate extremes, each for temperature and precipitation, considered for this study using daily GCM and reference data sets remapped to a common grid of $1^\circ \times 1^\circ$ resolution. As a set of 27 indices provided by Sillmann et al. (2013a), we have focused only on some of the most relevant extreme temperature and precipitation indicators. Detailed descriptive information and a list of all ETCCDI climate indices can be found on http://etccdi.pacificclimate.org/list_27_indices.shtml. Warm spell duration index (WSDI) and cold spell duration index (CSDI) is considered for the temperature, while consecutive dry day index (CDD) and total precipitation from wet days (R95PTOT) are considered for precipitation indices. R95PTOT and CDD are relevant indicators for rainfall extremes and provide information for proper water management, agricultural management, and assessing flow storage magnitude and drainage. CDD is also an indicator of water stress which affects crop growth and helpful for drought assessment and low flow episodes. WSDI and CSDI are also important indicators of water stress and determine the process of evapotranspiration.

The indices are averaged over the 30 years for the reference data and the two future projections. Subsequently, the percentual changes of the projected period were calculated with respect to the reference period. During the refined selection, skill scores are calculated using the most relevant index for temperature and precipitation for each corner of the spectrum. For example, the models selected for the Dry-Cold corner, CDD and CSDI, are considered, while CDD and WSDI are considered for the Dry-Warm corner. Likewise, for the models selected from the Wet-Warm corner, R95PTOT and WSDI were considered, while R95PTOT and CSDI were considered for the Cold-Wet corner of the spectrum. The five models from each corner are ranked 1 to 5. For example, for the most relevant index for air temperature and precipitation in the Cold-Dry corner, the specific models with the maximum increment in CSDI and CDD, respectively, score five points. In contrast, the model runs with the lowest increment in CSDI, and CDD scores 1 for both temperature and precipitation index rank. Two GCM runs with the highest combined score values were selected for the next step. Therefore the total number of shortlisted model runs is reduced from five to two in each corner.

Table 2 Description of ETCCDI indices used for the study

Meteorological variable	ETCCDI index	Description of the ETCCDI index
Precipitation	R95PTOT	Precipitation due to extremely wet days (annual total precipitation when daily rainfall > 95th percentile)

	CDD	Consecutive dry days: maximum length of a dry spell when (Precipitation < 1 mm)
Temperature	WSDI	Warm spell duration index: count of days in at least six days where maximum temperature (TX) > 90th percentile
	CSDI	Cold spell duration index: count of days in at least six days where minimum temperature (TN) < 10th percentile

3.3 Final selection based on model performance to represent the past climate

The selected model runs in refined selection (step two) were processed further using a validation step to compare their performance in simulating the past climate using monthly average air temperature and precipitation data. The study area is divided into three subregions; the upper, middle, and lower subregions of UAB. This evaluation is done per subregion for a more detailed regional model selection analysis to avoid omission and underestimations in the entire study area. These subregions are selected bearing in mind that they show more or less similar climatic features. A method adapted from Sánchez et al. (2009) was used for the precipitation skill score calculation. This procedure involves five skill score functions considering all the behavioral aspects of precipitation averaged over the 30-year historical period (1981–2010). The skill score equations are described therein.

$$f_1 = 1 - \left(\frac{|A_{GCM} - A_{NCEP-DOE}|}{2 A_{NCEP-DOE}} \right)^{0.5} \quad (2)$$

$$f_2 = 1 - \left(\frac{|A_{GCM}^+ - A_{NCEP-DOE}^+|}{2 A_{NCEP-DOE}^+} \right)^{0.5} \quad (3)$$

$$f_3 = 1 - \left(\frac{|A_{GCM}^- - A_{NCEP-DOE}^-|}{2 A_{NCEP-DOE}^-} \right)^{0.5} \quad (4)$$

$$f_4 = 1 - \left(\frac{|\overline{P}_{GCM} - \overline{P}_{NCEP-DOE}|}{2 \overline{P}_{NCEP-DOE}} \right)^{0.5} \quad (5)$$

$$f_5 = 1 - \left(\frac{|\sigma_{GCM} - \sigma_{NCEP-DOE}|}{2 \sigma_{NCEP-DOE}} \right)^{0.5} \quad (6)$$

Where A_{GCM} and $A_{NCEP-DOE}$, are areas below the PDFs of the GCMs and reference data, respectively. A^+ and A^- are areas above and below the 50th percentile, P is the mean annual precipitation over the given subregion, and σ is the standard deviation of the PDF. The distribution is taken into account through the total area below the probability density function (Equation 3). The mean Precipitation (Equation 6) of GCMs and reanalysis are taken in Equation 1 and Equation 4, respectively. Similarly, by calculating the amount of 50th percentile precipitation value of both GCM and reanalysis data, the higher (Equation 4) and lower (Equation 5) precipitation value are accounted for by analyzing amounts below and above the 50th percentile limit, respectively, whereas (Equations 7) the shape of the distribution is defined through the variance. The five skill score functions are multiplied (Equations 8) to get the total skill score of given GCM precipitation per subregion.

$$Total_{skill\ score} = (f_1 \cdot f_2 \cdot f_3 \cdot f_4 \cdot f_5) \quad (7)$$

For temperature skill score calculation, the commonly used Taylor diagram approach was applied (Taylor 2005). The approach involves using the Taylor diagram software (https://agrimetsoft.com/taylor_diagram_software) to compute the correlation of air temperature between the reference and GCM model datasets. If a GCM simulates the

observed data perfectly, the correlation value will be 1. On the contrary, if a model simulation showed a significant deviation from the observed data, the skill score or correlation will be near zero. The correlation and skill score values for temperature and precipitation, respectively, indicate the relative similarity or deviation between the GCM model and reference data sets.

$$E'^2 = \sigma_f^2 + \sigma_r^2 - 2\sigma_f\sigma_r R \quad (8)$$

Where R is the correlation coefficient between simulated and reanalysis data, E' is the centred RMS difference and σ_f^2 and σ_r^2 are the variances of the simulated and reference data. The average is taken from the control period skill score of temperature and precipitation, and these scores are ranked for the three subregions separately. As a final step, to get the general ranking of each model run, the rank of each subregion is summed, resulting in a ranking for the entire UAB area. The highest-ranked GCM indicates the best performance with the least bias, while the lowest-ranked GCM indicates the worst performance with the largest bias. Based on this ranking, one model qualifies as the best model at every corner.

The multi-criteria method adopted in this study to select the best model runs with the best capability to represent the past and possible future climate for UAB is in line with the techniques proposed by Kim et al. (2020); Lutz et al. (2016); Sánchez et al. (2009) and Sillmann et al. (2013b)

3.4 Climate data downscaling and bias correction

There are two methods to downscale raw GCM outputs: dynamical downscaling (DD) and statistical downscaling (SD). The SD develops a statistical relationship between local-scale climate variables and large-scale GCM outputs (S. H Gebrechorkos et al. 2019; Kaini et al. 2020). Besides, SD is simple, requires less resources, and is computationally efficient. It is suitable to achieve spatial downscaling and bias correction of multiple models, and their resolution is higher than DD. Also, they are widely used in different sectors (Brown et al. 2008; Wilby et al. 2002). On the other hand, DD techniques use local physical factors such as topographic features nested within a GCM to produce local or Regional Climate Models (RCMs) at a fine-scale resolution, usually 50 km (Endris et al. 2013). In addition, it requires many resources and is time-consuming (Trzaska and Schnarr 2014).

After selecting the representative GCMs, the models were downscaled from coarser to a finer spatial resolution using observed data from 20 stations retrieved from the National Meteorological Agency of Ethiopia. This paper used the SD-GCM V2.0 software to statistically downscale the GCMs spanning through the study period of 2031-2060 and 2061-2090. We used three distinct methods of SD approach, the Delta change (Hay et al. 2000), the Quantile Mapping (QM) (Wood et al. 2004), and the Empirical Quantile Mapping (EQM) (Boé et al. 2007). These three approaches have been applied for all selected GCMs. We subjected the models to different efficiency criteria, Pearson Correlation, Spearman and Index of Agreement as performance indicators with respect to observations. This method has been effectively applied in the hydrological application for different purposes (Themeßl et al. 2012).

Fig 2. Flow chart showing the steps adopted in this study for climate model selection

4 Results and discussion

4.1 Climate model selection

4.1.1 Climate Models selection based on Changes in Climatic Means (step 1)

As described in Section 3.1, the first step is based on projected changes in mean air temperature (ΔT) and annual precipitation (ΔP) between future and reference periods, as shown in Supplementary Tables S1-S4. We calculated the

average annual air temperature and precipitation for the reference dataset and 200 GCM runs over UAB. The historical value of rainfall and the average temperature of the basin was 1225.8 mm and 16.3 °C, respectively. The ΔT projection values of the end of the century (2061-2090) are higher than the mid-century (2031-2060). On the contrary, the change in annual precipitation (ΔP) projections for the end of the century are less than the mid-century projections in both SSPs of 4.5 and 8.5. ΔT and ΔP vary from +1.1 °C to +8.0 °C and – 4.4% to +16.7%, respectively, under the mid-term period for SSP4.5. In comparison, SSP8.5 vary from 1.3 °C to +8.2 °C and –4.6% to +17.0%. Similarly, the ΔT and ΔP vary from 1.6 °C to +8.7 °C and –4.4% to +16.65%, respectively, in the 2061-2090 period for SSP4.5. While, for SSP8.5, these ranges are from 2.68 °C to +10.45 °C and – 3.2% to +16.71%. The range of ΔT and ΔP for ensemble models under the SSP8.5 was higher than those under SSP4.5 in the respective durations. We selected the five models closest to each corner of the spectrum, making a total of 20 models for every radiative forcing and study period. The model runs are shown in Figure 3.

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Fig. 3 Projected changes in annual precipitation sum (ΔP) and mean air temperature (ΔT) between the Historical period (1980–2010), mid-century (2031–2060), and end-of-century (2061–2090) for all included models (a) and (b) for mid-century considering SSP4.5 and SSP8.5 respectively, (c) and (d) is for the end-of-century considering SSP4.5 and SSP8.5 respectively. Red spots indicate the 10th and 90th values for ΔT and $\Delta P\%$. The model runs selected for Step 2 are marked with the lemon, yellow, pink, and orange colors indicate the selected GCM models for corner one (D-W), two (W-W), three (D-C), and four (W-C), respectively

4.1.2 Selection based on changes in climatic extremes (Step 2)

The remaining models from step one are subjected to two extreme climate indices for temperature and precipitation during the mid-century and end-of-century periods with respect to the reference data set. Supplementary Table S5-S8 presents the ETCCDI extreme indices of future and historical period, T index rank, P index rank, and combined score for the entire GCMs selected from step 1. Two models with the highest combined score are selected for each spectrum corner. If two models appear to have the same second combined score, three models were selected for that corner. Tables 3 and 4 show the models with the highest combined score for the study periods painted light gray.

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329 **Table 3** Model runs were analysed in step two for mid-century SSP4.5 and SSP8.5. Models selection for Step 3 are marked light gray

Projection	Models SSP4.5 (2031-2060)	Pr	Tm	Δ CDD%	Δ R95PTOT%	Δ WSDI%	Δ CSDI%	T index rank	P index rank	Combined score
W-D	CanESM5_r6i1p1f1	-3.5	7.8	-4.5	33.9	11810	-100.0	4	1	2.5
	CanESM5_r25i1p2f1	-3.6	7.8	26.3	24.5	11847	-100.0	5	3	4
	CanESM5_r20i1p1f1	-3.5	7.9	13.7	35.4	11802	-100.0	3	2	2.5
	CanESM5_r21i1p2f1	-3.4	7.7	29.8	37.6	11703	-100.0	1	4	2.5
	CanESM5_r10i1p2f1	-3.4	7.8	42.7	36.3	11704	-100.0	2	5	3.5
W-W	INM-CM5-0_r1i1p1f1	0.6	5.5	-18.5	-48.0	10719	-100.0	5	1	3
	INM-CM4-8_r1i1p1f1	3.0	5.4	-18.2	-29.5	10482	-100.0	4	2	3
	CESM2_r1i1p1f1	0.8	5.2	26.3	51.5	9770	-100.0	1	5	3
	CESM2_r4i1p1f1	0.5	5.3	24.2	42.8	9949	-100.0	2	4	3
	CESM2_r10i1p1f1	0.1	5.4	45.6	37.7	10152	-100.0	3	3	3
C-D	MPI-ESM1-2-LR_r4i1p1f1	-3.0	2.5	91.8	-79.2	7644	-61.8	5	5	5
	NESM3_r1i1p1f1	-3.1	3.2	60.4	-54.6	9164	-98.9	2	4	3
	MPI-ESM1-2-LR_r6i1p1f1	-2.7	2.6	46.4	-77.7	8142	-87.8	4	3	3.5
	MPI-ESM1-2-LR_r8i1p1f1	-2.6	2.5	40.0	-77.5	7796	-92.4	3	1	2
	NESM3_r2i1p1f1	-3.3	3.4	45.3	-60.2	9640	-100.0	1	2	1.5
C-W	IPSL-CM6A-LR_r14i1p1f1	1.7	2.9	42.6	21.3	5918	9.6	5	3	4
	IPSL-CM6A-LR_r3i1p1f1	1.8	3.0	35.9	38.1	6358	-31.5	1	5	3
	IPSL-CM6A-LR_r6i1p1f1	2.0	3.0	44.3	35.0	6307	4.6	3	4	3.5
	IPSL-CM6A-LR_r1i1p1f1	1.3	3.0	38.0	18.8	6174	5.0	4	2	3
	IPSL-CM6A-LR_r4i1p1f1	1.1	3.0	46.6	16.9	6157	-12.7	2	1	1.5

330

Projection	Models SSP8.5 (2031-2060)	Pr	Tm	Δ CDD%	Δ R95PTOT%	Δ WSDI%	Δ CSDI%	T index rank	P index rank	Combined score
W-D	CanESM5_r22i1p2f1	-2.8	8.2	35.8	34.5	11897	-100.0	5.0	5.0	5.0
	CanESM5_r18i1p2f1	-2.3	8.0	17.1	39.6	11854	-100.0	2.0	3.0	2.5
	CanESM5_r5i1p2f1	-2.1	8.1	18.5	43.7	11863	-100.0	4.0	4.0	4.0
	CanESM5_r12i1p2f1	-2.0	8.0	8.4	50.4	11813	-100.0	1.0	2.0	1.5
	CanESM5_r20i1p2f1	-1.9	8.0	-3.3	56.2	11859	-100.0	3.0	1.0	2.0
W-W	CESM2_r10i1p1f1	2.2	5.9	51.6	70.2	10871	-100.0	3.0	3.0	3.0
	CESM2_r4i1p1f1	2.6	5.9	48.7	72.6	10820	-100.0	2.0	4.0	3.0
	INM-CM4-8_r1i1p1f1	3.5	5.8	-23.1	-24.6	10957	-100.0	4.0	2.0	3.0
	INM-CM5-0_r1i1p1f1	1.4	5.8	-9.5	-36.0	11146	-100.0	5.0	1.0	3.0
	CESM2_r11i1p1f1	0.7	5.8	14.6	92.1	10803	-100.0	1.0	5.0	3.0
C-D	MPI-ESM1-2-LR_r3i1p1f1	-2.6	2.7	56.0	-77.6	8320	-94.0	1.0	2.0	1.5
	MPI-ESM1-2-LR_r6i1p1f1	-2.6	2.8	49.7	-74.3	8409	-92.0	2.0	1.0	1.5
	MPI-ESM1-2-LR_r4i1p1f1	-2.5	2.6	60.4	-77.7	8023	-56.5	5.0	4.0	4.5
	MPI-ESM1-2-LR_r8i1p1f1	-2.5	2.6	57.5	-79.7	8040	-87.6	4.0	3.0	3.5
	MPI-ESM1-2-LR_r5i1p1f1	-2.5	2.9	77.8	-81.7	8664	-91.4	3.0	5.0	4.0
C-W	IPSL-CM6A-LR_r1i1p1f1	2.7	3.2	29.9	56.9	6849	-26.6	5.0	5.0	5.0
	IPSL-CM6A-LR_r4i1p1f1	2.3	3.3	34.9	31.1	7140	-59.8	1.0	3.0	2.0
	IPSL-CM6A-LR_r14i1p1f1	2.4	3.4	24.9	38.3	7301	-57.1	2.0	4.0	3.0
	IPSL-CM6A-LR_r2i1p1f1	1.7	3.4	40.6	22.0	7265	-56.3	3.0	1.0	2.0
	IPSL-CM6A-LR_r6i1p1f1	1.7	3.5	51.3	29.4	7470	-52.0	4.0	2.0	3.0

332 **Table 4** Model runs were analyzed in step two for end-century SSP4.5 and SSP8.5. Models selection for Step 3 are marked light gray

Projection	Models SSP4.5 (2061-2090)	Pr	Tm	Δ CDD%	Δ R95Ptot%	Δ WSDI%	Δ CSDI%	T index rank	P index rank	Combined score
W-D	CanESM5_r16i1p2f1	-2.4	8.6	13.1	53.8	11972	-100	2	4	3
	CanESM5_r7i1p2f1	-2.3	8.6	6.2	55.9	11977	-100	4	2	3
	CanESM5_r18i1p2f1	-2.2	8.5	-7.2	62.2	11975	-100	3	1	2
	CanESM5_r10i1p2f1	-2.2	8.5	9.9	57.4	11923	-100	1	3	2
	CanESM5_r4i1p2f1	-2.1	8.6	30.4	55.1	11991	-100	5	5	5
W-W	CESM2_r10i1p1f1	2.1	6.1	19.2	81.8	11174	-100	2	5	4
	CESM2_r11i1p1f1	2.0	6.2	12.3	81.2	11297	-100	4	4	4
	CESM2_r4i1p1f1	1.6	6.3	13.7	75.0	11410	-100	5	3	4
	INM-CM4-8_r1i1p1f1	3.7	5.8	-26.8	-18.7	11048	-100	1	2	2
	INM-CM5-0_r1i1p1f1	1.0	5.9	-26.1	-39.1	11224	-100	3	1	2
C-D	MPI-ESM1-2-LR_r1i1p1f1	-2.4	3.2	24.0	-77.9	9327	-99	1	1	1
	MPI-ESM1-2-LR_r2i1p1f1	-2.6	3.2	44.3	-76.4	9375	-98	2	3	3
	MPI-ESM1-2-LR_r6i1p1f1	-2.6	3.2	63.0	-79.2	9372	-96	4	5	5
	MPI-ESM1-2-LR_r5i1p1f1	-2.3	3.1	58.5	-77.3	9200	-94	5	4	5
	MPI-ESM1-2-LR_r9i1p1f1	-2.3	3.1	41.8	-82.0	9224	-97	3	2	3
C-W	IPSL-CM6A-LR_r2i1p1f1	3.0	3.9	29.8	50.0	8577	-96	2	5	4
	IPSL-CM6A-LR_r14i1p1f1	2.8	3.9	27.6	45.3	8522	-88	4	3	4
	IPSL-CM6A-LR_r1i1p1f1	2.8	4.0	16.5	40.8	8706	-96	2	2	2
	IPSL-CM6A-LR_r4i1p1f1	3.4	3.8	41.6	49.6	8417	-89	3	4	4
	IPSL-CM6A-LR_r3i1p1f1	2.2	3.9	23.6	37.7	8588	-86	5	1	3

Projection	Models SSP8.5 (2061-2090)	Pr	Tm	Δ CDD%	Δ R95PTOT%	Δ WSDI%	Δ CSDI%	T index rank	P index rank	Combined score
W-D	ACCESS-CM2_r2i1p1f1	-2.4	8.1	23.9	-1.1	12111	-100	4	5	4.5
	ACCESS-CM2_r1i1p1f1	-1.8	7.9	19.0	1.1	12109	-100	2	4	3
	ACCESS-CM2_r3i1p1f1	-2.0	7.9	8.8	-4.5	12115	-100	5	3	4
	CanESM5_r24i1p2f1	1.0	10.3	-15.5	88.4	12110	-100	3	2	2.5
	CanESM5_r6i1p2f1	1.3	10.3	-18.1	91.4	12102	-100	1	1	1
W-W	CESM2_r4i1p1f1	4.4	8.0	18.8	102.9	12040	-100	2	5	3.5
	MIROC-ES2L_r1i1p1f2	6.6	7.4	-27.1	15.4	12024	-100	1	1	1
	CanESM5_r1i1p2f1	2.9	10.0	29.8	17.9	12110	-100	5	2	3.5
	CESM2_r11i1p1f1	3.7	8.1	8.5	87.7	12045	-100	3	3	3
	CESM2_r10i1p1f1	3.7	8.1	-2.1	95.1	12049	-100	4	4	4
C-D	MPI-ESM1-2-LR_r6i1p1f1	-1.7	4.3	57.0	-78.5	11046	-100	1	5	3
	MPI-ESM1-2-LR_r4i1p1f1	-1.8	4.3	53.4	-75.5	11168	-100	1	3	2
	MPI-ESM1-2-LR_r8i1p1f1	-1.7	4.2	52.1	-71.3	11042	-100	1	2	1.5
	MPI-ESM1-2-LR_r10i1p1f1	-1.8	4.1	47.5	-73.7	10998	-100	1	1	1
	MPI-ESM1-2-LR_r7i1p1f1	-1.7	4.1	54.7	-75.8	10998	-100	1	4	2.5
C-W	IPSL-CM6A-LR_r2i1p1f1	5.9	5.5	29.8	76.9	10980	-99	4	2	3
	IPSL-CM6A-LR_r1i1p1f1	5.9	5.6	22.9	92.0	10989	-99	4	4	4
	IPSL-CM6A-LR_r14i1p1f1	5.7	5.6	27.4	92.7	11047	-100	2	5	3.5
	IPSL-CM6A-LR_r3i1p1f1	6.0	5.7	11.9	88.7	11059	-98	5	3	4
	IPSL-CM6A-LR_r6i1p1f1	7.2	5.6	3.5	88.7	11017	-100	2	3	2.5

This procedure of calculating a combined score based on the ranking of indices value can result in the situation whereby GCM runs with the highest value in one of the ETCCDI indices are not selected due to the lowest change in another ETCCDI indices. For example, in the W-C corner, considering the mid-century period for SSP4.5, the IPSL-CM6A-LR_r3i1p1f1 model is not selected while it projects the largest changes in R95PTOT. Similarly, the W-W corner for the SSP8.5 CESM2_r1i1p1f1 model is not selected, although it projects the higher changes in R95PTOT in the end-century period. From the C-W corner, IPSL-CM6A-LR_r14i1p1f1 is not selected even though it projects the largest changes in R95PTOT. The refined selection based on the changes in four ETCCDI indices between the base and future period is provided in Supplementary Table S1- S8.

It is worth mentioning that the model with a large or low change of mean precipitation or temperature also coincides with the highest change in the relevant extreme indices. For example, CanESM5_r22i1p2f1 considering SSP8.5 projected the slightest change in ΔT (8.2 °C) and ΔP (-2.75%) in the W-D corner for the middle-term period, which also projected the largest increase in WSDI (11897%) and CDD (35.8%), also the largest decrease in CSDI and R95PTOT. CDD increases in mid-century -18.5% to +91.8% and -23.1% to +77.8% under SSP4.5 and SSP8.5, respectively. Similarly, at the end-century, CDD is projected to increase from -26.8% to +63.0% and -27.1% to +57.0%, considering SSP4.5 and SSP8.5, respectively. The models estimated an increase in R95PTOT from -79.2% to +51.5% and -81.7% to +92.1% for SSP4.5 and SSP8.5 respectively, in the mid-century, but from -82.0% to +81.8% and -78.5% to +102.9% for the respective SSP in the end-century. An increase in R95PTOT forecasts more precipitation in the coming periods. The WSDI is projected to increase for all scenarios and periods, and it is estimated at 6849% to 11897% for SSP4.5 and 6849% to 12,115% for SSP8.5 in the mid and end century, respectively.

Also, an increase in WSDI forecasts an increase in maximum temperature in the future compared to the historical period. Increasing trends of WSDI indicate a warmer future, which may affect water resources management, natural ecosystems, and human health. The increase in CSDI projected -100.0% to 9.6% and -100.0% to -26.6% for SSP4.5 and SSP8.5, respectively, during mid-century and an increase from -100% to -86% and -100% to -98% in the end-century for the respective SSPs. Generally, the four selected climate extreme indices found an increased trajectory in the mid and end of the 21st century. Severe climate extremes such as El Niño may frequently occur in the coming decades, resulting in a significant loss of livestock, crop failure, and serious economic impacts. The increase in climate extremes that highly influence climate variability could increase the region susceptibility to drought.

4.1.3 Final selection based on models past performance (Step 3)

Model validation based on past performance to the reference data set is the final model selection step as shown in Table 7. Skill scores for precipitation and temperature in the three subregions are shown in Table 5. And Table 6 shows the precipitation and temperature skill scores remaining from step two for each sub-region and the combined or general score. The final selection of models is based on the lowest combined bias score or performance of the GCM to the reference data. Based on the mentioned multi-criteria approach to select capable climate models, we select limited climate models with the appropriate performance to represent the possible future climate projection of UAB. Therefore, the final selected four GCM models with different ensemble members code "r" (realizations) "i"

382 (initialization methods), "*p*" (physics details) "*f*" (forcing) are namely, CanESM5, MPI-ESM1-2-LR, IPSL-CM6A-
383 LR, INM-CM4-8, and ACCESS-CM2.

384 **Table 5** Skill scores for model runs remaining after Step 2. Skill scores are calculated for precipitation and temperature for three
385 subdomains independently

SSP/Year	Projections	GCM runs	Precipitation SS			Temperature SS		
			LR	MR	UR	LR	MR	UR
SSP4.5/2031-2060	W-D	CanESM5_r25i1p2f1	0.07	0.13	0.07	0.63	0.73	0.66
		CanESM5_r10i1p2f1	0.08	0.15	0.07	0.57	0.68	0.49
	W-W	INM-CM5-0_r1i1p1f1	0.31	0.41	0.15	0.79	0.65	0.79
		INM-CM4-8_r1i1p1f1	0.61	0.68	0.18	0.76	0.53	0.77
	C-D	MPI-ESM1-2-LR_r4i1p1f1	0.10	0.10	0.05	0.64	0.58	0.66
		MPI-ESM1-2-LR_r6i1p1f1	0.11	0.09	0.06	0.71	0.66	0.70
	C-W	IPSL-CM6A-LR_r14i1p1f1	0.28	0.28	0.11	0.73	0.69	0.70
		IPSL-CM6A-LR_r6i1p1f1	0.24	0.20	0.09	0.74	0.74	0.73
	SSP4.5/2061-2090	CanESM5_r16i1p2f1	0.08	0.13	0.07	0.60	0.70	0.65
		CanESM5_r7i1p2f1	0.08	0.15	0.07	0.58	0.70	0.65
		CanESM5_r4i1p2f1	0.08	0.15	0.08	0.58	0.69	0.64
	W-W	INM-CM4-8_r1i1p1f1	0.61	0.68	0.18	0.77	0.53	0.77
		INM-CM5-0_r1i1p1f1	0.31	0.41	0.15	0.79	0.65	0.79
	C-D	MPI-ESM1-2-LR_r2i1p1f1	0.13	0.10	0.05	0.69	0.67	0.72
		MPI-ESM1-2-LR_r6i1p1f1	0.11	0.09	0.06	0.71	0.66	0.70
	C-W	MPI-ESM1-2-LR_r5i1p1f1	0.10	0.09	0.05	0.70	0.68	0.72
		MPI-ESM1-2-LR_r9i1p1f1	0.11	0.09	0.05	0.60	0.62	0.52
		IPSL-CM6A-LR_r2i1p1f1	0.37	0.29	0.10	0.74	0.72	0.72
		IPSL-CM6A-LR_r14i1p1f1	0.28	0.28	0.11	0.73	0.69	0.70
		IPSL-CM6A-LR_r4i1p1f1	0.36	0.27	0.10	0.75	0.74	0.73
		IPSL-CM6A-LR_r3i1p1f1	0.33	0.25	0.09	0.72	0.70	0.71
SSP8.5/2031-2060)	W-D	CanESM5_r22i1p2f1	0.08	0.13	0.07	0.58	0.69	0.64
		CanESM5_r5i1p2f1	0.07	0.12	0.07	0.59	0.69	0.63
	W-W	INM-CM4-8_r1i1p1f1	0.61	0.68	0.18	0.76	0.53	0.77
		INM-CM5-0_r1i1p1f1	0.31	0.41	0.15	0.79	0.65	0.79
	C-D	MPI-ESM1-2-LR_r4i1p1f1	0.10	0.10	0.05	0.64	0.58	0.66
		MPI-ESM1-2-LR_r5i1p1f1	0.10	0.09	0.05	0.70	0.68	0.72
	C-W	IPSL-CM6A-LR_r1i1p1f1	0.38	0.30	0.10	0.68	0.72	0.57
		IPSL-CM6A-LR_r6i1p1f1	0.24	0.20	0.09	0.74	0.74	0.73
	SSP8.5/2060-2090	ACCESS-CM2_r2i1p1f1	0.10	0.08	0.04	0.74	0.77	0.73
		ACCESS-CM2_r3i1p1f1	0.11	0.09	0.04	0.72	0.75	0.73
	W-W	CanESM5_r1i1p2f1	0.08	0.13	0.07	0.52	0.47	0.62
		MPI-ESM1-2-LR_r6i1p1f1	0.11	0.09	0.06	0.71	0.66	0.70
	C-D	MPI-ESM1-2-LR_r7i1p1f1	0.12	0.10	0.06	0.66	0.61	0.68
		IPSL-CM6A-LR_r1i1p1f1	0.38	0.30	0.10	0.68	0.72	0.57
	C-W	IPSL-CM6A-LR_r3i1p1f1	0.33	0.25	0.09	0.72	0.70	0.71

LR; Lower region, MR; middle region, UR; Upper region, SS; Skill scores

Under SSP4.5 during the mid-century, CanESM5_r25i1p2f1, INM-CM4-8_r1i1p1f1, MPI-ESM1-2-LR_r6i1p1f1, IPSL-CM6A-LR_r14i1p1f1 show a smallest General Rank (GR) values, for W-D, W-W, C-D, C-W corners respectively, indicating their high performance in simulating past climate. Similarly, CanESM5_r7i1p2f1, INM-CM4-8_r1i1p1f1, MPI-ESM1-2-LR_r5i1p1f1, IPSL-CM6A-LR_r4i1p1f1 are the selected models considering SSP4.5 during the 2061-2090 period. CanESM5_r22i1p2f1, INM-CM4-8_r1i1p1f1, MPI-ESM1-2-LR_r5i1p1f1, IPSL-CM6A-LR_r6i1p1f1, ACCESS-CM2_r2i1p1f1, CanESM5_r1i1p2f1, MPI-ESM1-2-LR_r6i1p1f1, and IPSL-CM6A-LR_r3i1p1f1 have good performance in simulating the past climate under SSP8.5 during mid and end century. Overall, 16 most suitable GCM models were selected for predicting the future precipitation and temperature pattern in the UAB.

This method of GCM selection will neglect those models that have good skills for certain subregions. For example, under SSP4.5, CanESM5_r4i1p2f1 was selected for the W-D corner with the highest combined score value (5) in step two but was not selected in the final step due to lack of performance in simulating the past climate. The model CanESM5_r7i1p2f1 was selected as it has a better performance in past simulations with the lowest bias score. Finally, MPI-ESM1-2-LR_r6i1p1f1, INM-CM4-8_r1i1p1f1 and MPI-ESM1-2-LR_r5i1p1f1 showed a good performance and are selected for both forcing scenarios.

Table 6 Ranking of the GCM runs for the three subdomains

SSP/Year	Projection	GCM runs	Rank per subdomain			Total	General rank
			LR	MR	UR		
SSP4.5/2031-2060	W-D	CanESM5_r25i1p2f1	25	18	24	67	24
		CanESM5_r10i1p2f1	32	23	36	91	33
	W-W	INM-CM5-0_r1i1p1f1	5	4	4	13	4
		INM-CM4-8_r1i1p1f1	2	1	1	4	2
	C-D	MPI-ESM1-2-LR_r4i1p1f1	22	34	27	83	29
		MPI-ESM1-2-LR_r6i1p1f1	17	29	20	66	21
	C-W	IPSL-CM6A-LR_r14i1p1f1	11	11	11	33	9
		IPSL-CM6A-LR_r6i1p1f1	13	15	9	37	12
SSP4.5/2060-2090	W-D	CanESM5_r16i1p2f1	27	22	29	78	27
		CanESM5_r7i1p2f1	29	19	25	73	25
		CanESM5_r4i1p2f1	30	21	26	77	26
	W-W	INM-CM4-8_r1i1p1f1	1	1	1	3	1
		INM-CM5-0_r1i1p1f1	5	4	4	13	4
	C-D	MPI-ESM1-2-LR_r2i1p1f1	19	28	17	64	20
		MPI-ESM1-2-LR_r6i1p1f1	17	29	20	66	21
		MPI-ESM1-2-LR_r5i1p1f1	20	26	15	61	18
		MPI-ESM1-2-LR_r9i1p1f1	24	32	35	91	33
	C-W	IPSL-CM6A-LR_r2i1p1f1	8	9	8	25	8
		IPSL-CM6A-LR_r14i1p1f1	11	11	11	33	9
		IPSL-CM6A-LR_r4i1p1f1	4	10	7	21	7
		IPSL-CM6A-LR_r3i1p1f1	10	13	13	36	11

SSP8.5/2031-2060	W-D	CanESM5_r2i1p2f1	28	24	30	82	28
		CanESM5_r5i1p2f1	31	25	31	87	32
	W-W	INM-CM4-8_r1i1p1f1	2	1	1	4	2
		INM-CM5-0_r1i1p1f1	5	4	4	13	4
	C-D	MPI-ESM1-2-LR_r4i1p1f1	22	34	27	83	29
		MPI-ESM1-2-LR_r5i1p1f1	20	26	15	61	18
	C-W	IPSL-CM6A-LR_r1i1p1f1	9	7	33	49	14
		IPSL-CM6A-LR_r6i1p1f1	13	15	9	37	12
	W-D	ACCESS-CM2_r2i1p1f1	15	17	19	51	15
		ACCESS-CM2_r3i1p1f1	16	20	18	54	16
SSP8.5/2010-2090	W-W	CanESM5_r1i1p2f1	33	36	32	101	36
		MPI-ESM1-2-LR_r6i1p1f1	36	29	20	85	31
	C-D	MPI-ESM1-2-LR_r7i1p1f1	35	33	23	91	33
		IPSL-CM6A-LR_r1i1p1f1	26	7	33	66	21
	C-W	IPSL-CM6A-LR_r3i1p1f1	34	13	13	60	17

LR; Lower region, MR; middle region, UR; Upper region

For temperature, some GCMs underestimated, and others overestimated the observed probability. Overall, the skill score of 33 out of the 36 models exceeds 0.6 in each subregion. INM-CM5-0_r1i1p1f1 (0.79), ACCESS-CM2_r2i1p1f1 (0.77), INM-CM5-0_r1i1p1f1 (0.79), from the lower, middle and upper subregion represents a good correlation between model and observed dataset. While from the middle subregion of the study area, CanESM5_r1i1p2f1 (0.47) and from the lower subregion CanESM5_r10i1p2f1 (0.49) performs the worst, while no model scores less than 0.5 in the upper subregion. In general, GCM runs PDFs for air temperature showed a good agreement against NCEP/DOE observations. For SSP4.5 during the mid-century period, the skill score obtained for the individual subregions and corners shows that CanESM5_r10i1p2f1 has (0.57) for W-D corner, INM-CM4-8_r1i1p1f1 (0.53) for W-W, and CanESM5_r10i1p2f1 (0.49) for the W-D corner in the lower, middle and upper subregions respectively. While INM-CM5-0_r1i1p1f1 (0.79) for W-W corner, IPSL-CM6A-LR_r6i1p1f1 (0.74) C-W corner and INM-CM5-0_r1i1p1f1 (0.79) W-W corner under the respected subregions. This result showed that INM-CM5-0_r1i1p1f1 and IPSL-CM6A-LR_r6i1p1f1 models perform well in replicating the observed temperature. However, the remaining models had limited skills. For SSP4.5 in the end-century period INM-CM5-0_r1i1p1f1 (0.79) for W-W corner, IPSL-CM6A-LR_r2i1p1f1 (0.72) for C-W corner and INM-CM5-0_r1i1p1f1 (0.9) for W-W are the best performing models out of 13 GCMs in lower, middle and upper subregions respectively. While CanESM5_r7i1p2f1 (0.58) CanESM5_r4i1p2f1 (0.58), INM-CM4-8_r1i1p1f1(0.56) and MPI-ESM1-2-LR_r9i1p1f1 (0.52) had a less skill for temperature for W-D, W-W and C-D corners respectively for the respected corners. This implied those models have less capability in simulating the climate of the study area. The overall performance of the models over observed PDF is generally good. Taylor diagram (TD) simulates the degree of agreement between GCM models and the reanalysis dataset. Figure 4-6 show the TD for temperature over the individual subregion in UAB. The golden dot and aqua dot (radial axis) inside the graph indicate RMSE and correlation coefficient between the modelled and reference data set, while the blue line shows each dataset standard deviation.

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430 **Fig. 4** The Taylor diagram for evaluating the model and reanalysis monthly temperature over LR of UAB

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Fig. 5 The Taylor diagram for evaluating the model and reanalysis monthly temperature over MR of UAB

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Fig. 6 The Taylor diagram for evaluating the model and reanalysis monthly temperature over UR of UAB

In general, the skill score value of the specific model in temperature among the lower, middle, and upper subregions are not too varying, and the overall performance of the models over the specific subregions is generally good. The GCM air temperature reasonably simulated the observed PDFs. Finally, those climate models that are skillful over the UAB are identified, and those models will be applicable for future impact assessments.

For precipitation, the skill score result obtained for the individual subregions showed INM-CM4-8_r1i1p1f1 (0.61) in the lower subregion INM-CM4-8_r1i1p1f1 (0.68) in the middle subregion are the best performers in capturing the observed PDFs. INM-CM4-8_r1i1p1f1 is closer to observation than any individual model. And a few GCM models perform well and fit the observed precipitation PDF. In contrast, the upper subregion is the worst performing area, with INM-CM4-8_r1i1p1f1 having the highest value of 0.18. Many models are also less than 0.5 in the three subregions. For many models, the comparison is not good. The monthly PDFs of GCMs are underestimated compared to observations in the three subregions. Temperature simulated the observed data better than precipitation variables, the correlation between the GCMs and observed precipitation data is low. MPI-ESM1-2-LR_r4i1p1f1, CanESM5_r25i1p2f1, and CanESM5_r10i1p2f1 are the worse-performing models with the scores of 0.05, 0.07, and 0.08, respectively. Therefore, models with low combined skill scores are omitted, indicating high bias. Overall, the PDFs of GCMs simulation do not fit the observed dataset except for the INM-CM4-8_r1i1p1f1 model. In different periods and under different SSPs, different models are selected. Many models could capture the major properties of UAB climatology and can be applied for future climate projections. The final selected model outputs were used for downscaling and bias correction of the climate variables intended for future impact assessment studies.

Table 7 Final selected GCM runs with projected changes in mean air temperature, precipitation and ETCCDI indices between 1981–2010 and 2031–2060, 2061–2090 averaged over the study area

SSP /Year	Projection	GCM Run	ΔP (%)	ΔT (°C)	ΔCDD (%)	$\Delta R95PTOT$ (%)	$\Delta WSDI$ (%)	$\Delta CSDI$ (%)
SSP4.5/2031-2060	W-D	CanESM5_r25i1p2f1	-3.6	7.8	26.3	24.0	11847.0	-100.0
	W-W	INM-CM4-8_r1i1p1f1	3.0	5.4	-18.2	-29.5	10481.6	-100.0
	C-D	MPI-ESM1-2-LR_r6i1p1f1	-2.7	2.6	46.4	-77.7	8142.2	-87.8
	C-W	IPSL-CM6A-LR_r14i1p1f1	1.7	2.9	42.6	21.3	5917.6	9.6
SSP4.5/2061-2090	W-D	CanESM5_r7i1p2f1	-2.3	8.6	6.2	55.9	11977.3	-100.0
	W-W	INM-CM4-8_r1i1p1f1	3.7	5.8	-26.8	-18.7	11048.5	-100.0
	C-D	MPI-ESM1-2-LR_r5i1p1f1	-2.3	3.1	58.5	-77.3	9200.0	-94.3
	C-W	IPSL-CM6A-LR_r4i1p1f1	3.4	3.8	41.6	49.6	8416.5	-89.2
SSP8.5/2031-2060	W-D	CanESM5_r22i1p2f1	-2.8	8.2	35.8	34.5	11897.2	-100.0
	W-W	INM-CM4-8_r1i1p1f1	3.5	5.8	-23.1	-24.6	10957.2	-100.0
	C-D	MPI-ESM1-2-LR_r5i1p1f1	-2.5	2.9	77.8	-81.7	8664.2	-91.4
	C-W	IPSL-CM6A-LR_r6i1p1f1	1.7	3.5	51.3	29.4	7470.4	-52.0
SSP8.5/2061-2090	W-D	ACCESS-CM2_r2i1p1f1	-2.4	8.1	23.9	-1.1	12111.0	-100.0
	W-W	CanESM5_r1i1p2f1	2.9	10.0	29.8	17.9	12109.7	-100.0
	C-D	MPI-ESM1-2-LR_r6i1p1f1	-1.7	4.3	57.0	-78.5	11045.9	-100.0
	C-W	IPSL-CM6A-LR_r3i1p1f1	6.0	5.7	11.9	88.7	11058.7	-98.0

460 **Table 8** Performance indicator value of the three statistical downscaling methods in terms of their skill in limiting the biases relative to observation datasets.

				Precipitation				Temperature			
				Performance indicators				Performance indicators			
Projection	SSP/Year	Models	Method	Pearson	Spearman	Index of agreement	Best method	Pearson	Spearman	Index of agreement	Best method
W-D	SSP4.5/ 2031-2060	CanESM5_r25i1p2f1	Delta	0.367	0.518	0.599		0.57	0.558	0.708	
			QM	0.403	0.525	0.526	EQM	0.57	0.558	0.752	EQM
			EQM	0.524	0.554	0.616		0.57	0.561	0.751	
C-D		MPI-ESM1-2-LR_r6i1p1f1	Delta	0.675	0.638	0.81		0.547	0.582	0.729	
			QM	0.675	0.637	0.65	Delta	0.547	0.582	0.729	QM
			EQM	0.668	0.632	0.636		0.531	0.582	0.718	
C-W		IPSL-CM6A-LR_r14i1p1f1	Delta	0.679	0.639	0.821		0.713	0.73	0.835	
			QM	0.645	0.627	0.717	Delta	0.713	0.73	0.84	QM
			EQM	0.584	0.62	0.664		0.707	0.727	0.837	
W-W		INM-CM4-8_r1i1p1f1	Delta	0.601	0.622	0.741		0.725	0.77	0.845	
			QM	0.594	0.616	0.511	Delta	0.725	0.77	0.844	QM
			EQM	0.575	0.61	0.488		0.731	0.769	0.848	
W-D	SSP4.5/ 2061-2090	CanESM5_r7i1p2f1	Delta	0.326	0.493	0.564		0.555	0.553	0.71	
			QM	0.36	0.498	0.483	EQM	0.555	0.553	0.745	QM
			EQM	0.487	0.522	0.584		0.552	0.558	0.742	
C-D		MPI-ESM1-2-LR_r5i1p1f1	Delta	0.665	0.644	0.804		0.568	0.631	0.739	
			QM	0.665	0.642	0.65	Delta	0.568	0.631	0.739	Delta
			EQM	0.661	0.638	0.638		0.572	0.637	0.741	
C-W		IPSL-CM6A-LR_r4i1p1f1	Delta	0.679	0.647	0.821		0.716	0.738	0.834	
			QM	0.644	0.633	0.715	Delta	0.716	0.738	0.841	QM
			EQM	0.579	0.615	0.656		0.709	0.737	0.837	
W-W		INM-CM4-8_r1i1p1f1	Delta	0.601	0.622	0.741		0.725	0.77	0.845	
			QM	0.594	0.616	0.511	Delta	0.725	0.77	0.844	QM
			EQM	0.575	0.61	0.488		0.731	0.769	0.848	
C-D	SSP8.5 /2030-2060	MPI-ESM1-2-LR_r5i1p1f1	Delta	0.665	0.644	0.804		0.57	0.558	0.708	
			QM	0.665	0.642	0.65	EQM	0.57	0.558	0.752	QM
			EQM	0.661	0.638	0.638		0.57	0.561	0.751	

W-D		CanESM5_r22i1p2f1	Delta	0.371	0.508	0.606		0.563	0.557	0.714	
			QM	0.405	0.516	0.523	Delta	0.563	0.557	0.748	QM
			EQM	0.522	0.542	0.607		0.554	0.561	0.74	
W-W		INM-CM4-8_r1i1p1f1	Delta	0.601	0.622	0.741		0.725	0.77	0.845	
			QM	0.594	0.616	0.511	Delta	0.725	0.77	0.844	QM
			EQM	0.575	0.61	0.488		0.731	0.769	0.848	
C-W		IPSL-CM6A-LR_r6i1p1f1	Delta	0.719	0.654	0.843		0.716	0.744	0.835	
			QM	0.691	0.644	0.748	Delta	0.716	0.744	0.841	QM
			EQM	0.63	0.637	0.69		0.713	0.743	0.839	
W-D	SSP8.5 /2061-2090	ACCESS-CM2_r2i1p1f1	Delta	0.327	0.257	0.578		0.716	0.738	0.834	
			QM	0.326	0.257	0.456	Delta	0.716	0.738	0.841	EQM
			EQM	0.327	0.26	0.449		0.709	0.737	0.837	
W-W		CanESM5_r1i1p2f1	Delta	0.333	0.551	0.55		0.569	0.559	0.724	
			QM	0.371	0.557	0.479	EQM	0.569	0.559	0.755	QM
			EQM	0.503	0.583	0.594		0.558	0.555	0.747	
C-D		MPI-ESM1-2-LR_r6i1p1f1	Delta	0.675	0.638	0.81		0.547	0.582	0.729	
			QM	0.675	0.637	0.65	Delta	0.547	0.582	0.729	QM
			EQM	0.668	0.632	0.636		0.531	0.582	0.718	
C-W		IPSL-CM6A-LR_r3i1p1f1	Delta	0.638	0.6	0.796		0.703	0.73	0.827	
			QM	0.609	0.592	0.685	Delta	0.703	0.73	0.834	
			EQM	0.561	0.589	0.638		0.697	0.728	0.831	QM

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4.2 Statistical downscaling and bias correction (SDBC)

A total of 16 climate projections of daily precipitation and average air temperature are downscaled over UAB. Three performance indicators, namely: Pearson, Spearman and Index of Agreement, were used to identify the performances of CMIP6 relative to the observed dataset. Table 8 compared the performance indicator value of the three statistical downscaling methods in terms of their capability to downscale models with effectively removing the climate model biases relative to observation datasets. Precipitation increased in the upper section while decreased in the lower section of UAB. The most significant increases of average monthly precipitation were projected for Sendafa station located upstream, among the highest elevation of the UAB, while the least increases were projected in the downstream section of the basins called Meki station. Over the 20 stations, the selected GCM runs compared to base years precipitation, future monthly percentage changes ranging are expected to increase from 0.42% to 2.82% in mid-century and 0.15% to 3.79% in end century considering the SSP4.5. For the SSP8.5 forcing scenario, monthly average precipitation increases in the range of 1.45% to 5.51% in mid-century and 2.57% to 9.78% in end-century. The downscaled precipitation model outputs revealed that, under the SSP8.5 forcing scenario, the increment is more significant for the upstream stations than the downstream stations of the basin during 2061-2090. In contrast, during the successive periods of 2031-2060 and 2061-2090, the most robust decrease in precipitation is found in the upper section of the basin called Addis Ababa Obs. station, considering the SSP4.5 forcing scenario. Therefore, the final selected four GCM models with different ensemble members code "r" (realizations) "i" (initialization methods), "p" (physics details) "f" (forcing) are namely, CanESM5, MPI-ESM1-2-LR, IPSL-CM6A-LR, INM-CM4-8, and ACCESS-CM2. In the two forcing scenarios and study periods, the maximum monthly average precipitation in all stations is expected to increase for CanESM5 and IPSL-CM6A-LR. While in the mid-term period, three of the four GCMs were found to be decreased, namely MPI-ESM1-2-LR_r6i1p1f1 (-0.81%), INM-CM4-8_r1i1p1f1 (-0.45%) and MPI-ESM1-2-LR_r5i1p1f1 (-0.90%), INM-CM4-8_r1i1p1f1 (-0.09%) for SSP4.5 and SSP8.5 respectively in Addis Ababa Obs. stations. In contrast, average monthly precipitation was found to increase for CanESM5_r25i1p2f1 (+2.82%) in Koka Dam station, IPSL-CM6A-LR_r14i1p1f1 (+0.42%) in Meki station and CanESM5_r22i1p2f1 (5.51%) Meki station IPSL-CM6A-LR_r6i1p1f1 in Sendafa station (1.45%) under SSP4.5 and SSP8.5 forcing scenarios respectively. During 2061-2090 period, three of the four ensemble models in the two forcing scenarios have predicted an increased in precipitation for CanESM5_r7i1p2f1 (+3.79%) Koka Dam station, IPSL-CM6A-LR_r4i1p1f1 (+2.81%) Sendafa station, INM-CM4-8_r1i1p1f1 (0.15%) Addis Ababa Obs station, considering SSP4.5 and CanESM5_r1i1p2f1 (+2.57%) in Koka Dam station, MPI-ESM1-2-LR_r6i1p1f1 (+9.78%) in Sendafa station, and IPSL-CM6A-LR_r3i1p1f1 (+4.18%) Sendafa station considering SSP8.5. However, one ensemble model out of four selected model runs decreased the monthly maximum precipitation in both scenarios, MPI-ESM1-2-LR_r5i1p1f1 (-0.40%) Addis Ababa Obs., ACCESS-CM2_r2i1p1f1 (-0.88%) busa station, considering SSP4.5 and SSP8.5 forcing scenario, respectively. Generally, the ensemble mean of the selected GCMs revealed variability for precipitation changes in the UAB.

The monthly average temperature is expected to increase in the 2031-2060 period, which is projected to be from 0.68°C to 1.55°C and 0.19°C to 1.98°C, under SSP4.5 and SSP8.5 forcing scenarios, while that in 2061-2090 was from 0.09°C to 1.92°C and 2.37°C to 7.00°C under the respective scenarios. The SSP8.5 is projected to increase more than the SSP4.5 scenarios for the two future periods. In addition, there is a high-temperature variation between the base and future periods among the Upper Awash stations. During the base

period, the highest monthly average temperature was recorded in the Koka dam station (27.38°C) in the lower region of the basin. Similarly, the most significant increases are projected for Melkasa station (31.8 °C) in the lower region of the basin. The historical temperature records align with what we found for the future projection. The historical and projected average temperature values are high at the lowest elevation of the river basin. A higher increase in temperature is expected in the lower section of the basin compared to the upper region of the basin at the end-of-century period. In contrast, the lowest increases are projected for the most upstream parts of the basins, including Addis Ababa, the capital of Ethiopia. Our study reveals that elevation-dependent warming may become more pronounced in the future in this river basin. PDF and CDF of downscaled precipitation and average temperature respectively for observed and GCM runs per station is shown in Figure 7 and 8.

(a)

(b)

(c)

Fig. 7 PDF of monthly downscaled precipitation for observed and GCM runs per station (a) CanESM5_r25i1p2f1 CanESM5_r25i1p2f1 (b) CanESM5_r7i1p2f1 (c) CanESM5_r22i1p2f1 respectively

Fig. 8 CDF of monthly downscaled average temperature for observed and GCM runs per station (a) MPI-ESM1-2-LR_r5i1p1f1 (b) IPSL-CM6A-LR_r6i1p1f1 (c) IPSL-CM6A-LR_r3i1p1f1 respectively

5 Conclusion

The model selection and downscaling approach were applied for future climate projections of two socio-economic pathways (SSPs), SSP4.5, SSP8.5, and two study periods (2031-2060 and 2061-2090). The annual projected mean of temperature and precipitation, climate extreme indices, and model skill in simulating the past

climate with respect to the NCEP-DOE reference data set were applied to identify a representative set of climate model runs. Average temperature and precipitation variables from GCMs were downscaled and bias-corrected for the two periods. The GCM runs identified using the method described in the current study are planned to be used as input to SWAT models for future climate impact assessment over UAB in later stages of the research.

The downscaled temperature and precipitation distribution show distinct patterns across the study region. Precipitation spatial distribution for all periods/scenarios considered a decrease in the downstream section of the basin, but an increase in the mountainous parts of the basin, highly an increasing pattern also observed for temperature in all parts of the region. Both increments in temperature and precipitation during the two study periods are higher under the SSP8.5 scenario than in the SSP4.5 scenario. Proper management is necessary for an important basin such as the UAB, which is primarily used for domestic, agricultural and industrial water supply for a very populace city such as Addis Ababa, the capital of Ethiopia, and other surrounding urban cities.

This study presents a representative GCM run selection method for impact studies intended to combine the strength of two approaches of envelope-based and past-performance-based, which contains multiple criteria to select the appropriate models for climate impact studies over UAB, Ethiopia. The adopted technique allows more accuracy and reduces uncertainties in the futuristic investigation. The advanced envelope-based technique addresses the drawback of the previous selection approaches and provides a modified method. However, certain limitations are discussed therein.

During the initial and refined selection, the analysis considered the step-wise screening of the several ensemble models based on projected change of annual mean and extremes, respectively. Both the projected mean change and mean change in the extreme are spatially averaged over the entire area. The application scale in both steps may dilute the spatial variation in projected changes. Additionally, the selection approach of changes in means may reduce GCMs, resulting in fewer available models that will undergo climatic extremes evaluation. Similarly, the skill score-based simulation for evaluating past performance may have missed good models that can simulate the past climate with good ability. This is because the approach is presented in the final step, with fewer climate models available than the first and second steps. Therefore, the selected models could not necessarily have the best skill in simulating past climates. The other limitation has to do with the final skill scores calculation. The final skill score was calculated based on the minimum combined bias score of temperature and precipitation; such a way may have omitted those models with good performance in other subdomains.

The impact of climate change is evident around the world, including Ethiopia. Numerous studies are conducted on climate change in UAB but lack proper utilization of GCMs. Uncertainties exist in applying these models as the number of models increases. Therefore, this study is the first of its kind in Ethiopia, and the established result is vital for regional climate change impact analysis. It will be helpful to the Awash Basin Authority and potential researchers for proper usage of these models, including forcing hydrological models.

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Data availability The full set of raw data and the analyzed output that supports the findings of this study are available in the supplementary file.

Code availability The codes that support the findings of this study are available from the corresponding author (wzyhhu@gmail.com).

Author contribution Selamawit Haftu Gebresellase contributed to conceptualization, data curation, conducted formal analysis, methodology, investigation, analyzed all datasets, results, visualization, writing the original manuscript, review and editing. Zhiyong Wu (as the corresponding author) contributed to supervision, project administration, pursuing ideas and guidance, revised and edited the manuscript. Huating Xu contributed to review and to editing. Wada Idris Muhammad contributed to editing.

Declarations

Consent for publication The authors give their consent to the publication of all details of the manuscript, including texts, figures, and tables.

Conflict of interest The authors declare no competing interests.

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