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Climate Change Induced Temperature Prediction and Bias Correction in Finchaa Watershed

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Abstract: The issue of climate change impacts on hydro-climatic variables has received considerable critical attention. The main objective of this study is to evaluate the ability of selected Regional Climate Models in the Coordinated Regional Climate Downscaling Experiment (RCM-CORDEX) climate models and bias correction methods in temperature simulations and forecast future temperature under RCP4.5 (intermediate emission) and RCP8.5 (high emission) climate change scenario in Fichaa watershed, a sub-basin of Blue Nile basin. The performance of each climate model and bias correction method were evaluated using statistical indicators. The result indicated that, climate models simulations were limited to reproduce observed maximum and minimum temperature and demanded bias correction. Distribution mapping (DM) method of bias correction shows better performance in improving the simulation of climate models. The projection of future maximum and minimum temperature showed the rising trend up to 2.3°C at end of fifth and half decades of 21st century. This necessitated the implementation of appropriate adaptation strategies in the Finchaa watershed to cope up with the changing climate.

Key words: Climate Change · Temperature · Bias Correction · Climate Model · Scenario

INTRODUCTION

Climate change is increasingly recognized as a serious phenomenon affecting socio-economic and agricultural development activities around the globe. According to Intergovernmental Panel on Climate Change (IPCC) [1] climate change can be defined as significant alteration of climate in mean or variability persisting for decades or even longer either due to human activities or natural factors. Thus, climate change is may be change in precipitation intensity, location, time and amount, increase in air and water temperature, rise in sea level, decline in water quality and others.

Several attempts have been made to forecast and analyze climate change induced changes on normal and extreme hydrologic cycle components (including climate variables) [2-8] and water resources [9, 10] as well as on yields and water requirements of crop [11-13], livestock production and health [15-16], urban storm water infrastructures [17], hydropower generation [18], public health [19] and other environmental resources [20] in the past and future times. For instance, the work of authors of Marvel and Bonfils [7] and Bhuvandas *et al.* [8] stated that all the processes involved in the movement of water between earth, water body and atmosphere can be affected by climate change. The report of FAO-IPCC expert meeting also [21] revealed that climate-induced changes and variability in precipitation and temperature affects the amount of water entering river basins and affects evapotranspiration rate, resulting in dryer river basins respectively. The projected climate change scenarios indicates decrease in stream flow and groundwater availability [4] and intensify existing shortage of irrigation water demand in future [12].

According to Intergovernmental Panel on Climate Change reports [1], the global surface temperature is totally increased by 0.78°C in the second half of 19^{th} century (1850 to 1900). IPCC report also projects that the average surface temperature of the Earth is likely to increase by 1.5°C by the end of the 21st century, compared to 1850 to 1900 under all Representative Concentration Pathways (RCPs) scenario except RCP2.6. Rising in surface temperature anticipated to increase evapotranspiration [12, 21-23] and leads to intensification hydrologic cycle [7].

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Previous studies conducted in Blue Nile basin as a whole or sub-basins level using different climate models have reported that there is evidences for changed (increased) in temperature in the past decades and likely increases in both maximum and minimum temperature in the future. For example, Meron and Willems [22] indicated that, in the second half of 21st century, both minimum and maximum air temperatures are predicted to increase by greater than unity (°C) in the upper Blue Nile River Basin using LARS-WG (Long Ashton Research Station Weather Generator) and QPM (Quantile Perturbation Method) models. Degnenet and Markus [24] used LARS-WG and SDSM (statistical downscaling model) models to analyze the future impacts of climate change of Upper Blue Nile River Basin. Their work also highlighted that, minimum and maximum temperatures may increase in the basin under different RCPs scenario. Other previous studies strengthen that, the temperature in Blue Nile Basin will be rising in trend [10, 12, 20, 25-27].

Majority of the previous works in Blue Nile Basin used GCM climate models. Therefore, there is a need to use and analyze the ability of RCM-CORDEX climate models to reproduce climate variables in the basin. Compared with several regional climate change assessment projects performing downscaling over a specific region such as Prediction of Regional Scenarios and Uncertainties for Defining European Climate Change Risks and Effects (PRUDENCE) [28], Ensemble-Based Predictions of Climate Change and their Impacts (ESSEMBLES) [29], Climate Change Assessment and Impact Studies (CLARIS) [30] and North American Regional Climate Change Assessment Program (NARCSAP) [31], Regional Climate Models in the Coordinated Regional Climate Downscaling Experiment (RCM-CORDEX) project [32] allows international coordination and knowledge transfer between these projects and facilitates easier analysis. The goal of this study is to evaluate the ability of selected RCM-CORDEX climate models and bias correction methods in temperature simulations and to forecast future temperature under climate change scenario in Fichaa watershed.

MATERIALS AND METHODS

Description of Study Area: Finchaa watershed is one of the sub-basins of Blue Nile basin (Abbay Basin), which is the largest river Basin of Ethiopia based on mean annual renewable flow. It is located in the southern part of the Blue Nile basin at coordinate of 9°30' to 10°00' North and 37°15' to 37°30' East (Figure 1). The upstream watershed divide (ridge) of Finchaa sub-basin separates Blue Nile River Basin from Omo-gibe basin. Finchaa sub-basin covers 2082 km^2 area of land.

Observed Temperature Data: Long year (1981 to 2016 i.e. 36 years) temperature (Maximum and Minimum) daily recorded data were collected from Ethiopian National Meteorological Agency for the stations located in and near the study watershed. Historical daily recorded data indicated that, mean maximum air temperatures range from 26°C in August to 34°C in March, whereas long

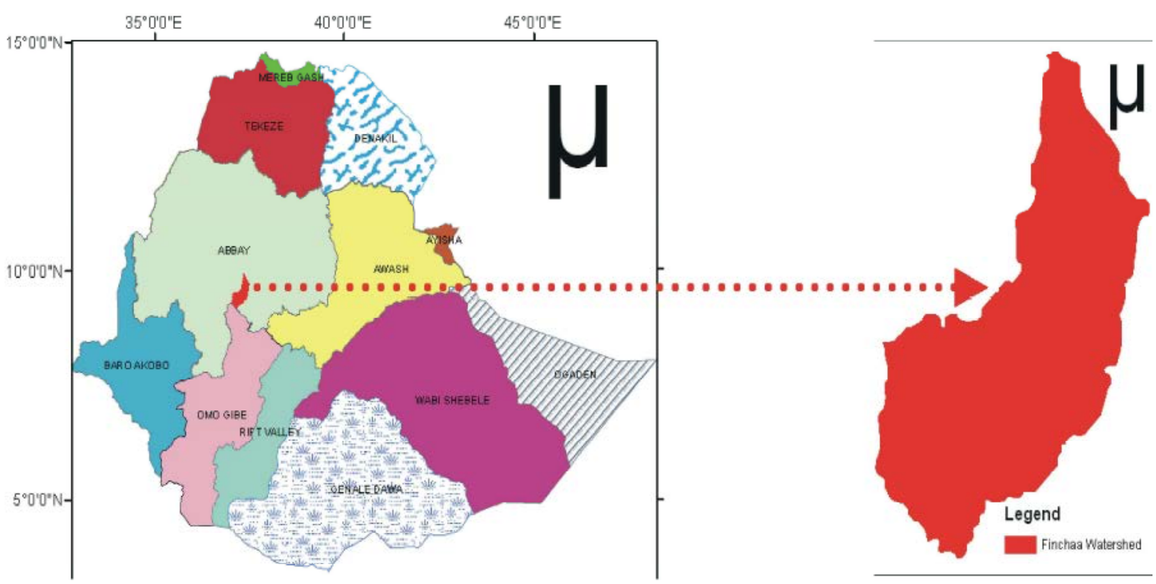

Fig. 1: Location Map of Finchaa Watershed

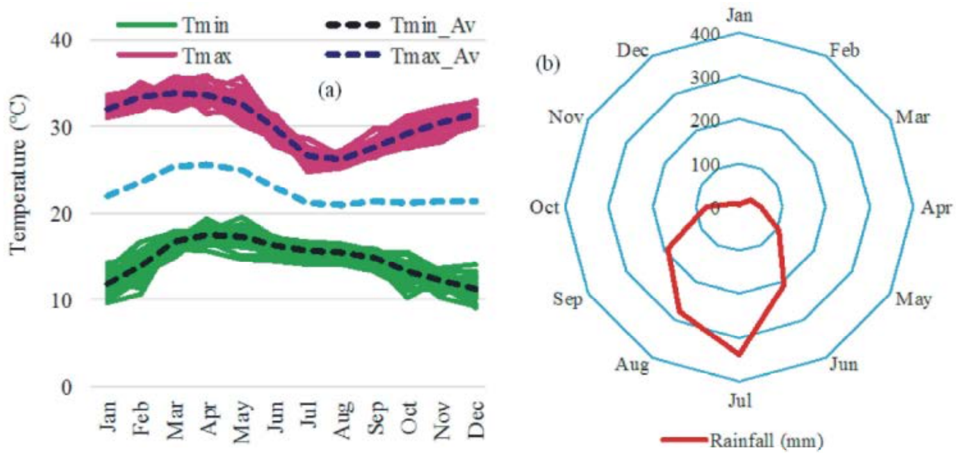

Fig. 2: Monthly Minimum, Maximum and Mean (light blue hatched line) Temperature (a) and Rainfall (b) of Finchaa watershed

Table 1: List of selected RCM-CORDEX Climate Models.

RCM	Model Center	Short Name
CLMcom COSMO-CLM (CCLM) version 4.8	Climate Limited-Area Modelling (CLM) Community	CCLM
SMHI Rossby Center Regional Atmospheric Model (RCA4)	Sveriges Meteorologiska och Hydrologiska Institut (SMHI), Sweden	RCA4

year mean minimum temperatures varies from 11.3°C in December to 17.5°C in April. Minimum air temperatures begin to decline around September and reach their lowest levels in December and January (Figure 2a). Mean monthly rainfall (P) in the watershed is low (3.2 mm) in January and reaches highest depth (340.8 mm) in July (Figure 2b).

Climate Model Data: In this study, simulated temperature data from two RCM (Regional Climate Model) models in the Coordinated Regional Climate Downscaling Experiment (CORDEX) database were used, namely SMHI-RCA4 and CCLcom-CCLM4-8-17 (Table 1). They dynamically downscaled from CNRM-CERFACS-CNRM-CM5 (Centre National de Recherches Météorologiques—Groupe d'études de l'Atmosphère Météorologique and Centre Européen de Recherche et de Formation Avancée) global climate model (GCM). For both climate change models, daily maximum and minimum temperature data for historical period (1981-2005) as well as for future (2006-2055) for the representative concentration pathways (RCP) of RCP4.5 and RCP8.5 scenarios from the African domain with a grid of 0.44° x 0.44° (equivalent with 50 km x 50 km) resolution were freely downloaded with registration from ESGF (Earth System Grid Federation) (https://esgf.llnl.gov/) different nodes of databases.

Bias Correction Methods: In order reduce the difference between observed and climate model simulated (raw data) temperature data bias correction is required. In current study, climate models simulated minimum and maximum temperature values were corrected using four bias correction methods. These are Linear Scaling (LS), Delta Change Correction (DC), Distribution Mapping of Temperature (DM) and Variance Scaling of Temperature (VS). The detail descriptions of each method were available in the previous work of authors of Teutschbein and Seibert and Fang *et al.* and Yèkambèssoun *et al.* [33-35].

Performance Evaluation Climate Models and Bias Correction Methods: Statistical parameters were used to evaluate the performance of Climate models and bias correction methods. Among the variety of model evaluation techniques available in [36], the performance of the selected RCM models and bias correction methods were evaluated using four techniques viz., Correlation coefficient (R), Coefficient of determination (R^2), Root mean square error (RMSE) and Nash Sutcliffe Efficiency (NSE) methods.

Correlation coefficient (R) is the measure of degree of linear relationship between observed and simulated data. It ranges from -1 to 1. It is represented mathematically as:

$$R = \frac{\sum_{i=1}^{n}(Obs_i - \overline{Obs}_i) \times (Sim_i - \overline{Sim}_i)}{\sqrt{\sum_{i=1}^{n}(Obs_i - \overline{Obs}_i)^2 \times \sum_{1=1}^{n}(Sim_i - \overline{Sim}_i)^2}}$$

The coefficient of determination (R^2) compares the explained variance of modeled data with the total variance of the observed data [37] and the value ranges from 0 to 1. The mathematical representation is given below:

$$R^2 = \frac{\sum_{i=1}^{n}(Sim_i - \overline{Obs}_i)^2}{\sum_{i=1}^{n}(Obs_i - \overline{Obs}_i)^2}$$

The RMSE is one of the error indices and use to measure of the difference between observed and simulated values. RMSE has the same unit as the observed variable making its interpretation relatively easy. The RMSE value of 0 represents the perfect fit.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(Obs_i - Sim_i)^2}{n}}$$

The NSE determines the relative magnitude of variance of residues and measured data. It ranges from $-\infty$ to 1 with 1 being the optimal value. The values below 0 represent unacceptable performance whereas values within 0 to 1 indicate acceptable levels of performance.

$$NSE = 1 - \frac{\sum_{i=1}^{n}(Obs_i - Sim_i)^2}{\sum_{i=1}^{n}(Obs_i - \bar{O}bs_i)^2}$$

Calibration and Validation of Temperature: In current study observed temperature data were used for calibration and validation of climate models simulations outputs after bias corrections. Therefore, calibration was done using for 25 years (1981-2005) data which is called calibration period whereas validation was performed using 11 years (2006-2016) observed and simulated minimum and maximum temperature data.

Projection of Future Temperature: Future temperature projections were done to mid of twenty first (21st) century (2055). For analysis purposes, in this study the future projections were done by categorizing the data into two time slices viz., 2006 - 2030 (25 years) and 2031 - 2055 (25 years), hereafter 2020s' and 2040s' respectively. Future projections were performed for two time slices under two different scenarios viz., RCP4.5 and RCP8.5 scenarios.

Software Used: The data were downloaded in NetCDF file format and extracted by a tool called CMhyd. It was designed to work with the CORDEX data archive, which provides downscaled regional climate model data. It also used to correct the bias of climate change models minimum and maximum temperature simulation for historical and future period of analysis under both RCP4.5 and RCP8.5 scenarios.

RESULTS

Performance of Climate Models: The ability of the two RCM-CORDEX climate models (CCLM and RCA4) to simulate the observed minimum and maximum temperature of Finchaa watershed at daily, monthly and seasonal time scale were statistically and graphically evaluated using 1981 - 2005 data. Statistical summary of both models performance was presented in Table 2.

All the selected statistical parameters indicated that, CCLM climate model has the ability to reproduce observed daily minimum temperature of the Finchaa watershed than RCA4 climate model. Correlation coefficient (R) and Coefficient of determination (R^2) values indicated that CCLM performed better than RCA4 model in reproducing maximum daily temperature. However, RMSE and NSE revealed opposite one. This indicates that, RCA4 climate model well simulates daily maximum temperature trends than CCLM climate model.

Both CCLM and RCA4 models have the ability to capture the pattern mean monthly observed maximum temperature of Fichaa watershed with considerable under estimation. Similarly, the pattern of mean monthly minimum temperature was well captured by both climate models with slight overestimation in some of months and underestimation in most the months. CCLM climate change model has the ability to simulate observed average monthly minimum temperature than RCA4 model. The result of current study also shows that, RCA4 climate model underestimated both maximum and minimum temperature for all months of the year. CCLM climate change model, like that of RCA4, highly underestimated monthly maximum temperature (Figure 3).

Table 2: Statistical Performance Measures of Climate Models simulation of Maximum and Minimum Temperature

Statistical Performance Indicator	Climate Model			
	CCLM Model		RCA4 Model	
Daily	Tmin	Tmax	Tmin	Tmax
R	0.85	0.86	0.77	0.84
R^2	0.72	0.73	0.60	0.70
RMSE	1.35	9.61	2.96	5.28
NSE	0.58	-12.44	-1.05	-3.06
Monthly				
R	0.88	0.88	0.84	0.88
R^2	0.77	0.78	0.70	0.77
RMSE	1.29	9.59	2.92	5.26
NSE	0.61	-12.43	-0.99	-3.04
Seasonal				
R	0.94	0.98	0.97	0.96
R^2	0.88	0.96	0.94	0.92
RMSE	1.35	9.49	2.97	5.18
NSE	0.51	-14.44	-1.34	-3.61

R: Correlation coefficient; R^2: Coefficient of determination; RMSE: Root mean square error; NSE: Nash Sutcliffe Efficiency; Tmax: Maximum temperature; Tmin: Minimum temperature

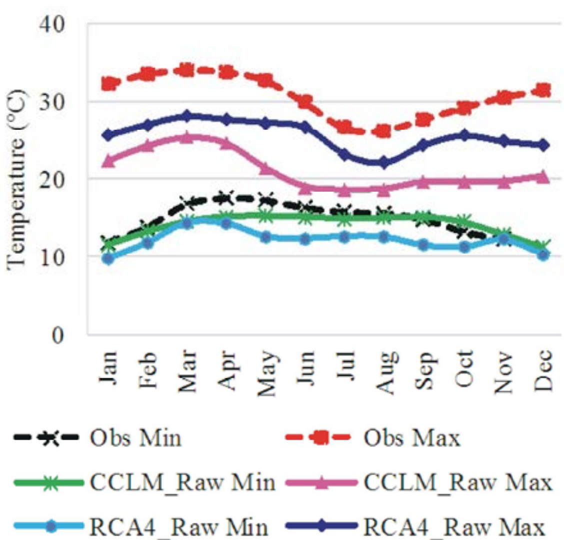

Fig. 3: Observed and Simulated average monthly temperature

Moreover, CCLM climate model underestimated the mean monthly maximum temperature in all months by the average value of 9.51°C ranging from 7.63°C in August to the highest 11.25°C in May. In addition, it underestimated the mean monthly minimum temperature for most of months and overestimated in September, October and November only by 0.23°C, 1.23°C and 0.62°C respectively. Similarly, RCA4 climate model underestimated the average monthly minimum and maximum temperature by average value of 2.65°C and 5.08°C respectively. The difference between observed and simulated mean monthly maximum/minimum temperature varies from 3.17°C/0.11°C in June/November to 7.04°C/4.74°C in August/May.

Overall, these results indicate that positive association between observed and climate model simulation outputs of both monthly maximum and minimum temperature. As indicated in Figure 4, better correlation between observed and simulated of mean monthly maximum and minimum temperature is obtained from RCA4 and CCLM climate model respectively.

The result of statistical performance evaluation criteria indicates that, both CCLM and RCA4 climate models have the ability to reproduce seasonal minimum and maximum temperature. Even though it under estimates seasonal maximum and minimum temperature for the three seasons, RCA4 have more ability than CCLM model in capturing seasonal maximum temperature (Figure 5).

Likewise, mean monthly temperature, the seasonal average temperature pattern of the selected RCM-CORDEX models were shows good association with the observed seasonal temperature. The variation of average seasonal maximum temperature between CCLM model simulated and the observed were 9.62°C, 8.68°C and 10.11°C in MAM, JJAS and ONDJF season respectively. Similarly, it underestimated seasonal mean monthly minimum temperature for MAM (2.25°C) and JJAS (0.64°C) seasons. Further analysis of current study shows that, for RCA4 climate model the MAM, JJAS and ONDJF seasonal mean maximum (minimum) temperature were less than the observed one by 5.77°C (3.51°C), 3.55°C (3.43°C) and 5.88°C (1.52°C) respectively.

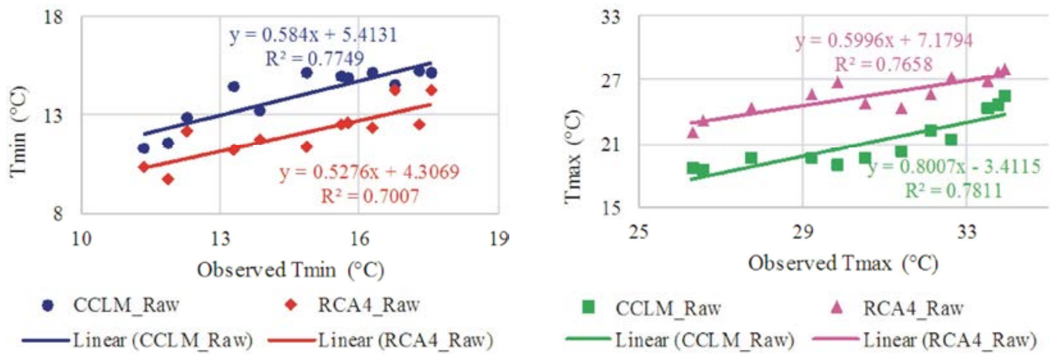

Fig. 4: Correlation of Observed and Simulated mean monthly (a) minimum and (b) maximum temperature.

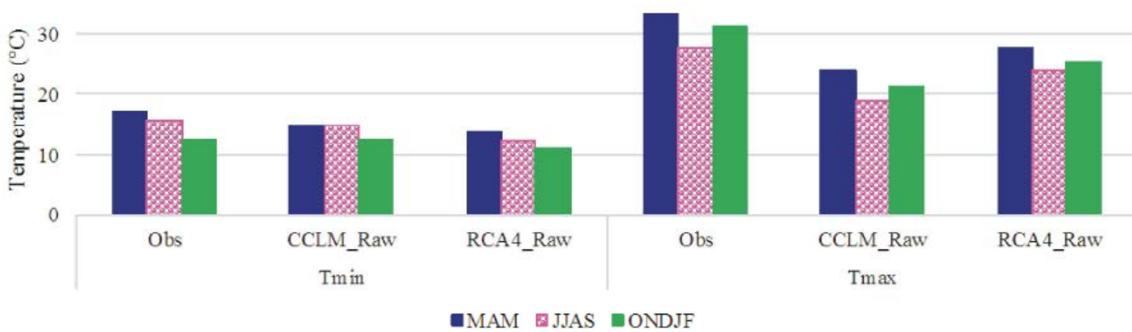

Fig. 5: Observed and Simulated Seasonal temperature

Table 3: Statistical performance measures of bias correction methods for daily Maximum and Minimum temperature.

Performance Indicators	Climate Model							
	CCLM Model				RCA4 Model			
Tmin	Raw	LS	VS	DM	Raw	LS	VS	DM
R	0.85	0.96	0.99	0.99	0.77	0.97	0.99	0.99
R^2	0.72	0.92	0.98	0.98	0.60	0.94	0.99	0.98
RMSE	1.35	0.60	0.27	0.32	2.96	0.54	0.25	0.33
NSE	0.58	0.92	0.98	0.98	-1.05	0.93	0.99	0.98
Tmax								
R	0.86	0.99	0.99	1.00	0.84	0.98	1.00	1.00
R^2	0.73	0.98	0.99	0.99	0.70	0.96	0.99	0.99
RMSE	9.61	0.38	0.27	0.22	5.28	0.54	0.26	0.22
NSE	-12.4	0.98	0.99	0.99	-3.06	0.96	0.99	0.99

R: Correlation coefficient; R^2: Coefficient of determination; RMSE: Root mean square error; NSE: Nash Sutcliffe Efficiency; Tmax: Maximum temperature; Tmin: Minimum temperature; LS: Linear Scaling; DM: Distribution Mapping; VS: Variance Scaling

Performance of Bias Correction Methods: Bias correction of RCM-CORDEX climate models simulations raw data were carried out using Linear Scaling (LS), Delta Change Correction (DC), Distribution Mapping of Temperature (DM) and Variance Scaling of Temperature (VS) methods for both calibration and validation period. Based on the statistical performance indicators result, all the selected temperature bias corrections techniques well removed the bias of RCA4 and CCLM climate models simulations (Table 3). All the bias correction methods performed satisfactorily for both maximum and minimum temperature at daily, monthly and seasonal time scales. However, Delta change (DC) method was not included in the comparison of bias correction methods due to it absolutely matched the observations data (R=1, R^2=1, RMSE=0, NSE=1) [33].

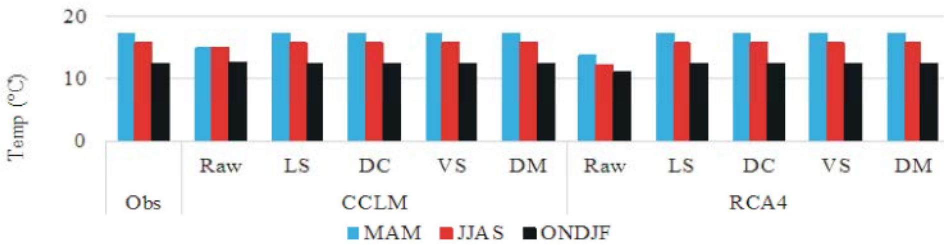

Fig. 6: Bias corrected Seasonal Minimum temperature

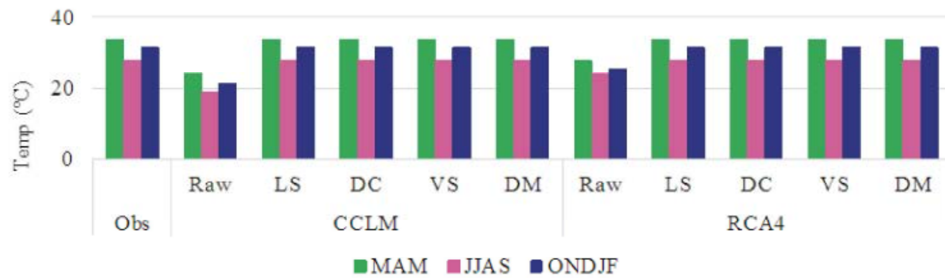

Fig. 7: Bias corrected Seasonal Maximum temperature.

The result obtained shows that, as presented in Table 3 all of the bias correction methods including delta change (DC) method have the ability to improve daily maximum and minimum temperature simulated by RCA4 and CCLM climate change models either without or with slight differences from observed. However, as compared the three of bias correction methods, statistical performance measures indicated that Linear Scaling (LS) method is the least performer in correcting the bias of both climate models temperature simulation. Variance Scaling (VS) and Distribution Mapping (DM) methods were not shows a clear difference in performance using monthly and seasonal maximum and minimum temperature. But, at daily time scale DM shows better relative performance of improving the bias of CCLM and RCA4 of RCM-CORDEX climate models. This is in agreement with the finding of Teutschbein and Seibert and Fang *et al.* [33, 34] indicated that DM and VS have better performance than LS in correcting simulated temperatures data, particularly in keeping frequency-based statistics such as 10th and 90th percentile. Furthermore, bias corrected RCM-CORDEX climate models (CCLM and RCA4) simulated seasonal maximum and minimum temperature completely matched with observed under all methods of corrections (Figure 6 and 7).

Therefore, based on the statistical evidences, the finding of this study shows that, DM bias correction method was the best performer in bias correction of the selected RCM-CORDEX climate model temperatures simulations in the Finchaa watershed. It suggested that, DM method well suited and applicable in the watershed. In light of this, the future projection of temperatures was done using DM bias corrected temperatures for both RCP4.5 and RCP8.5 scenarios.

Statistical measures also consistent with the graphical presentation of the current study. For instance, for seasonal maximum temperature LS, DC, VS and DM corrected simulated data have 1 NSE value. This finding is in agreement with [34] findings which showed all selected methods perform equally well in removing bias of raw temperature data.

Interestingly, the result of current study revealed that, observed and simulated raw and biased corrected maximum temperatures were in agreement on that the highest seasonal maximum temperature can be reached in MAM season and followed by ONDJF season, whereas lowest maximum temperature can be observed in JJAS, which is rainy season of Finchaa watershed. Again, minimum seasonal temperatures were ranked as MAM, JJAS and ONDJF from the highest to lowest for both observed and bias corrected minimum temperature. However, for the CCLM climate model, raw minimum temperature showed the highest value in JJAS, while lowest in ONDJF season.

Calibration and Validation of Bias Corrected Temperature: The calibration and validation of the two bias corrected (using Distribution Mapping method) RCM-CORDEX climate model simulations were performed using 36 years (1981-2016) for both maximum

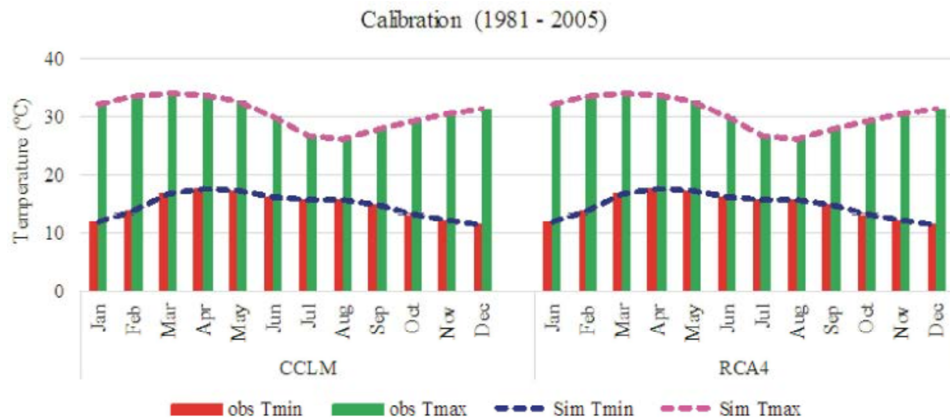

Fig. 8: Calibration of mean Monthly Minimum and Maximum Temperature

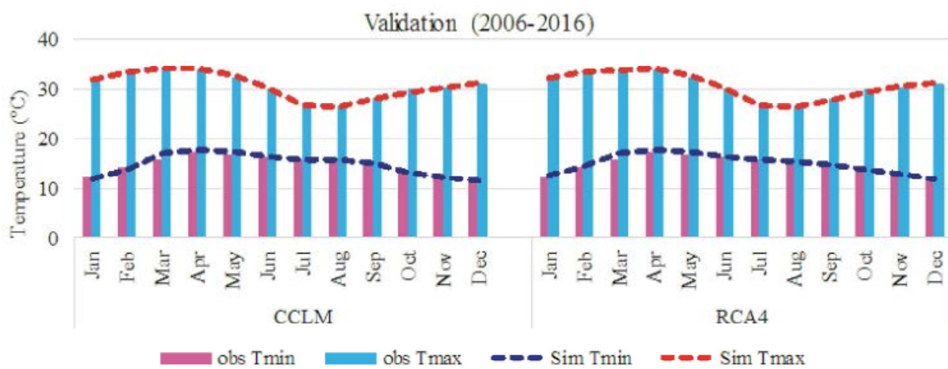

Fig. 9: Validation of mean Monthly Minimum and Maximum Temperature

and minimum temperature. As stated in methods and materials section, 1981 to 2005 data were used for calibration, whereas the data from 2006 to 2016 were used for model validation. Figure 8 illustrated the calibration graphs of bias corrected CCLM and RCA4 climate for the mean monthly maximum and minimum temperature with the observed. This figure shows an acceptable agreement between the observed and simulated data for both models data. Thus, the models have sufficient power in reproducing observed temperature during calibration period.

During the calibration period, both climate change model not indicated significant difference between observed data and simulated data for both minimum and maximum monthly temperature. As illustrated in Figure 9, during the validation period, the highest overestimation of mean monthly maximum (minimum) temperatures were observed as 0.61°C and 0.45°C in May (1.09°C and 1.07°C in March) for CCLM and RCA4 climate change models respectively. On the other hand, the largest underestimation was obtained in October for both maximum and minimum temperature for both models. CCLM (RCA4) model simulation of maximum and minimum temperatures were reduced by 0.47°C (0.56°C) and 0.92°C (0.32°C) compared with observed data, respectively. Therefore, both selected RCM-CORDEX climate models shows good and valid performance after bias correction in reproducing observed minimum and maximum temperature in the Fichaa watershed.

Future Temperature Projection: The finding of this study showed a rising trend in mean annual maximum temperature in Finchaa watershed for both selected RCM-CORDEX climate model simulations under RCP4.5 and RCP8.5 in the two time windows in future (2020s and 2040s). Based on the RCA4 climate model simulation average annual maximum temperature of Finchaa watershed will be increased by 0.16°C and 0.21°C in 2020s under RCP4.5 and RCP8.5 scenarios respectively. It also projected that annual average maximum temperature will rise by 0.46°C (under RCP4.5) and 0.6°C (under RCP8.5) at the end of 2055 in the watershed. This is due to increase in emission of greenhouse gases to the atmosphere as a result of human activities like burning of fossil fuels, industrial discharge and deforestation [38].

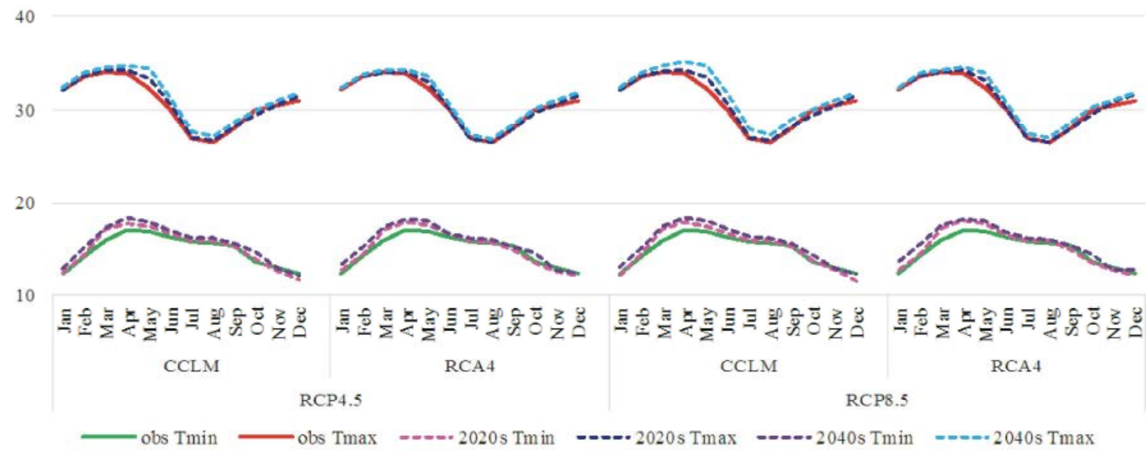

Fig. 10: Projected mean monthly future temperature

Alike RCA model the result of CCLM model also shows the increasing trend of annual average maximum by 0.23°C (0.24°C) and 0.72°C (0.9°C) under RCP4.5 (RCP8.5) for the respective time horizons of 2020s and 2040s as compared with control period (1981 - 2005). Both climate models show the highest increase of mean annual maximum temperature under RCP8.5 compared with RCP4.5 for the same time horizons. Plus, for both time windows the highest projection of maximum temperature was observed in 2040s for the same scenario. This indicated that, as time move from 2020s to 2040s there will increment of increase in maximum temperature. The same trend for both intermediate and high emission scenarios under considerations.

Similarly, there was an increasing of mean annual minimum temperature in the watershed according to the simulation of the selected climate change models. The average minimum temperature on annual basis will increase by 0.17°C (0.23°C) and 0.62°C (0.66°C) at 2020s and 2040s respectively under RCP4.5 scenario for CCLM (RCA4) RCM climate model and reaching the increase of 0.19°C (0.27°C) and 0.65°C (0.76°C) under RCP8.5 scenario for the same time horizons and climate models.

The future mean monthly minimum and maximum temperature shows rising tendency in all months compared with baseline period. The result of simulation of climate models shows that, both average maximum and minimum temperature will rise at the end 2055 by the highest increase up to 2.28°C (≈2.3°C). As demonstrated in Figure 10 the increase in both mean maximum and minimum temperature was higher from February to July for both models as compared with the remaining months.

Like that of the mean annual temperature, the increase in average monthly temperature also higher under RCP8.5 than RCP4.5 in the coming up years. The result further shows that, for the CCLM climate change model the highest increase in mean monthly maximum temperature will be 0.88°C (1.99°C) and 1.12°C (2.3°C) under RCP4.5 and RCP8.5 scenarios respectively in 2020s (2040s) in the month of May. While the highest rise in mean monthly minimum temperature will be 1.15°C (1.18°C) and 1.41°C (1.44°C) in respective time slices of 2020s and 2040s under RCP4.5 (RCP8.5) in the month of March. Correspondingly, for RCA climate the highest climbing of mean monthly maximum and minimum temperature will be observed in the month of May and March respectively under both RCP4.5 and RCP8.5 scenarios at the end of 2055 in Fichaa watershed.

DISCUSSION

The performance of both CCLM and RCA4 climate models in simulating the maximum and minimum temperature of Finchaa watershed shows better pattern or shape of observed temperature at daily, monthly and annual time scale. However, both models were limited in reproducing the observed temperature amount. Especially, they highly underestimated maximum temperature of the study area. This demanded in bias correction measures to improve their ability in capturing observed temperature (Figure 11). Comparatively, the RCA model was performed well in recovering maximum temperature than CCLM climate model in the Finchaa watershed and vice versa. However, the capability of both models in capturing observed or measured data were increased as time resolution decreased. To put it in another way, the performance of both model at seasonal time scale were better than daily time scale.

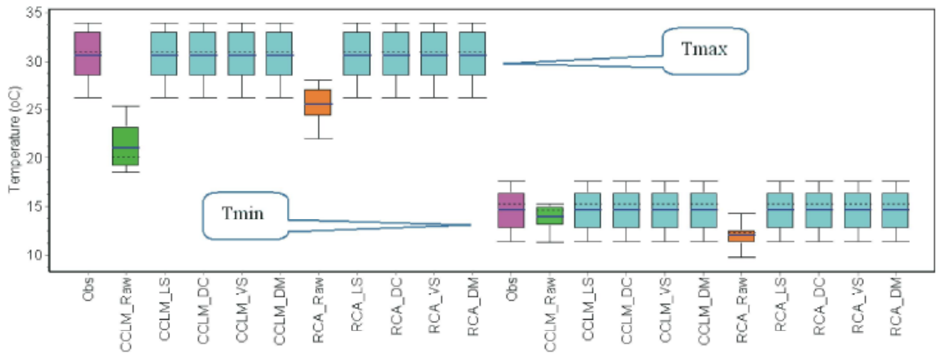

Fig. 11: Boxplot of bias corrected mean monthly temperature

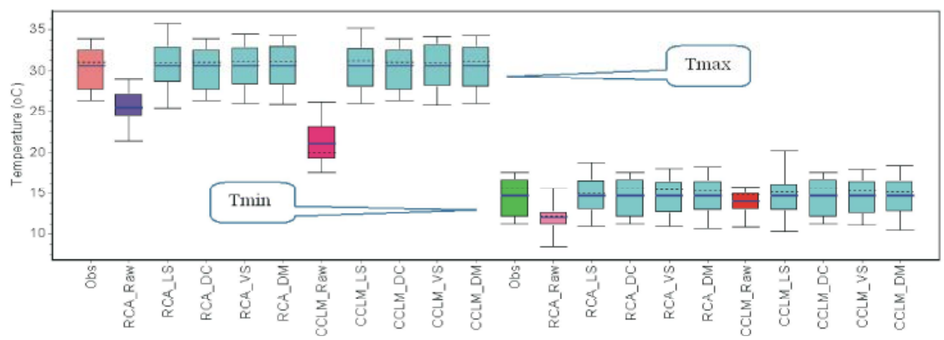

Fig. 12: Boxplot of bias corrected mean daily temperature

The biases of the selected models simulation were corrected using four selected bias correction methods (Figure 11 and 12). LS shows consistent result with [33, 34] that state, relatively poor performance due to low ability to recover frequency based statistics of the observed temperature and based on statistical performance indicators value at daily, monthly and seasonal time line. In contrast, the DC method shows perfectly matching the observed temperature for control period at different time scales. Since the DC method highly dependent on the observed data, it assumes similar changes for present and future conditions neglecting climate variability. Due to this, it was excluded from assessment and comparison with other methods. This was in good agreement with finding of Teutschbein and Seibert [33] and Yang *et al.* [39] as cited by Yèkambèssoun *et al.* [35].

Excluding DC method, DM bias correction method has better ability to remove the bias of both climate models simulation and maintaining the mean, variance, standard deviation and median of the observation. Further it indicates better performance measures output than VS and LS at daily, monthly and seasonal time scales for both CCLM and RCA4 climate models. This fits the previous findings of Teutschbein and Seibert [33] and Fang *et al.* [34].

Following the bias correction using the distribution mapping temperature (DM) method, during the calibration period, the deviation between observed and simulated maximum and minimum temperature both models shows insignificant. During the validation period, RCA4 model recover maximum (minimum) temperature with only +0.05°C (+0.23°C) average bias. The average discrepancy of CCLM model in capturing observed maximum (minimum) temperature in Finchaa valley was +0.09°C (+0.023°C) for the same period. Therefore, both CCLM and RCA4 of RCM-CORDEX climate models were validated as suitable and applicable to predict the temperature of Fichaa watershed with the proper bias corrections.

The future projection of annual, seasonal, monthly and daily mean maximum shows a clear rise under both RCP4.5 and RCP8.5 scenarios in the Finchaa sub-basin. At the end of 2055 mean annual maximum temperature was expected to rise by 0.46°C to 0.72°C and 0.6°C to 0.9°C under RCP4.5 and RCP8.5 scenarios respectively in the watershed. The monthly mean maximum temperature will be attaining the higher increment by 1.99°C and 2.3°C in the month of May under respective scenario of RCP4.5 and RCP8.5 (Figure 13).

The annual mean minimum temperature of Finchaa watershed also indicated increasing trend ranging from 0.62°C to 0.66°C and 0.66°C to 0.76°C under RCP4.5 and

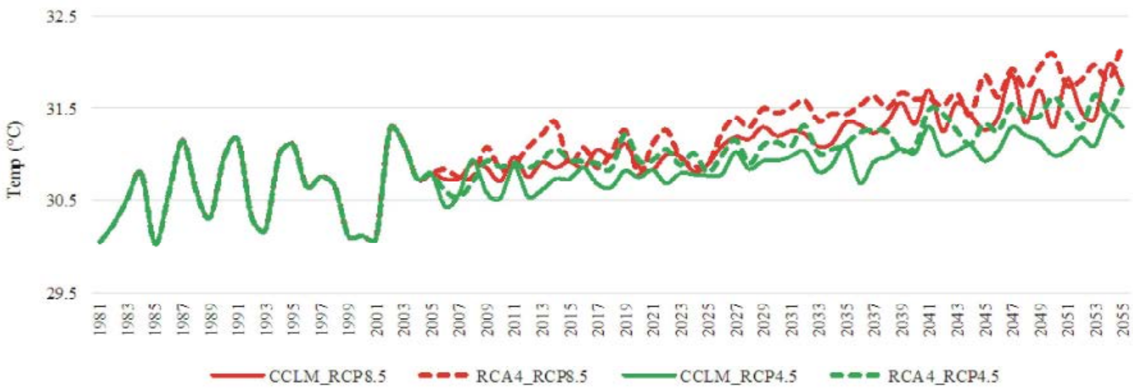

Fig. 13: Future annual cycle of projected maximum temperature

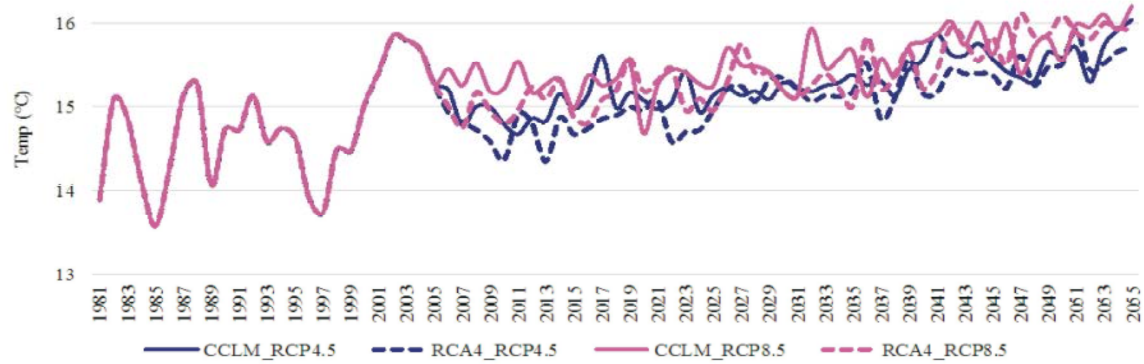

Fig. 14: Future annual cycle of projected minimum temperature

RCP8.5 respectively at the end of fifth and half decades of 21st century. Figure 14 shows that there has been a gradual increase in minimum temperature under RCP4.5 and RCP8.5 for both climate models.

The projected future minimum and maximum temperature of Finchaa watershed based on the simulation of CCLM and RCA4 RCM-CORDEX climate change models are consistent with the findings of Solomon Hailu Gebrechorkos *et al.* [20], Taye and Willems [22], Fenta Mekonnen and Disse [24], Gebrekidan Worku *et al.* [25], Ayalew *et al.* [26], Hulme *et al.* [27] in terms of direction of change. But, the magnitude of change in future temperature shows slight difference from the findings of Taye and Willems [22], Fenta Mekonnen and Disse [24], Ayalew *et al.* [26]. The differences may arise from climate change models type and number as well as the bias correction methods used in the studies. Further, this difference indicated that even though there will be a rising temperature in Blue Nile river basin, the magnitude of increment is varied from sub-basin to sub-basin.

In general, potential change in future maximum and minimum temperature will boldly observed at the end of 2055 in MAM and start JJAS season. This may cause the dryer condition at the early of rainy season which may in turn cause increase in evapotranspiration rate and late start of rain in the area. This situation highly affects rain fed agricultural practices, especially for those crops having longer growth length period. Further it probably rises irrigation water requirement under reduced water supply and increased demands for water that may reduce crop yield as found by the previous work of Olubanjo and Alade and Ayele *et al.* [11, 12]. The projected rise in future temperature in Finchaa watershed possibly affects hydrologic cycle components [23] and water resources systems [10] such as water quality, hydropower [18] and water use. Adaptation, therefore, of suitable strategies such as improved water management and irrigation systems [40] to counter balance the climate change impact in the watershed is mandatory.

CONCLUSION

This study has shown that the simulation ability of the CCLM and RCA4 RCM-CORDEX climate models were lacked to capture the observed temperature in the Fichaa watershed. Both models totally underestimated maximum temperature and in most of months they also underestimated minimum temperature. Their ability in reproducing the observed data were increased as time resolution decreased. It was also shown that implementation of different bias correction techniques can improve recovering ability of the climate models. DM bias correction method performed well than others in improving the simulated data at daily time scale relatively.

The future mean monthly minimum and maximum temperature shows rising tendency in all months compared with the baseline period. The result of simulation of climate models shows that, both average maximum and minimum temperature will rise at the end 2055 by the highest increase up to 2.3°C. The increase in both mean maximum and minimum temperature is higher from February to July for both models as compared with the remaining months.

The increase in temperature may affects hydrological and water resources components which possibly resulted in rising evapotranspiration and water demand; and reduction of rainfall and water availability in the Finchaa watershed. Consequently, devising appropriate mechanisms for adaptation of climate change is suggested. Further investigation of climate change impacts on temperature and other variables using more climate models is critical to further explore the future impacts of climate change in the watershed and in order to represent different aspects of the watershed.

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