ORIGINAL PAPER

Climate change projection using the statistical downscaling model in Modjo watershed, upper Awash River Basin, Ethiopia

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Abstract

Global circulation models have been used to project future climate changes, which encourage experts to design mitigation measures. Still, it is challenging to use the raw data at a local scale without downscaling. Hence, this study applied a statistical downscaling model to downscale daily data generated from the second generation of the Canadian Earth System Model under two Representative Concentration Pathways scenarios (RCP4.5 and RCP8.5) using observed data for model calibration and validation. The downscaled results showed that the maximum temperature likely to increases in the range of 2.04–2.50 °C for RCP4.5 in the 2050s (2041–2070) and 2080s (2071–2099), respectively, and the minimum temperature indicate an increase by 0.87 °C in 2050s and 1.56 °C in 2080s averaged over the watershed level. The projected mean annual and seasonal air temperatures are likely to increase up to the end of the twenty-first century at all stations. The utmost annual rainfall change is projected to be 14.5% in the 2080s for RCP4.5 at Modjo. The highest seasonal precipitation change is projected to be 30.9% (RCP8.5) in the main rainy season (Kiremt) at Chefedonsa. Seasonal-based future projection of the precipitation shows non-significant trends, except the Kiremt season. The study revealed that the temperature was highly influenced by altitude and slightly affected by corresponding land use land cover type. In general, the increase in temperature could worsen the environmental conditions in warm seasons; and an increase in precipitation in the Kiremt season is expected to bring a likely risk of flooding.

Keywords Climate change · Global circulation model · Temperature · Precipitation · Predictands · Predictors

Introduction

The increasing trends in emissions of greenhouse gases have caused increasing temperature trends throughout the world (UNFCCC 2007; Calow et al. 2011; Montt et al. 2013; Costanza et al. 2014; UNEP 2017, European Union 2018). Warming of the world aligned with the emission of

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Greenhouse Gases (GHGs) is nowadays absolute, and the atmospheric concentration of carbon dioxide (CO_2) has increased significantly which induced the mean global temperature to increases (UNFCCC 2007). Investigating how temperature and precipitation changes could affect the real world and involves answering how much climate variation there will be, what impacts will follow and how best to adapt and mitigate the causes (Baede et al. 2001; Bates et al. 2008; FAO 2018).

The rising trend of temperature has made different hydro-climatological threats with many socio-economic aspects and also will cause changes in cropping patterns and the spreading of disease vectors putting several portions of the world at risk (Kabat et al. 2002; UNEP 2017). It has been agreed that the rising trend of air temperature has altered the intensity and patterns of hydrologic cycle elements especially precipitation (Sonali and Nagesh 2013; Wagesho et al. 2013). Assessing the trends and changes of temperature and rainfall is very vigorous for worthwhile and real water resources management and development in a sustainable

manner (Rao and Legesse 2013; Semiromi et al. 2014; Gemechu et al. 2015; Amirabadizadeh et al. 2016; Asfaw et al. 2018; Wei et al. 2018; Lu et al. 2019). The future projection of precipitation and temperature studies have enormous benefits for water resource development activities, moisture management in rainfed agriculture and academics in this area to describe the spatiotemporal variability. Future climate changes have direct influences on the surface runoff which highly depends on precipitation intensity and patterns (Mahmood and Babel 2014; Alemu and Dioha 2020). Thus, estimating precipitation and temperature changes in future is required for streamflow information, which is very important for projects related to water resources development and construction and equally to mitigating the world's climate-changing trends (Robinson 2008; FAO 2011).

Developing countries are commonly affected by climate change due to more belief in climate reliant natural resources and limited finance for adaptation (McSweeney et al. 2010), and East Africa is obvious as a susceptible home for climate change (Gebrechorkos et al. 2019). Ethiopia, part of East Africa, is typically influenced and vulnerable place for climate change, for the reason that its economic development highly depends on rainfed agriculture. Mengistu et al. (2014) reported that the temperature over the Upper Blue Nile River Basin of Ethiopia has increased by 0.1 °C to 0.15 °C/decade. Mekonen and Berlie (2020) reported that the increasing trends of minimum, average and maximum temperatures at the ratio of 0.098 °C, 0.069 °C and 0.041 °C per decade, respectively and declining trends of rainfall at a level of 6.5 mm per decade in the Northeastern parts of Ethiopia. Additionally, Abebe and Kebede (2017) reported an increasing trend of +0.57 °C for the maximum temperature while the minimum temperature indicates a declining trend by 0.6 °C in Megech catchment in Ethiopia. The study also discovered that the mean annual temperatures in the northern part of Ethiopia are increasing by about 0.54 °C per decade (Gebrehiwot and Veen 2013). Changes in temperature and precipitation patterns have a direct impact on the hydrological cycle and water resources availability. For that reason, it is vital to assess the future trends of air temperature and precipitation in the country. The Modjo catchment is one of the affected areas by rainfall variability due to climate change. The catchment is characterized as a sensitive area to climate change and has been experienced by high floods during rainy season and droughts in dry season. It is also witnessed that the consequence of the climate change over time on precipitation due to high variability of temperature has been visible.

The numerous findings revealed that future climatic change projection will be significant by employing different Global Climate General Circulation Model (GCM) and Regional Climate Model (RCM). The GCMs are commonly employed to evaluate climate change projection and the key

tools for studying global change, provide realistic projection with an accuracy of present climate condition when evaluated as of global and continental scales (Trzaska and Schnarr 2014). However, the GCMs are coarse in resolution and may not be directly applied to local scale studies to evaluate the probable climate change impact (Dibike and Coulibaly 2005). Thus, there was an in-need on behalf of high-resolution scenarios at a catchment or local scale level that results much finer than that obtained by a global or even some regional climate models. Subsequently, the downscaling techniques were developed as a tool to minimize a gap between the GCMs and the local scales necessary at the catchment level (Eden et al. 2012; Trzaska and Schnarr 2014; Cannistra 2016). The downscaling techniques of climate models aim to solve this scale mismatch (Cannistra 2016). The core downscaling approaches regularly used in the generation of higher resolution climate scenarios for certain areas are statistical and dynamical downscaling approaches (Hewitson and Crane 1996; Eden et al. 2012; Trzaska and Schnarr 2014; Cannistra 2016; Smid and Costa 2018). Dynamical downscaling develops climate scenario data for local scales by developing and using Regional Climate Models (RCMs) with the coarse GCM data used as boundary conditions (Hay and Clark 2003). On the other side, Statistical Downscaling Method (SDSM) works by developing numerical relationships between large-scale atmospheric variables, the predictors, local surface variables and the predictands (Wilby et al. 2004). The SDSM has been employed at different places over the world for future changes in temperatures and precipitation projections (Liu et al. 2017; Feyissa et al. 2018; Al-Mukhtar and Qasim 2019; Phoung et al. 2020; Shitu and Tesfaw 2021).

Numerous spatiotemporal numerous studies have been done on the projection of air temperature and precipitation under climate change ranging from watershed to river basins wide-reaching by using data of statistical downscaling techniques in Ethiopia (Kebede et al. 2013; Feyissa et al. 2018; Gebremeskel and Kebede 2018; Tesfaye et al. 2019). The results from those studies show the applicability of the technique in the country and its good correlation with the observed climate data (Kebede et al. 2013; Feyissa et al. 2018).

The study of climate change is believed to provide information about the air temperature and precipitation changes, to mitigate the crisis due to spatiotemporal variability under climate change conditions, to secure food demand and improve living standards of the local communities in the area. Thus, many problems and challenges will come up with climate change if there are no continuous evaluation and mitigation measures. In particular, Modjo watershed is vulnerable to erratic rainfall and moisture stress problems. Thus, the study was designed to evaluate the potential future changes of temperatures and precipitation under

climate change during the two future periods in the 2050s (2041–2070) and 2080s (2071– 2100), using the GCM data of CanESM2 model under two Representative concentration pathways (RCP4.5 and RCP8.5) outputs downscaled using the SDSM model, in Modjo watershed, Awash River Basin, Ethiopia.

Materials and methods

Description of the study area

Modjo watershed is located in the upper Awash River basin, Ethiopia (Fig. 1), and its total area coverage is 1901.69 km². Geographically it is placed between the longitude 38°50´E and 39° 17´E, and latitudes 8° 25´ N and 9°07´N. The watershed drains to Modjo River, then flows to Koka dam and join Awash River as one tributary of the Basin. The watershed altitude range from 1573 to 3049 m above sea level. The rainfall pattern of the watershed is characterized by bimodal with two peaks throughout the year in April for the short rainy season (which start from February and extends up to May) and July for the main rainy season (which ranges from June to September) (Eshetu 2020). The mean rainy season locally known as Kiremt contributed above 80% of the annual rainfall and the short season which starts from February to May is locally known as Belg. The monthly total rainfall distribution in the watershed varies commonly from as small as 3.5 mm for the driest month (December) at Modjo station to 290.7 mm for the rainy month (July) at Aleltu station (Gessesse et al. 2015). Accordingly, the annual rainfall distribution of the watershed varies from 1040 mm in the upstream to 873 mm in downstream parts.

The total mean annual rainfall of the watershed ranges from 852.45 mm at Bishoftu station to 993.78 mm at Modjo station gained from the observed data collected from the respective station (1985–2014). The mean temperature is also ranging from 16.6 °C (Chefedonsa station) to 21 °C (Bishoftu station) in the watershed. The land use land cover map is indicated that the dominant one is an agricultural land use in the watershed. Lithic Leptosols, Vertic Cambisols, Chromic Luvisols, Eutric Vertisols and Haplic Luvisols are the major soil groups in the watershed (Gessesse et al. 2015).
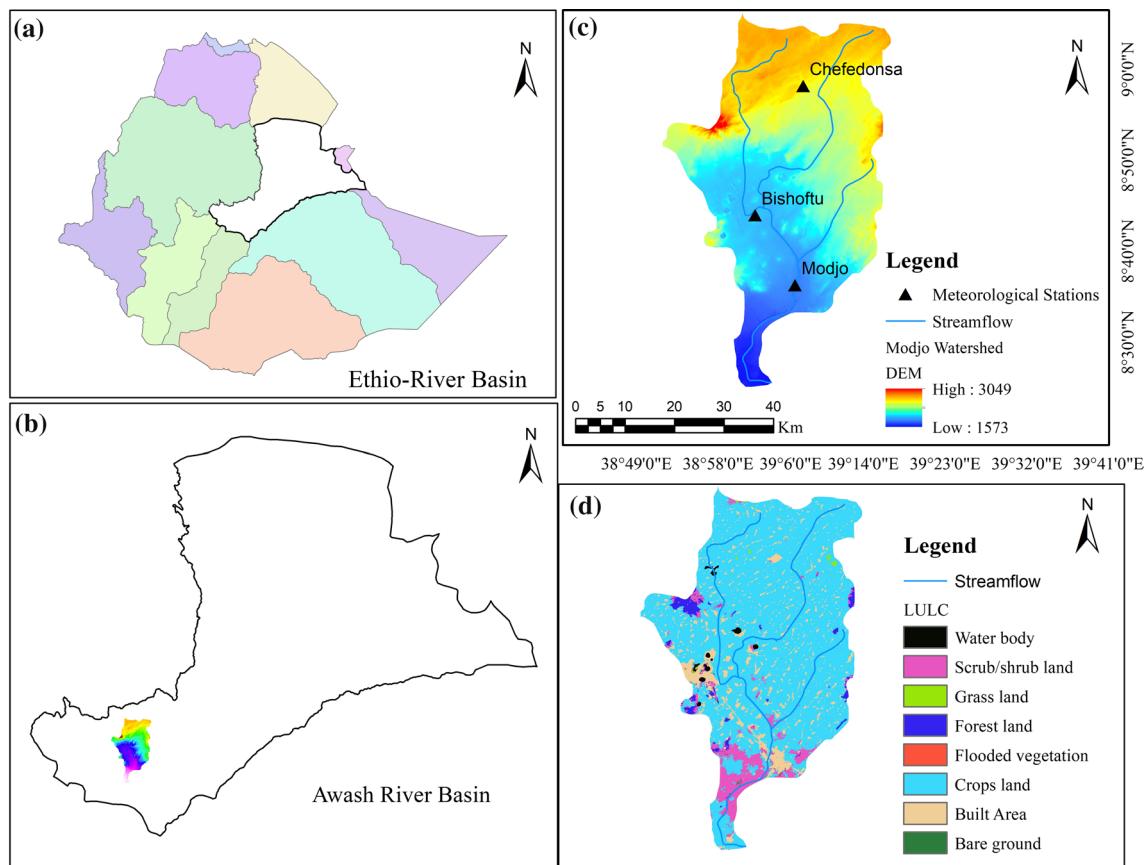

Fig. 1 Study area **a** Ethiopian-River basin; **b** Awash River Basin; **c** Mojo watershed and **d** Mojo watershed Land use land cover

Data analysis and processing

To evaluate changes in precipitation and temperature trends in future decades, the Statistical Downscaling Model (SDSM) has been employed as a tool to downscale GCM outputs to a local scale. Downscaling process established a link between large-scale atmospheric variables (predictors) and the climate variables on a local scale (predictands) (Wilby and Dawson 2007). To achieve the set of objectives, two types of data were required and collected: (1) daily observed precipitation and temperatures for three stations (Chefedonsa from the upstream, Bishoftu from the middle and Modjo from the downstream part of the watershed) throughout 1985–2014 from the Ethiopian National Meteorological Agency (ENMA), (2) the predictor's data was downloaded from a Canadian climate data and scenarios website (https://climate-scenarios.canada.ca). The quality of observed data was checked based on the homogeneity test and normality of the Kolmogorov–Smirnov test at a significance level of 95%.

The general circulation model employed in the discovery was: National Center of Environmental Prediction (NCEP), a resolution of 2.5°, the homogenized (gridded) records of atmospheric data was downloaded from the so-called reanalysis project of the National Centers for Environmental Prediction (NCEP)—National Center for Atmospheric Research (NCAR). The model was developed to support climate change investigating scholars by integrating data from numerous climate sources with modeled future forecasts (Kalnay et al. 1996; Schoof and Pryor 2003). The soundness and easy availability of the NCEP dataset makes it a selective climate data center for an investigation related to climate variability and impacts studies (Schoof and Pryor 2003). NCEP data was used to correlate GCM models and observed data during the historical periods.

The Second Generation of the Canadian Earth System Model (CanESM2) was designed at the Canadian Centre for Climate Modeling and Analysis (CCCma). The model comprises the physical coupled atmosphere–ocean model CanCM4, coupled to a terrestrial carbon model (CTEM) and an ocean carbon model (CMOC) (Merryfield et al. 2013). The model provides long-term climate projections for Phase 5 of the Coupled Model Inter-comparison Project, which in turn informed the Fifth Assessment Report (AR5) of the Intergovernmental Panel on Climate Change (Taylor et al. 2012; Merryfield et al. 2013). The CanESM2 model has a resolution of 2.79° latitude and 2.81° longitude.

Future local climate scenario generation

Climate scenarios data obtained from GCM outputs are commonly applicable at a large-scale, whereas not suitable for study at the catchment level to evaluate the impact

and adaptation investigations that need in-depth local data (Mearns and Hulme 2001; Mearns et al. 2003; Auffhammer and Hsiang 2011; Xue et al. 2014). The global yields from GCM outputs are downscaled to local areas by employing either two methods of downscaling such as statistical or dynamical downscaling. Statistical downscaling has usual and recognized statistical procedures for downscaling. It is a unique model among various downscaling methods and simple for usage and inexpensive (Wilby et al. 1998; Abbasnia and Toros 2016; Gebrechorkos et al. 2019). Several findings over the world point out that the SDSM gives trustworthy estimates of future temperatures and precipitation, extreme events, seasonal and annual precipitation, and areal characteristics of precipitation (Sun et al. 2015; Abbasnia and Toros 2016; Sayad et al. 2016; Gebremeskel and Kebede 2018; Gebrechorkos et al. 2019; Tesfaye et al. 2019). The model has been used as a suitable tool for downscaling of GCMs output at the local scale and feasibly generates meteorological climate data by employing an integration of stochastic weather generator and multiple linear regression (Hewitson and Crane 1996; Wilby and Dawson 2007). The origin of this method is designing multiple regression models. Therefore, to simulate climatic parameters at an appropriate time scale, a multivariate linear regression model was established between predicted climatic variables at station scale (as dependent variable) and large-scale predictors (as independent variables) through the following steps:

Selection of predictors

Selecting a predictor is the first step in the downscaling process. It is an iterative practice that comprising a free screening of likely settings and predictors, which is repeated until an objective function is enhanced (Wilby et al. 1998). The predictors with the maximum correlation are selected using the screen selecting predictor's tool in the SDSM. First, the predictors downloaded from GCM for historical periods are associated with the observed minimum temperature, maximum temperature and precipitation in the baseline. Then, the highest correlation predictors are chosen. The chosen number of predictors for the study stations differs based on objective function from two to five. The relation concerning the predictors and predictands are established based on the p-value and correlation statistics values.

The most appropriate sets of predictor variables are selected based on partial correlation and percentage of explained variance (E) analysis among the predictands and the individual predictors. Acceptable prediction results were generated based on the values of the correlation of predictors with a p-value less than 0.05. The SDSM model considered the default value for bias correction factor as one for temperature. The 'Bias Correction' parameter compensations

for any inclination in the downscaling model to under and over prediction the variance of the downscaling conditional process. The screened predictors for precipitation and temperature at Modjo, Bishoftu and Chefedonsa stations are given in Table 1.

Calibration and validation of the model

Before using the outputs of the SDSM model, a model must be confirmed for its reliability, accuracy and predictive performances (Osman and Abdellatif 2016). At the first calculation, the model will not often give satisfactory objective function results. SDSM models require the selection of predictors based on objective function values to minimize mismatch modeled output with the observed collected data for the selected stations.

There are many predictors in the SDSM model, which can be selected during calibration and validation based on the objection function values (Wilby et al. 2004). During calibration of the SDSM, regression models were developed for every month of the year based on the association between predictands and selected predictors. The first 2/3 of the observed data which is 20 years (predictand) and reanalysis (predictors) datasets are used as input during calibration of the model, and the last 10 years for validation of the model. The period from 1985–2005 was used for model calibration and 2006 –2014 for model validation for all Modjo, Bishoftu and Chefedonsa stations. During calibration time the performance of a model was evaluated using objective functions such as the coefficient of determination (R^2) and mean absolute error (MAE). These objection function results

decide the model significance of climate change projection at selected study areas.

After successful calibration and validation, the daily, monthly and annual time series data of maximum temperature (Tmax), minimum temperature (Tmin) and precipitation (PC) were simulated for two classes of future periods namely, the 2050s (2041–2070) and the 2080s (2071–2100) under future climate scenarios for the predictors of RCP4.5 and RCP8.5 scenarios of CanESM2 GCM. In this study, the performance of generated results was evaluated using statistical objective criteria to check any biases in the simulated data. For this, more recent datasets for the period of 1985–2014 were applied to calculate mean monthly biases using observed and simulated (RCP4.5 and RCP8.5) temperatures (Tmax and Tmin) and precipitation.

Results and discussion

Spatiotemporal observed data analysis

Figure 2 indicated the patterns and trends of mean annual temperatures (maximum and minimum) and precipitation data of Modjo, Bishoftu and Chefedonsa stations for 30 years period (1985 − 2014). The collected daily temperatures and precipitation data were statistically examined for their spatiotemporal variations based on the annual time interval to avoid their characteristic seasonality effect on the analyses. Figure 2a and b presents the trend of mean daily temperature and annual precipitation of Bishoftu station, Fig. 2c and d reflected the mean daily temperature and

Table 1 The selected predictors for minimum and maximum temperatures and precipitation for all stations

Predictors	Symbol	Modjo station			Bishoftu station			Chefedonsa		
		Tmin	Tmax	P	Tmin	Tmax	P	Tmin	Tmax	P
Mean sea level pressure	ncepmslpgl			✓						
	Ncepp1_ugl								✓	
500 hpa vorticity	ncepp_zgl			✓						
500hpa geopotential height	ncepp500gl		✓							
500hpa wind direction	ncepp5thgl		✓			✓				
500hpa divergence	ncepp5zhgl									
850 hpa airflow strength	ncepp8_fgl									
850 hpa zonal velocity	ncepp8_ugl	✓		✓						✓
850 hpa meridional velocity	ncepp8_vgl		✓						✓	
850 hpa wind direction	ncepp8thgl				✓					✓
850 hpa divergence	ncepp8zhgl									
	Ncepprcgl	✓				✓	✓			
Specific humidity at 500 hpa	nceps500gl						✓	✓		✓
Specific humidity at 850 hpa	nceps850gl				✓					
Surface specific humidity	ncepshumgl									
Mean temperature at 2 m	nceptempgl	✓				✓	✓	✓	✓	

Where Tmin is the minimum temperature, Tmax is the maximum temperature and *P* is the precipitation
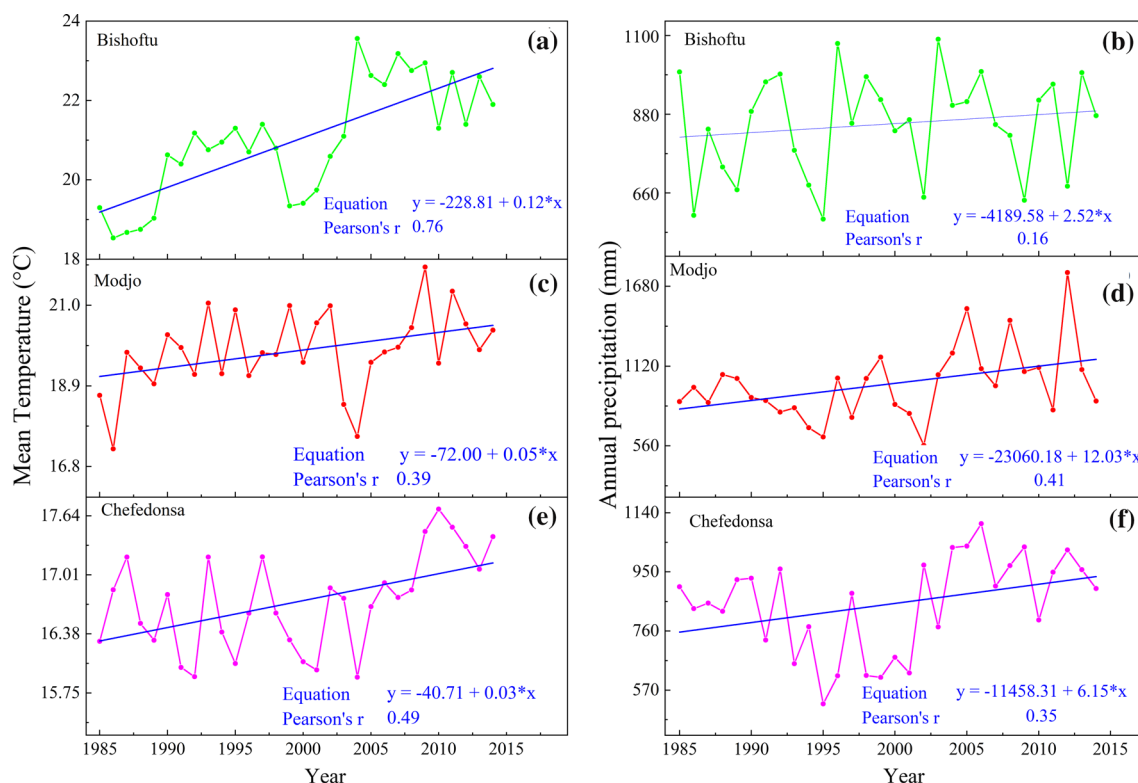
Fig. 2 Mean daily temperatures and annual precipitation of 30 years (1985–2014) of all stations

annual precipitation of Modjo station whereas, Fig. 2e and f also reflected the mean daily temperature and annual precipitation of Chefedonsa station, respectively. The figures indicated that the mean daily temperature is generally shown an increasing trend over 30 years period at all stations. However, the precipitation shows insignificant patterns. For instance, annual precipitation at Bishoftu station did not show a significant pattern in trends (Fig. 2b). However, at Chefedonsa station, annual precipitation shows decreasing trends from 1985 to 2003 and then increasing up to 2014 (Fig. 2f). This finding is in line with the finding by Eshetu (2020) whereby reported both annual and seasonal rainfall showed a non-significant trend at all study stations for the past 30 (1983–2010) years in the Modjo River watershed. Besides, as indicated in Fig. 2, the projected temperature and precipitation did not follow the same patterns spatially and temporally both annually and seasonally. Earlier studies also show an inverse relationship between change in temperature and precipitation (Nandozi et al. 2012).

Performance evaluation of downscaling model

Before downscaling future temperatures and precipitation from the CanESM2 model at the station's scale, the simulation performance of SDSM was evaluated based on the objective functions. Then, the daily minimum and maximum

temperatures and precipitation were projected based on the model-scenarios in two future periods in the 2050s (2041–2070) and 2080s (2071– 2100). Lastly, the future period's changes in minimum, maximum temperature and precipitation were compared with baseline (1985–2014). Hence, to confirm highly correlated results, predictors from the NCEP re-analyzed data were selected based on their statistical significance during calibration, i.e., significant partial correlation (r) at the 5% confidence level. The selected predictors for all stations were given in Table 2 based on their statistical correlation measures with each predictands that were used for future temperatures and precipitation projections.

The statistical parameters used for SDSM performance were listed with their calibration and validation values (Table 3). The calibration results revealed that there was a statistical agreement between observed and simulated data at all stations (Fig. 3). Then, the ten years of data (2005–2014) were employed to validate the performance of the model. The results also indicated a sounded agreement between the observed and simulated values at all stations with the coefficient of determination (R^2) > 0.6 and mean absolute error of less than 0.56 (Table 3 and Fig. 3). However, the minimum temperature for Chefedonsa meteorological station for October to December was overestimated by the model compared

Table 2 List of predictands per station with their respective selected predictors

Station	Predictands	Predictors (NCEP Re-analysis) NCEP code	Partial r
Modjo	Precipitation	ncepp1_fgl	0.173
		ncepp8_ugl	0.304
	Maximum temperature	ncepp500gl	0.266
		ncepp5thgl	0.359
		ncepp8_vgl	0.164
	Minimum temperature	ncepp8_ugl	0.224
		ncepprcpgl	0.122
		nceptempgl	0.237
Bishoftu	Precipitation	ncepp1_ugl	0.376
		ncepp1thgl	0.247
		nceps500gl	0.146
	Maximum temperature	ncepp5thgl	0.077
		ncepprcpgl	0.093
		nceptempgl	0.449
	Minimum temperature	ncepp850gl	0.222
		ncepp8thgl	0.155
Chefedonsa	Precipitation	ncepp8_ugl	0.107
		ncepp8thgl	0.066
		nceps500gl	0.162
	Maximum temperature	ncepp8_vgl	0.136
		nceptempgl	0.159
	Minimum temperature	ncepp1_ugl	0398
		ncepp500gl	0.204
		nceptempgl	0.230

Table 3 Statistical performance evaluation of SDSM for calibration and validation periods

Station	Parameter	Calibration period		Validation period	
		R^2	MAE	R^2	MAE
Modjo	Precipitation	0.71	0.102	0.64	0.08
	Tmax	0.89	0.144	0.86	0.138
	Tmin	0.79	0.56	0.84	0.28
Bishoftu	Precipitation	0.97	0.14	0.69	0.16
	Tmax	0.78	0.203	0.82	0.039
	Tmin	0.89	0.53	0.91	0.21
Chefedonsa	Precipitation	0.82	0.27	0.74	0.18
	Tmax	0.79	0.44	0.76	0.37
	Tmin	0.73	0.2	0.81	0.16

to observed data that could be related to the elevation and rugged topography of the area (Fig. 3) (Akhtar et al. 2009).

Future temperature and precipitation change scenarios

Temperature

The projected future temperatures (minimum and maximum) from the SDSM model under both RCP scenarios of the CanESM2 show increasing trends up to the end of the twenty-first century. The results from the model under both future climate scenarios revealed that both minimum and maximum temperatures will continue increasing. The change in maximum temperature is higher for the RCP8.5 than the RCP4.5 for all stations (Fig. 4 and Table 4). The maximum temperature is predicted to increase by 4.27 °C and 4.31 °C under RCP4.5 and RCP8.5, respectively in the 2080s relative to the baseline period at Modjo station (Table 4 and Fig. 4a and b). The results of the model projection show that change in minimum temperature is 0.91 °C to 1.07 °C under RCP4.5 and from 1.29 to 1.95 °C for RCP8.5 in the 2050s and 2080s, respectively for Modjo Station (Table 4 and Fig. 4c and d). At Modjo station the higher changes of minimum temperature are projected to be 1.29 °C and 1.95 °C in the 2050s and 2080s, respectively under RCP8.5 (Fig. 4d).

Although the projected increasing trend in the minimum temperature is lower under both RCP scenarios compared to the maximum temperature at all stations except, Chefedonsa station (Fig. 4(a-l)). At Bishoftu station, the increasing trends of minimum temperature are projected to be 0.27 °C and 0.35 °C in the 2050s and 2080s, respectively under RCP4.5 (Fig. 4g). At Chefedonsa station, the increasing trends of maximum temperature are projected to be 0.8 °C and 0.9 °C in the 2050s and 2080s, respectively under RCP4.5 (Fig. 4i) and while, the change of minimum temperature ranges from 0.5 °C for RCP4.5 and 1.8 °C for RCP8.5 in 2080s period (Fig. 4l). The change of minimum and maximum temperatures projections for both scenarios are tabulated in-depth in Table 4 for all stations. In both future projection periods, Tmin and Tmax will be warmer under RCP8.5 relative to RCP4.5.

Generally, it is worth noting that the obtained results based on both model-scenarios represent an increase in minimum and maximum temperatures at all stations during the future projection periods. However, increases in minimum and maximum temperatures are diverse under both climate scenarios at all stations and for both future periods. Remarkably some studies have investigated the future changes of temperatures from different GCMs at different places in Ethiopia and reported increasing changes (Tessema 2011; Kassie 2014; Kassie et al. 2014; Mekasha et al. 2014; Asfaw et al. 2018; Mekonnen and Disse 2018; Gebremeskel and Kebede 2018; Gedefaw et al. 2018; Tesfaye et al. 2019; Alemu and Dioha 2020; Mekonen and Berlie 2020; Tadese
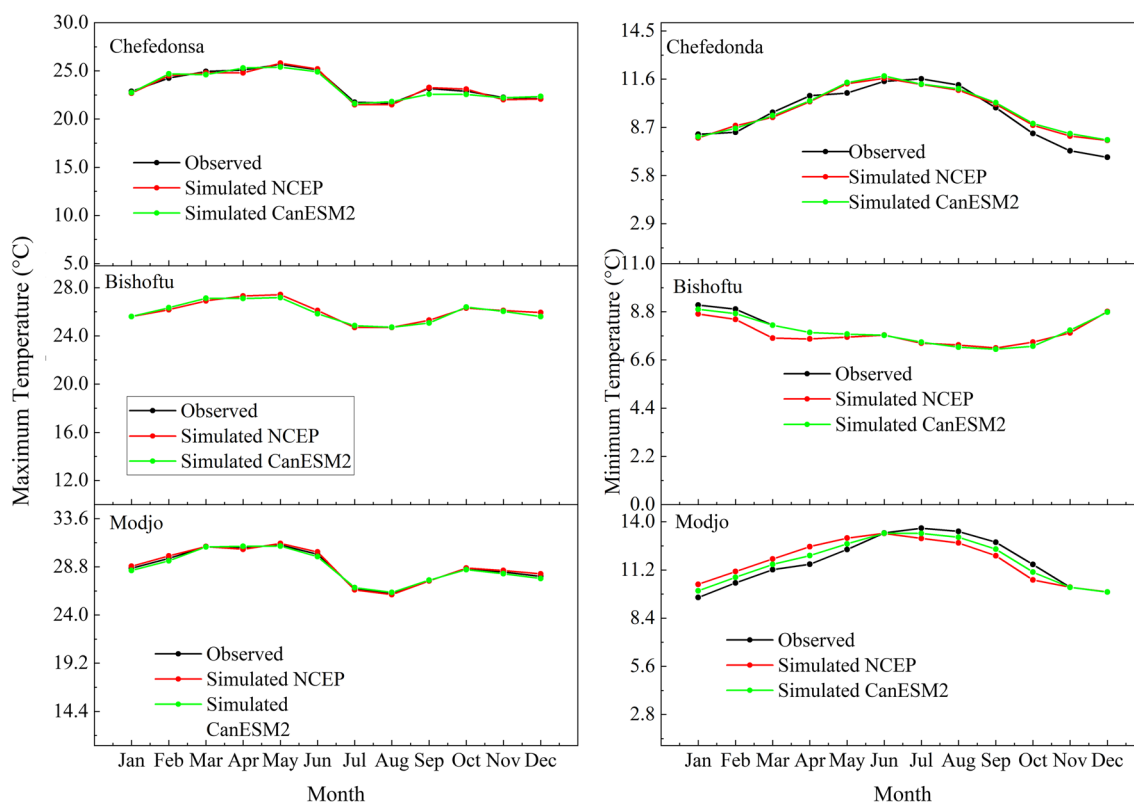
Fig. 3 Monthly mean observed and simulated maximum and minimum temperatures by NCEP and CanESM2 models for each station

et al. 2020). Ayele et al. (2016) reported that the projected temperature increases in an average of 1.6 °C over the short-term period 2021–2040 and nearly 4 °C over the long-term period 2081–2100 in the Gilgel Abbay watershed in Ethiopia. Besides, the study conducted in Kessem watershed in Awash River Basin in Ethiopia also reported that the increment of maximum temperature would range from 1.6 to 6.1 °C and 2.3 to 7.5 °C over the short time 2015–2044 and long period 2045–2075, respectively (Yadeta et al. 2020).

Precipitation

The average annual outputs from the CanESM2 model under both RCP scenarios revealed that precipitation will also show increasing until the end of the twenty-first century (Table 4). At Modjo station, the percentage rise in annual precipitation will be 7.6% and 14.5% for RCP4.5 and 2.6% and 9.1% for RCP8.5 in the 2050s and 2080s, respectively. At Bishoftu station, the percentage change in annual precipitation will be 8.3% and 10.3% for RCP4.5, and 7.7% and 12.9% for RCP8.5 in the 2050s and 2080s, respectively. Similarly, the percentage change of annual average precipitation will be 2.5% and 6.8% for RCP4.5, and 1.1% and 10.9% for RCP8.5 at Chefedonsa station. The results revealed that the percentage change in precipitation is minimum at

Chefedonsa station under RCP8.5 in the 2050s compared to the baseline period. In parallel to this, the maximum percentage change was projected under RCR4.5 in the 2080s at Modjo station. Generally, the model projected the increasing trends of annual precipitation for both projection periods in both scenarios for all study stations. This finding is aligned with the study that reported an annual increasing trend of rainfall for five among eight stations considered during investigation in Ethiopia (Gedefaw et al. 2019). Similarly, several studies confirmed the annual increasing trends at different stations in Ethiopia (Kebede et al. 2013; Mengistu et al. 2014; Feyissa et al. 2018; Meseret and Belay 2019; Alemayehu et al. 2020).

Seasonal change projections

The seasonal change values are more significant for local impacts studies on climate change than annual values. In most parts of Ethiopia, there are two rain seasons, the short (locally named as Belg) and long rainy (locally named as Kiremt) seasons. The long rainy season is from June to September while the short rain season is from February – May, the dry season is from October – January, respectively (Gebrechorkos et al. 2019; Gedefaw et al. 2019; Jilo
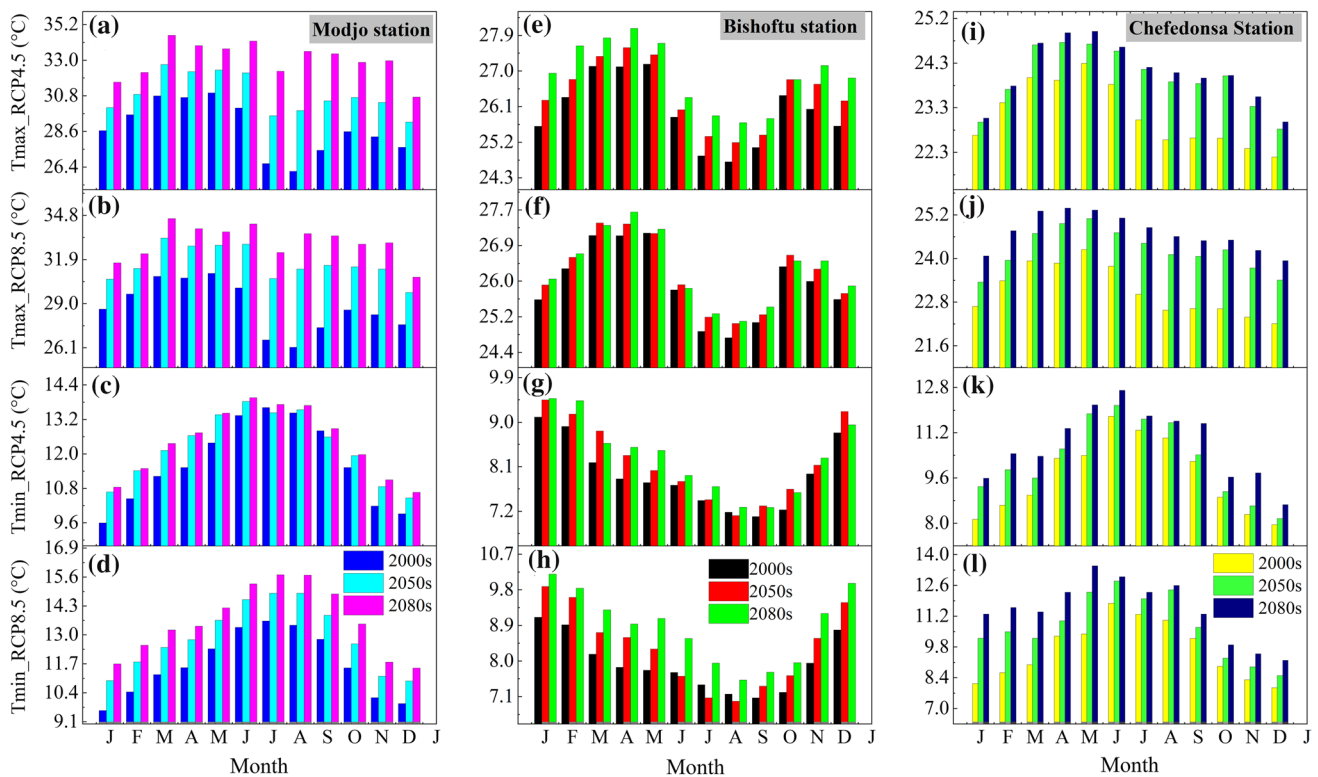
Fig. 4 Monthly mean observed (1985–2014) vs the projected future two periods (2050s and 2080s) for both the maximum and minimum temperatures for all stations using CanESM2 GCM future projection climate model under RCP4.5 and RCP8.5

Table 4 Downscaled changes in projected temperatures (Tmax and Tmin) (°C) and precipitation (%) for each selected stations

Predictands	Station	Modjo		Bishoftu		Chefedonsa	
	Projection periods	RCP4.5	RCP8.5	RCP4.5	RCP8.5	RCP4.5	RCP8.5
Precipitation (%)	2050s	7.6	2.6	8.3	7.7	2.5	1.1
	2080s	14.5	9.1	10.3	12.9	6.8	10.9
Tmax (°C)	2050s	2.17	2.91	0.86	1.2	0.8	1.1
	2080s	4.27	4.31	0.95	1.6	0.9	1.6
Tmin (°C)	2050s	0.91	1.29	0.27	0.39	0.5	1.2
	2080s	1.07	1.95	0.35	0.92	1.2	1.8

et al. 2019; Gurara et al. 2021a). In the country, the utmost essential rainy season is from June to September for rainfed agriculture.

The seasonal projections of minimum, maximum temperatures and precipitation under both RCPs (RCP4.5 and RCP8.5) indicates a significant change in climate variables at all stations (Table 5). Overall, temperature changes are more sounded among seasons and stations, also differ for both RCPs and projection periods. In the kiremt season in the 2050s, compared to the baseline period, minimum and maximum temperatures will increase by 0.92 °C and 1.51 °C at Modjo station. The increment of maximum temperature in Bega season under RCP4.5 scenario will be 1.91 °C in the 2050s and 3.88 °C in the 2080s from the baseline period,

while it will be 2.59 °C in the 2050s and 3.92 °C in the 2080s under RCP8.5 (Table 5). Similarly, in Belg season, the maximum changes in minimum and maximum temperatures will be 1.58 °C and 3.16 °C for RCP8.5 in the 2080s and detail seasonal changes at each station in each season under both RCPs were presented in Table 5.

On the other hand, the CanESM2 model projected outputs revealed that there will be a seasonal variation of minimum and maximum temperatures at Bishoftu station in both future projection periods (the 2050s and 2080s) under both RCPs (Table 5). In Kiremt season, the maximum temperature will increase by 0.75 °C in the 2050s and 0.81 °C in the 2080s under RCP4.5. In the Belg season, compared to the baseline period, the maximum changes in minimum and maximum

Table 5 Seasonal variation of minimum temperature (Tmin), maximum temperature (Tmax) in °C and precipitation (Prec) in mm for the two future periods under both RCPs at each station

Station		Modjo				Bishoftu				Chefedonsa			
		RCP4.5		RCP8.5		RCP4.5		RCP8.5		RCP4.5		RCP8.5	
Parameter	Seasons	2050s	2080s	2050s	2080s	2050s	2080s	2050s	2080s	2050s	2080s	2050s	2080s
Tmin	Kiremt	0.92	1.13	1.51	2.34	0.06	0.19	−0.08	0.6	0.4	0.5	0.9	1.2
	Bega	0.81	0.96	1.12	1.83	0.32	0.3	0.62	1.06	0.5	0.6	0.9	1.6
	Belg	0.99	1.11	0.9	1.58	0.4	0.55	0.62	1.1	0.9	0.6	1.4	2.6
Tmax	Kiremt	2.97	5.79	4.02	5.84	0.75	0.81	0.98	1.42	1.1	1.2	1.3	1.8
	Bega	1.91	3.88	2.59	3.92	0.81	0.91	1.23	1.66	0.8	0.9	1.2	1.7
	Belg	1.61	3.13	2.1	3.16	1.02	1.13	1.27	1.8	0.6	0.7	0.8	1.3
Prec	Kiremt	14.9	20.8	13	22	12.2	15.3	4.02	5.84	16.9	21.6	23	30.7
	Bega	8.5	21.8	3.4	9.1	5.9	7.4	2.59	3.92	−2.2	−1.2	−9.5	−3.7
	Belg	4.7	1.11	−8.5	−3.9	6.8	8.1	2.1	3.16	−4.9	0.1	−10	5.7

temperatures will increase by 1.10 °C and 1.80 °C in the 2080s under RCP8.5 at Bishoftu station. The change of maximum temperature in Bega season under RCP8.5 scenario will be 1.23 °C in the 2050s and 1.66 °C in the 2080s from the baseline period, while it will increase by 0.81 °C in the 2050s and 0.91 °C in the 2080s under RCP4.5 (Table 5). Generally, the projected minimum temperature shows decreasing trends in the Kiremt by 0.08 °C under RCP8.5 in the 2050s from the baseline period.

Similarly, the model projected outputs shown that there will be a seasonal variability of both the minimum and maximum temperatures at Chefedonsa station in both future projection periods under both RCPs (Table 5). In the Kiremt season, the minimum temperature will increase by 0.4 °C in the 2050s and 0.5 °C in the 2080s under RCP4.5. In the Bega season, the maximum changes in minimum and maximum temperatures will increase by 1.60 °C and 1.70 °C in the 2080s under RCP8.5 at Chefedonsa station. The mean change in minimum temperature in Belg season under RCP8.5 scenario will be increased by 0.9 °C in the 2050s and 1.6 °C in the 2080s (Table 5). Generally, the projected minimum temperature will be higher by 2.6 °C in the 2080s of RCP8.5 in Belg season than the projected maximum temperature by 1.8 °C in 2080s of RCP8.5 in Kiremt season.

Table 5 shows seasonal percentage changes in precipitation from the CanESM2 GCM downscaled results in the 2050s and 2080s projection periods for both RCP4.5 and RCP8.5 at all study stations. The results revealed that under both RCPs, different patterns of seasonal precipitation changes are projected at all stations over both future projection periods. In Kiremt season, increasing changes are projected over both future periods. However, in both RCP scenarios the projected precipitation values were different at all stations.

In the 2050s and 2080s periods, selected RCPs scenarios, the projected precipitation data was significantly changing. Especially, in the seasonal period, the maximum projected precipitation show changes up to 30.9% in the 2080s at Chefedonsa station under RCP8.5. In future, both RCPs shows similar rising trends in the Kiremt season, although the magnitudes of the changes are higher under RCP8.5 than RCP4.5. The extreme wettest season, 30.9%, is projected in the 2080s under RCP8.5 at Chefedonsa in the Kiremt season and 22% is projected in the same period in the Bega season at Bishoftu station. Table 5 presents comparatively the seasonal predicted future changes of precipitation at all stations for both future periods. The results show that the projected precipitations have similar changing trends under the two RCPs in Kiremt and Bega seasons, except for Bega season at Chefedonsa station where the changes will be decreasing in both future climates scenarios. The magnitude of precipitation changes in the 2080s is larger than that of the 2050s in all seasons and detail seasonal variation of precipitation for the two future periods was tabulated in Table 5.

The seasonal projected precipitation ranges from -10% to 30.9%, the smallest decrease is projected in the 2050s and the highest value is projected to happen in the 2080s at Chefedonsa in Belg and Kiremt seasons, respectively. This finding is in line with the reported increasing trends of annual rainfall in Adami Tulu Jido-Kombolcha watershed in Ethiopia (Gemechu et al. 2015). Bekele et al. (2017) reported an increasing trend of rainfall in Kiremt season in eight-station among twelve stations used for the study in Awash River Basin, Ethiopia. Similarly, Feyissa et al. (2018) reported that the rainfall in Kiremt rainy season will increase by 20.9% under RCP4.5 (2071–2100) relative to baseline in Addis Ababa, Ethiopia. On the other side, Asfaw et al. (2018b) evaluated the variability of rainfall in north-central Ethiopia and reported that the Kiremt and annual rainfall were shown a statistically significant decreasing trend while that of Belg was non-significant.

Fig. 5 The correlation between mean temperature and annual precipitation at Bishoftu and Chefedonsa stations
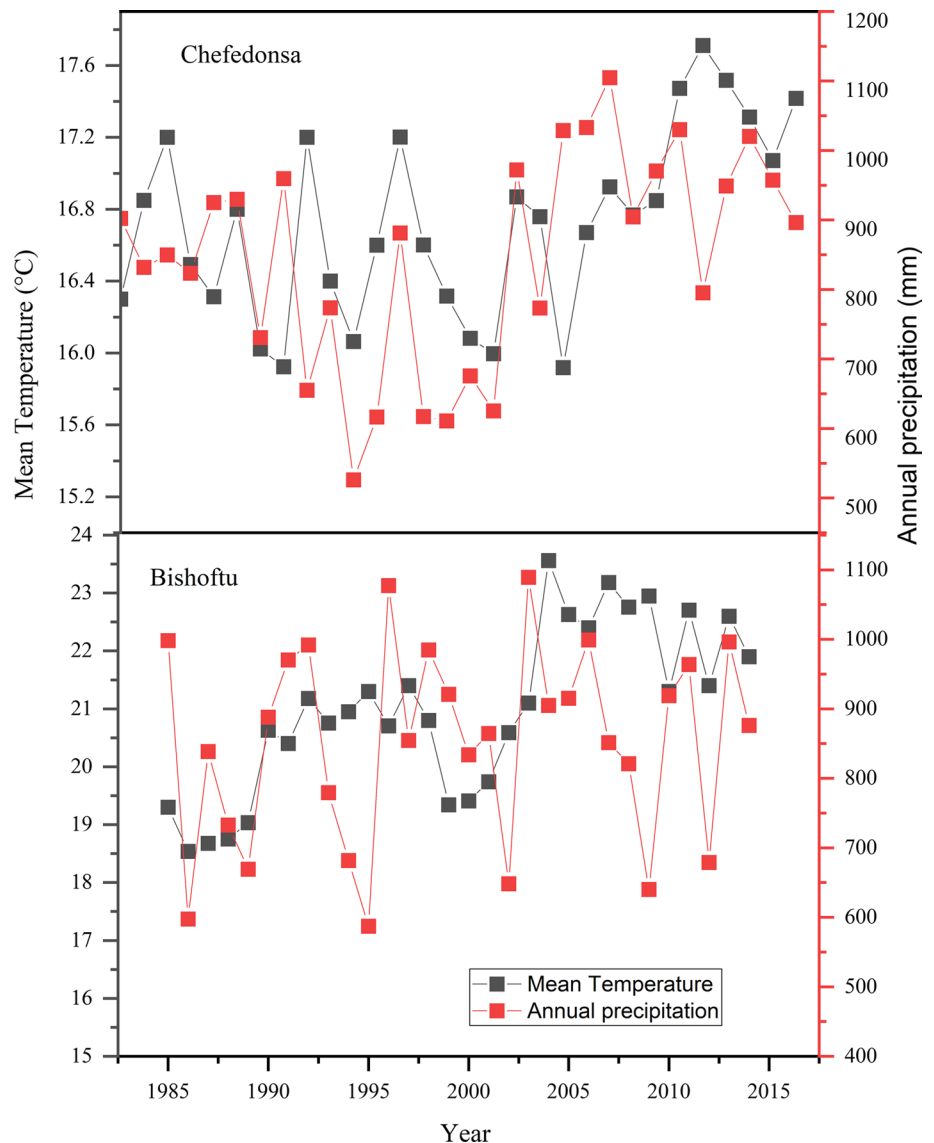
Relationship between temperatures and precipitation

Figure. 5 showed the trends of observed changes in mean temperatures and precipitation for each station and it can be observable that the relationships in the observed trends were not consistent annually. Significant negative correlations between observed yearly mean temperature and precipitation at some year while it was positively correlated at another year. The relationship is positive at Bishoftu and Chefedonsa stations and negative at Modjo station.

Future climate projection also confirmed that in the hot season over the watershed, higher temperatures are allied with lower precipitation amounts and vice versa. Hence, seasonally, strong negative correlations dominate, as dry conditions favor more sunshine and less evaporative cooling, while Kiremt wet season is cool. The projected mean maximum and minimum temperatures show increasing and the relationship of higher warm-season temperatures with lower precipitation during dry Bega season is projected to be consistently increasing and could alter the streamflow patterns (Gurara et al. 2021a). The study also confirmed that increasing trends of temperatures will increase potential evapotranspiration which exhibits evidence of increased drought severity in the upper Wabe Shebele Basin in Ethiopia (Gurara et al. 2021b). Nandozi et al. (2012) reported that the correlation of two climatic conditions such as rainfall and temperature patterns are seasonally variable in Uganda.

Impacts of altitude and Land use land cover on the Temperature

The investigations revealed that the temperature was influenced by altitude and corresponding land use land cover

type. The temperature condition is inversely related to the altitude. The low altitude area is characterized by high temperature while the lowest temperature is associated with high altitude. The highest temperatures were projected at Modjo station in the southern area of the watershed with low altitude, and the lowest temperature change is projected in the Northern part at Chefedonsa station where the area is characterized by high altitude (Fig. 1). Overall, as spatial variability, we observed approximately + 3.12 °C increment from the south to the north across the watershed from the average of thirty years observed data. Seasonally, air temperature is inversely correlated to precipitation. Kiremt (rainy) season is characterized by heavy precipitation with low temperatures and Bega (dry season) is characterized by warm temperature with very low precipitation.

In the study area, the impact of land use land cover was slightly significant as the large landscape of the watershed was covered by a single land use land cover (agriculture) (Fig. 1). The highest temperature zones observed in the southern parts may associate with the decline of forests, a rise of built-up area and expansion of industrialization. Besides, in the Northern part of the watershed, the projected changes in temperatures are minimum due to the large area coverage of cropland (Fig. 1). Remarkably, many findings reported that the decline of forest and agricultural land due to urbanization and industrialization causes an increment in air temperature (Setturu et al. 2013; Aik et al. 2021).

Conclusion

Increasing trends of air temperatures and variability of precipitation due to climate change are recently one of the substantial environmental agendas in today's world that has been considered as sensitive issues and a priority area for investigation. Thus, the study was designed to evaluate the potential future changes of temperatures and precipitation under climate change during the two future periods in the 2050s (2041–2070) and 2080s (2071– 2100), using the GCM data of CanESM2 model under two Representative concentration pathways (RCP4.5 and RCP8.5) outputs downscaled using the SDSM model. The calibration and validation result shows that the downscaled air temperatures and precipitation are in agreement with observed data.

The simulation results revealed an increase in both minimum and maximum temperatures and annual precipitation in both future projection periods. The projected future changes of maximum temperature show higher increasing trends under the RCP8.5 than the RCP4.5, while the projected precipitation is the reverse except in the 2080s at Bishoftu and Chefedonsa stations. The average rising trends of maximum temperature is range from 2.17 to 4.31 °C at Modjo, 0.86 to 1.6 °C at Bishoftu station, and 0.8 to 1.6 °C at Chefedonsa

station up to the end of twenty-first century. The rise in minimum temperature ranges from 0.58 to 1.95 °C at Modjo and 0.19 °C to 0.92 °C at Bishoftu station from the base period (1985–2014) up to the end of twenty-first century. In terms of spatial distribution, the highest projected increase in minimum and maximum temperatures are forecasted at Modjo station, but a high magnitude of precipitation is projected at Chefedonsa station. Temporally, the extreme of minimum and maximum temperatures are projected in the 2080s under RCP8.5 climate scenarios at all stations.

Seasonal changes in air temperatures and Kiremt precipitation are projected to be increasing, but in Bega and Belg seasons precipitation trends show insignificant increasing or decreasing trends. The forecasted increasing temperatures and variability of precipitation will affect the hydrological cycle for future planning and development of the watershed. Overall, what can be drawn from the investigation is that in both future periods; the temperature is rising which could bring drought in the area near future due to high evaporating demands of the atmosphere. Therefore, to overcome increasing risks of temperature and precipitation variability adaptation design like rainwater harvesting structures will be required. Coming studies on future climate change evaluation should underline to incorporate adaptation measures.

Data availability The data that support the findings of this study are openly available, except observed data collected from Ethiopian National Meteorology Service Agency. The authors have no authority to openly distribute those observed data.

Code availability Not applicable.

Declarations

Conflict of interest The authors declare no conflict of interest.

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