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# Performance evaluation of various climate models using observed and regional climate models for the Katar Watershed, Ethiopia

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## Abstract

Climate models are fundamental tools to estimate the reliable future climate change and its effects on the water resources and agriculture in basins. However, all climate models are not equally performed for all areas. Therefore, determining the most appropriate climate models for a specific study area is essential. The focus of this study was to evaluate the performance of the regional climate models with regard to simulating precipitation, and temperatures at Katar watershed. This study examines the performance of fourteen CORDEX-AFRICA-220 Regional Climate Models (RCMs) for the period of 1984–2005 using statistical metrics such as Pearson correlation coefficient (R), mean absolute error (MAE), root mean squared error (RMSE), and bias. The findings indicated that GERICS-MPI was better performed in representing Areta, and Bokoji station, GERICS-IPSL was better representing in Assela, Ketergenet, and Sagure station, CCCma-CanESM2-AFR22, and RCA4-ICHEC performed relatively better in representing the mean annual observed rainfall at the Kulumsa, and Ogolcho station respectively. However, RCA4-CSIRO performed weakly in estimation of annual rainfall at all stations. RCM model such as GERICS-MPI was relatively better than the others in replicating the annual pattern of the maximum temperature at Areta, Bokoji, and Ketergenet stations. Similarly, GERICS-IPSL were relatively better in replicating the annual maximum temperature at Assela, and Sagure stations, CCCma-CanESM2-AFR22 at Kulumsa station, and RCA4-ICHEC at Ogolcho station performed well in capturing the observed and simulated annual maximum temperature. Better performance was observed on minimum temperature at CCCma-CanESM2-AFR22 at Areta, Assela, and Ketergenet stations, GERICS-MOHE-AFR-22 at Bokoji station, GERICS-MPI at Kulumsa, and Ogolcho stations, RAC4-NOAA-2G at Sagure stations. However, weak performance was observed RCA4-CSIRO at all stations. RCM models of GERICS-MPI, and CCLM4-NCC-AFR-22 performed better than the other RCM models for correction of annual rainfall in Katar watershed. However, poor performance was observed at RCA4-ICHEC model on Katar watershed. The GERICS-MPI model performed well. However, poor performance was observed at RCA4-ICHEC on maximum temperature, and GERICS-NOAA-2M on minimum temperature in Katar watershed.

**Keywords** CORDEX-Africa, Climate models Performance, RCM

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## Introduction

Climate change increased extremely over Africa show the increased extreme weather conditions (very hot days, heat waves, and high fire-danger days) and in other ways it also the cause of flooding (Sidibé et al 2020). This may be due to partly in response to increased human activities such as deforestation and industrial developments which raise the greenhouse gas effect is the main cause changes in climate variables in a variety of ways, across a

variety of periods and in various geographical areas (Shivanna 2022). Such changes may have negative impact on climate-sensitive sectors if appropriate mitigation is not undertaken. Climate change consequences are growing more severe in impoverished nations due to their limited adaptive potential (Asfaw et al 2021). Rising temperatures and changes in rainfall patterns endanger Africa's agriculture, water security, and economic development. Sub-Saharan Africa is the most vulnerable to the escalating effects of climate change (Adenuga et al 2021).

Climate models are fundamental tools used in projecting future climate conditions to develop strategies for adaptation and mitigation methods (Luhunga et al 2018). Some advanced countries, such as the United Kingdom and Canada, established nation-specific techniques for analyzing local-scale climate change consequences, but African countries lack such instruments. To solve this issue, proper regional climate models (RCM) must be selected in order to effectively assess the effects of climate change at the local scale (Adugna and Sime 2021; Amin et al. 2022). General circulation models (GCMs) and regional climate models (RCMs) were developed to forecast future climate conditions and predict possible changes in precipitation and temperature trends. Global Climate Models (GCMs) are widely used for climate projections; however, their low spatial resolution can limit their effectiveness in capturing small-scale climate variations influenced by topography (Yimer et al 2022; Matiu et al 2020; Kaini et al. 2019). However, GCM outputs are not used explicitly to analyse the hydrological impact of climate change. The GCM does not provide useful information for hydrological variables at scales smaller than 200 kms (Islama et al. 2023). Therefore, downscaling GCMs to RCMs was introduced to resolve the discrepancy between the low spatial resolution climate models of GCMs and high spatial resolution regional climate models (RCMs) or hydrological point scales (Chokkavarapu and Mandla 2019).

Regional climate models (RCMs) provide a new opportunity for climate change effect analysis since they have a higher spatial resolution and more reliable results on a regional scale than general circulation models (GCMs). Numerous studies have shown that RCM outputs improve the representation of climate change information at the mesoscale by providing spatially and physically coherent outputs with observations (Min et al. 2018; Turco et al. 2017). However, the original RCM outputs still contain considerable bias, which is inherited from the forcing of GCMs or produced by systematic model errors (Min et al. 2018). According to Dibaba et al. (2019); Mutayoba, and Kashaigili, (2017), not all RCMs are equally important in terms of their effectiveness in capturing a localized study area. The inconsistency in the performance of RCMs when

capturing different regions and seasons implies an evaluation of the sensitivity of a region using several available RCMs, and it is necessary to select the most effective RCMs for specific regions (Daniel 2023).

Climate change has a greater impact on developing countries like Ethiopia. Nowadays, significant portion of the country is exposed to drought and desertification. Rift Valley River Basin such as Lake Ziway watershed is one of Ethiopia's most vulnerable river basins to climate changes and water variability (Mulugeta et al. 2020). Katar is the one which is affected by climate change in the Lake-Ziway sub-basin which contribute water for lake Ziway that are influenced by climate change (Abraham et al. 2018) which serves as a crucial water source for water supply for irrigation systems in the region. This lake plays a vital role in supporting agricultural activities and meeting the water needs of the aquatic animals such as Fishery which is majorly produces by local peoples.

Varies studies were conducted at varies places on climate change under RCM. Most of the previous studies on Ethiopia have concentrated on climate-change vulnerability and mitigation measures (Zewdu et al. 2020; Dula et al. 2021), some RCM models performed well in simulating air temperature, but poorly in simulating precipitation (Yonas et al. 2023), some models were biased at higher elevations, but work well for low-elevation regions (Hassler, and Lauer 2021; Getaneh et al. 2024; Gebrekidan et al. 2018; Haopeng et al. 2023), and some studies that have focused on the impact of climate change using single RCMs (Dibaba et al. 2019; Mutayoba, and Kashaigili 2017). A study conducted by Adugna and Sime (2021), Yared et al. (2021), Kebede et al. (2023), (Daniel (2023), Adugna and Sime (2021), and Bekan et al. (2023), were conducted using multiple RCM models. However, the performance of RCMs was varied on watershed, and location to location (Dibaba et al 2019; Mutayoba, and Kashaigili 2017; Abraham et al. 2018; Daniel 2023; Yonas et al. 2023; Meaza et al. 2023; Mengistu et al. 2021). Hence, in order to select the appropriate RCMs for a specific location using multiple RCM models decreases the bias of the models for accurate estimation of climate change. Therefore, this study evaluates the performances of RCM outputs using multiple RCM models for precondition of bias correction (BCM) on the Katar watershed for proper projection of climate variables for impact and adaptation studies.

## Materials and methods

### Location and topography of the study area

The Katar catchment is located in Ethiopia's Lake Ziway subbasin. The region was defined by geographical

coordinates of 7° 45' to 8° 30' N and 38° 15' to 39° 30' E, as shown in Fig. 1. The Katar River is the largest tributary in the subbasin of Lake Ziway and occupies a catchment area of approximately 3580 square kilometers. The river originates at approximately 4000–4250 m.a.s.l. in the eastern volcanic chains of the Arsi Zone and drains south and west of Lake Ziway from the highlands. The elevation of the catchment ranges from 1620 to 4180 m.a.s.l. with a mean elevation of 2266 m.a.s.l. Only one-third of the whole watershed area has an elevation below 1867 m.a.s.l., and more than 56% of the whole watershed has an elevation greater than 2000 m.a.s.l., which magnifies the upland terrain of most parts of the area, as shown in Fig. 1.

**Land use/land cover of the study area**

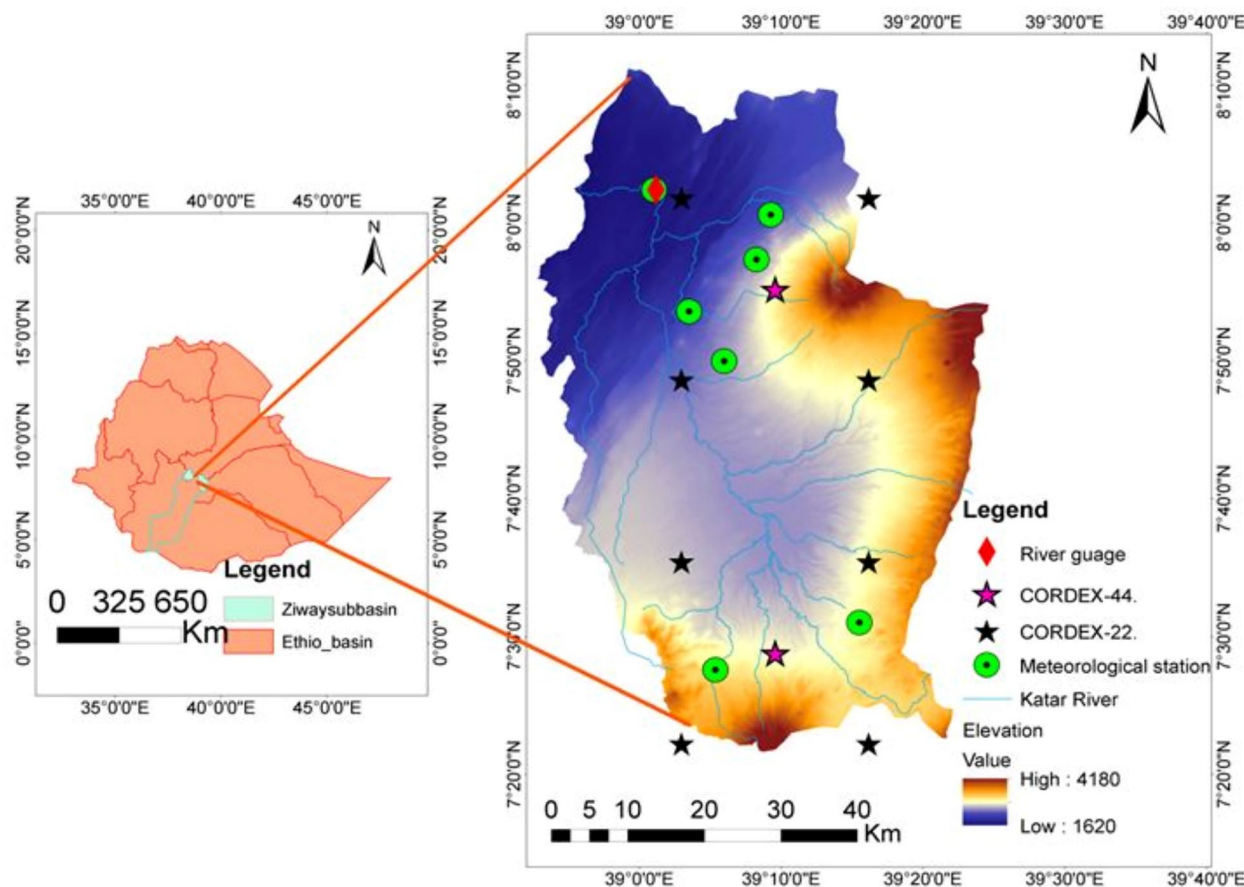
The dominant land use in the Katar watershed is agriculture, as shown in Fig. 2. The basin is intensively cultivated overall, and different crops are grown in the catchments using both rain and irrigation. The LULC map was generated by the Ministry of Water Irrigation and Energy (<https://www.mowe.gov.et/>). The major land use types of

the subbasin are intensively cultivated. Most of the lower portions are moderately cultivated, shrub land, while Afro alpine and some cultivated land cover are found in the upper portions of the basin.

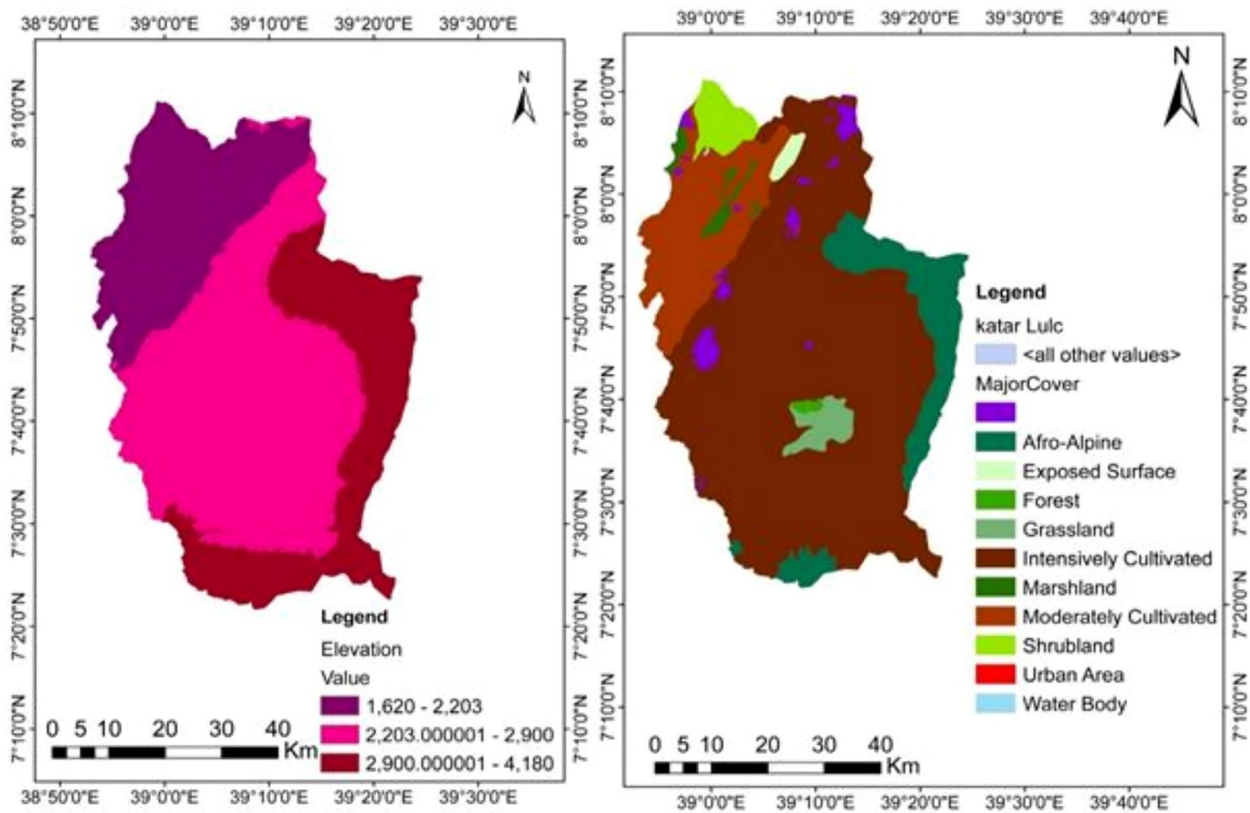
**Model climate data**

The station distribution and data availability are expressed in Table 1. The IHMS model typically requires elevation, evapotranspiration, and weather (precipitation and temperature) data to determine the impact on flow at the desired location in the watershed. The size and resolution of spatial data are dependent on the availability of sufficient ground data. Meteorological data from the EMI (Ethiopian Meteorology Institute) were obtained for this particular study. The number of meteorological variables and the duration of the data collected also varied from station to station.

Climate data, including rainfall, maximum and minimum temperatures, and other climate parameters for evapotranspiration estimations are needed as shown in Table 2. ARC-GIS 10.4 Used to obtain the physical parameters and spatial



**Fig. 1** Location map of the study area



**Fig. 2** Katar land use/land cover map

**Table 1** Data availability

Stations	Mean RF	Longitude	Latitude	Elevation
Ketera Genet	726.26	7.83	39.1	2400
Assela	1053.93	7.96	39.14	2413
Kulumsa	815.03	8.01	39.15	2211
Ogolcho	714.21	8.04	39.02	1682
Arata	774.17	7.98	39.06	1777
Sagure	835.12	7.46	39.09	2480
Bekoji	790.52	7.45	39.367	2940

information of the watershed, to generate the climate data from CODEX-Africa to the watershed and the terrain downloaded from Alaska satellite facility (<https://asf.alaska.edu/>) used 12.5×12.5 m resolution used for watershed delineation, to determine different parameters. The climate data such as rainfall, temperature, and evapotranspiration (1984–2005) downloaded from Ethiopian Meteorology Institute (EMI).

**Table 2** Data types and their sources

Data type	Sources of data	Description
ARC-GIS 10.4 Terrain	Researches From Alaska satellite facility <a href="https://asf.alaska.edu/">https://asf.alaska.edu/</a>	Used to obtain the physical parameters and spatial information of the watershed, to generate the climate data from CODEX-Africa to the watershed 12.5×12.5 m used for watershed delineation
Climate	National Meteorological Agency (NMA) <a href="http://www.ethiomet.gov.et/">http://www.ethiomet.gov.et/</a>	Rainfall, temperature, and evapotranspiration (1984–2005) are input data for bias correction

### Missing rainfall data estimation

Missing data resulting from a lack of appropriate records and changing station locations can lead to inaccurate, unclear results, which may misrepresent real reality. The missing rainfall data are filled, and the inverse distance (IDW) is used. IDW is employed because it provides a better representation and is a widely used technique in many watersheds using Eqs. 1–3 (Bayissa et al. 2015; Chen and Liu 2012; Yared et al. 2021; Wojciech 2020; Soorok et al. 2021; Wenjie et al. 2020).

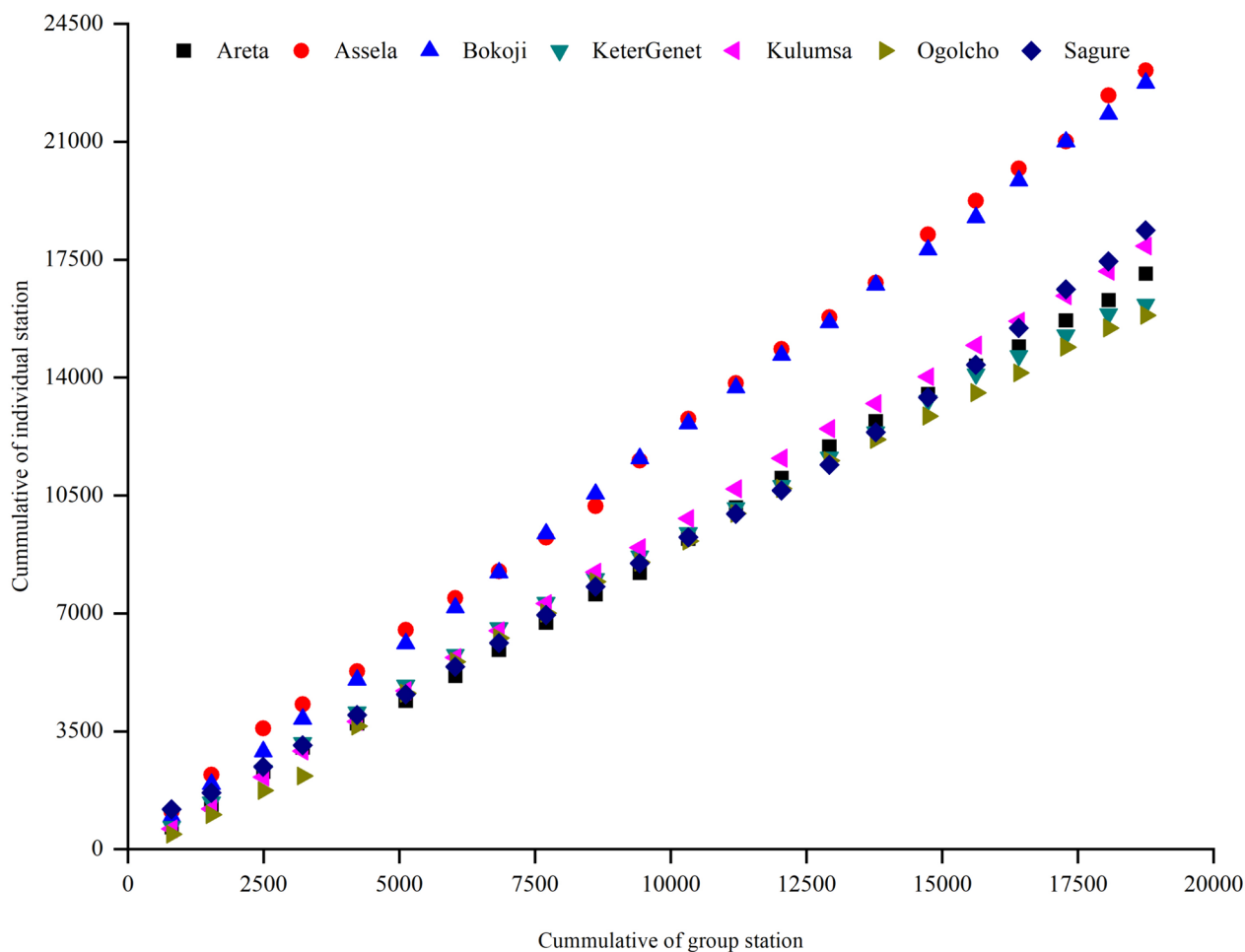
$$P_p = \sum_{i=1}^n W_i \times P_i \tag{1}$$

$$W_i = \frac{d_{pi}^{-m}}{\sum_{i=1}^n d_{pi}^{-m}} \tag{2}$$

$$P_p = \frac{\sum_{i=1}^n P_i \times d_{pi}^{-m}}{\sum_{i=1}^n d_{pi}^{-m}} \tag{3}$$

where;  $W_i$  is the weighting of individual rainfall stations,  $P_i$  is the rainfall data from the gauging station in mm,  $d_{pi}$  is the distance from each station to the required point,  $m$  is the exponent and the controlling factor fixed by the user,  $n$  is the number of gauging stations, and  $P_p$  is the required rainfall data in mm.

Double mass curve analysis was also used to determine the accuracy of the data for certain stations (Guoshuai et al. 2023). The cumulative values of one station are compared for the same duration with the aggregate values of the average values of the other stations. The double mass curve allows homogeneity in time series (especially jumps) to be examined when a shift is to be observed, when the rain gauge is to be used, and so on. Consistent data series may be modified to consistent values by proportionality (Fig. 3). It can be seen from the figure above all the stations are consistent.



**Fig. 3** Double mass curve of the rainfall data



### Regional climate models (RCM) selection

The performance evaluation of regional climate model outputs, nine dynamically downscaled GCM outputs from the CORDEX program archives were used as shown in Table 3. For this study, meteorological, hydrological, and water resource (land use/land cover digital elevation model and elevation) data were acquired. Three dynamically downscaled GCMs were obtained from CORDEX-22, and the remaining GCMs were obtained from CORDEX-44. These data were generated by a global climate model at horizontal resolutions of 25 and 50 km over the African domain for the period 1980–2005. The selected GCM-RCMs are developed by different research institute and universities over different countries. Five RCM models such as Climate Limited-Area Modeling Community Version 4 (CCLM4), Rossby Center Atmospheric Version 4 (RCA4) (Tumsa 2021), Canadian Centre for Climate Modelling and Analysis (CCCMA) (Yonas 2022, Tumsa 2021), Regional Model (GERICS) (Jacob 2001; Meaza et al. 2023) and African climate model completely new model were used.

### Statistical analysis of the models

The statistical parameters included bias; coefficient of determination (R), mean absolute error (MAE) and root mean square error (RMSE) are calculated using Eqs. 4–7. R, MAE, RMSE, and Bias are commonly used in multiple studies to evaluate the performance of CORDEX AFRICA- RCMs (Ayugi et al. 2020; Mendez et al. 2022; Yersaw and Mulusew 2024). The Pearson correlation coefficient (R) values showed the linear relationship between observed and simulated by RCMs. Pearson

correlation coefficient values can range from – 1 for a perfect negative correlation to 1 for a perfect positive correlation between the simulated and the observed climate variables (Schober et al. 2018). RMSE measures how accurately climate models simulate climate variables. Smaller values of RMSE close to zero had good model performance and vice versa (Chai, and Draxler 2014). The bias measures the systematic error between the observed and simulated climate variables and zero indicates good performance.

$$R = \frac{\sum (Obs_i - Obs_{mean}) * (S_i - S_{mean})}{\sqrt{\sum (Obs_i - Obs_{mean})^2 * (S_i - S_{mean})^2}} \quad (4)$$

$$MAE = \frac{\sum_{i=1}^n |S_i - Obs_i|}{n} \quad (5)$$

$$RMSE = \sqrt{\frac{\sum (S_i - Obs_i)^2}{n}} \quad (6)$$

$$Bias = \frac{1}{n} \sum_{i=1}^n (Obs_i - S_i) \quad (7)$$

where; R=Pearson correlation coefficient, MAE=Mean absolute error, RMSE=Root mean square error, Obs<sub>i</sub> and S<sub>i</sub> are the *i*th observed and simulated datasets, respectively, Bias=Bias (%), and Obs<sub>mean</sub> and S<sub>mean</sub> are the means of the observed and simulated variables, respectively.

**Table 3** List of RCM outputs used for the studies

RCM	Model center	Short name of RCM	Driving model	Short name for the study
CLMcom-CCLM4-8–17(CLMcom)	Climate Limited-area Modeling (CLM) Community	CCLM4-8–17	CNRM-CERFACS-CNRM-CM5 ICHEC-EC-EARTH MOHC-HadGEM2-ES	CCLM4-CNRM CCLM4-ICHEC CCLM4-MOHC
SMHI Rossby Center Regional Atmospheric Model (RCA4)	Sveriges Meteorologiska och Hydrologiska Institut (SMHI), Sweden	RCA4	ICHEC-EC-EARTH CSIRO-QCCCE-CSIRO-Mk3-6-0 NOAA-GFDL-GFDL-ESM2G	RCA4-ICHEC RCA4-CSIRO RCA4-NOAA-2G
GERICS REMO2009	Helmholtz-Zentrum Geesthacht, Climate Service Germany	GERICS	ICHEC-EC-EARTH IPSL-IPSL-CM5A-MR MPI-M-MPI-ESM-LR NOAA-GFDL-GFDL-ESM2M	GERICS-ICHEC GERICS-IPSL GERICS-MPI GERICS-NOAA-2 M
CCCma-CanRCM4	CCCma(Canadian Centre for Climate Modeling and Analysis, Victoria, BC, Canada	CCCma	CCCma-CanESM2	CCCma-CanESM2
AFR-22		CCCma	CCCma-CanESM2	CCCma-CanESM2-AFR-22
AFR-22	African climate model	GERICS	MOHC-HadGEM2-ES	GERICS-MOHE-AFR-22
		CCLM4-8–17	NCC-NorESM1-M	CCLM4-NCC-AFR-22

## Results and discussion

### Performance of RCMs in simulating annual rainfall in Katar sub stations

The performances of RCMs in simulating monthly rainfall in Katar sub catchments were shown in Table 4 and Fig. 4. The correlation ( $r$ ) of observed and model simulated mean annual rainfall was strong and very strong (0.68–1.00) in all sub stations at all models except CCLM4-ICHEC which showed weak correlation ( $R \leq 0.27$ ). This result coincides with a study conducted in Western Africa where the correlation coefficient value indicated that RCMs simulations of the annual rainfall well matched with the observed mean annual rainfall (Ilori, Balogun 2022; Mengistu et al. 2021). The findings indicated that GERICS-MPI was better performed in representing Areta, and Bokoji station, GERICS-IPSL was better representing in Assela, Katergenet, and Sagure station, CCCma-CanESM2-AFR22, and RCA4-ICHEC performed relatively better in representing the mean annual observed rainfall at the Kulumsa, and Ogolcho station respectively. The performance of RCM models varied at each station. However, RCA4-CSIRO performed weakly in estimation of annual rainfall at all stations. This might be resulting in the numerical model structure and formulation of RCM. Based on the study by Di Luca et al. (2015), there are two categories of factors influencing the RCMs: those that are related to numerical experimental design and those that are related to the particular climate statistics to be evaluated. Another issue is related to the scale difference between observed data (station data) and gridded data (RCM), the lack of enough spatial and temporal observed data, and the presence of orographic features (Rummukainen et al. 2015).

Most of the RCM models overestimated the annual rainfall with bias of  $-0.23$  mm to  $-2.21$  mm except RAC4-NOAA-2G, GERICS-MPI, and CCCma-CanESM2-AFR22 at Areta station with bias of 1.55 mm, 0.06 mm, and 0.74 mm respectively. Similarly most of the models overestimated the annual rainfall except CCLM4-ICHEC, CCLM4-MOHC, RAC4-NOAA-2G, CCCma-CanESM2-AFR22, GERICS-MOHE-AFR-22, CCLM4-NCC-AFR-22 with bias of 0.53% to 0.83% at Assela station. Models such as RAC4-NOAA-2G, CCCma-CanESM2, GERICS-MOHE-AFR-22, and CCLM4-NCC-AFR-22 with bias of 0.08 mm to 0.63 mm at Bokoji, RCA4-ICHEC, GERICS-IPSL, and CCCma-CanESM2 with bias of 0.52–1.71 mm at Katergenet station, and 0.33–0.88 mm at Kulumsa station, RCA4-ICHEC (bias=0.06 mm), CCCma-CanESM2 (bias=0.21 mm) at Ogolcho station, RAC4-NOAA-2G, GERICS-IPSL, GERICS-MPI, CCCma-CanESM2, and CCCma-CanESM2-AFR22 with bias of 0.14–0.29 mm at Sagure station under estimate the annual rainfall rather

than the other RCM models. Similar result was found in South west Ethiopia where, all evaluated CORDEX-AFRICA-RCMs overestimate the rainfall at most station at southwest, Ethiopia (Adugna and Sime 2021); and Meaza et al. (2023) at Zarima sub-basin northwestern Ethiopia.

Generally, most of the RCM models overestimate the monthly rainfall at most Katar sub stations. Similarly, Hernández-Díaz et al. (2013) reported that a dynamically downscaled version of CORDEX-AFRICA showed over estimation of the annual rainfall in the Ethiopian highlands and elevated area of Sudan; Ayugi et al. (2020) evaluated RCMs in East Africa and found that most of the models and ensembles overestimated the basin-average annual rainfall amount; Yimer et al. (2022), the RCMs tended to overestimate rain fall conducted an assessment of RCMs in the East Africa region and the Ethiopian highlands area. Additionally, Demessie et al. (2023) specifically examined the Guder sub basin of the upper Blue Nile basin, Kebede et al. (2023), Central Rift Valley Lakes Basin of Ethiopia, Tadase and Mamo, (2024) Arsi Zone Southeastern Ethiopia. Their study revealed that the mean annual rainfall in this sub basin was overestimated by the CORDEX-AFRICA-RCMs.

The MAE and RMSE value indicated the error occurred between the observed and the model simulated mean annual rain fall reached up to 276.1 mm, 368.8 mm (Table 3). The lowest MAE value was 2.3 mm, and RMSE was 3.30 mm, which was observed in GERICS-IPSL at Sagure station, while the highest MAE was 16.4 mm, and RMSE was 20.80 mm, which was seen in GERICS-MOHE-AFR-22 at Bokoji station. There is no single RCM or GCM output that has better performance in simulating the rainfall of the study area. The results agree with similar studies in different regions (Stefanidis et al. 2020a, b; Demessie et al. 2023; Gebrekidan et al. 2018). Therefore, intensive studies have been conducted to evaluate the skill of global climate models (GCMs) to simulate climate variables, mainly rainfall and temperature, in different parts, and there is a large difference between intermodal performance and simulated climate variables of the same region or station. Similar studies were conducted in Upper Blue Nile Basin of Jemma sub basin by Gebrekidan et al. (2018), and they recommend that the performance of models better in capturing the annual pattern of the rainfall at one station may performed weakly at the other station and had better correlation with observed than any single model (RCM).

### Performance of RCMs in simulating annual maximum temperature in Katar sub stations

The performances of RCM models on annual temperature in Katar sub stations were shown in Table 5 and

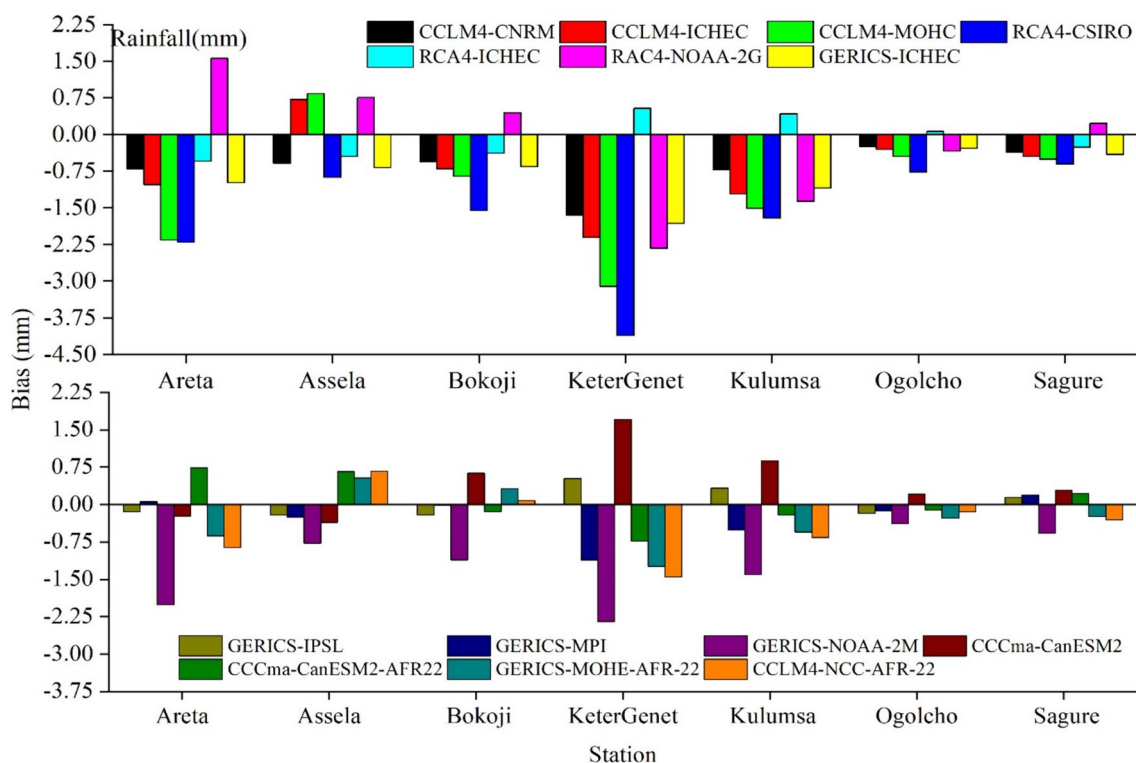
**Table 4** Mean monthly temperature

Station	Statically indicators	CCLM4-CNRM	CCLM4-ICHEC	CCLM4-MOHC	RCA4-CSIRO	RCA4-ICHEC	RCA4-NOAA-2G	GERICS-ICHEC	GERICS-IPSL	GERICS-MPI	GERICS-NOAA-2M	CCCma-CanESM2	CCCma-CanESM2-AFR22	GERICS-MOHE-AFR-22	CCLM4-NCC-AFR-22
Areta	R	0.94	0.83	0.89	0.89	0.47	0.96	0.82	0.99	0.91	0.88	0.76	0.91	0.97	0.97
	MAE (mm)	29.30	60.40	104.80	147.60	35.60	61.20	79.80	6.80	16.50	104.70	56.40	14.80	10.50	13.20
	RMSE (mm)	44.00	88.30	159.40	210.90	46.40	85.80	113.80	7.80	20.90	149.20	65.90	19.40	12.80	16.50
	PBIAS (mm)	-0.71	-1.03	-2.16	-2.21	-0.55	1.55	-0.99	-0.14	0.06	-2.01	-0.23	0.74	-0.63	-0.86
	Rank	6	10	13	14	4	11	9	2	1	12	3	7	5	8
Assela	R	0.92	0.86	0.86	0.86	0.48	0.93	0.82	0.97	0.96	0.86	0.72	0.95	0.96	0.94
	MAE (mm)	25.10	48.10	85.50	132.70	46.10	43.60	74.60	12.50	14.30	94.60	74.70	16.20	13.20	18.70
	RMSE (mm)	30.4	67.4	137.6	188.5	61.1	63.3	97	15.2	17.9	127.5	90.7	19.5	17.7	22.5
	PBIAS (mm)	-0.59	0.71	0.83	-0.88	-0.45	0.75	-0.68	-0.21	-0.25	-0.78	-0.36	0.66	0.53	0.67
	Rank	6	10	13	14	4	11	9	1	2	12	3	7	5	8
Bokoji	R	0.94	0.73	0.79	0.76	0.27	0.86	0.73	0.92	0.68	0.75	0.71	0.92	0.94	0.92
	MAE (mm)	34.00	222.50	235.10	276.10	61.80	24.70	124.10	18.40	33.90	243.30	75.10	18.60	16.40	19.50
	RMSE (mm)	43.50	294.20	286.60	368.80	80.30	35.70	180.10	25.00	42.70	330.50	86.30	24.50	20.80	25.10
	PBIAS (mm)	-0.56	-0.71	-0.86	-1.56	-0.39	0.44	-0.66	-0.21	-0.02	-1.11	0.63	-0.14	0.32	0.08
	Rank	8	11	12	14	6	7	10	4	1	13	9	3	5	2
Ketergenet	R	0.95	0.85	0.88	0.89	0.49	0.96	0.83	0.85	0.98	0.89	0.79	0.98	0.98	0.97
	MAE (mm)	32.00	59.00	106.30	146.30	35.30	64.10	78.10	17.60	16.00	101.30	57.40	12.70	19.30	25.60
	RMSE (mm)	43.20	87.90	159.60	210.70	47.10	86.40	112.50	23.50	21.60	148.50	67.60	13.80	24.20	33.40
	PBIAS (mm)	-1.66	-2.11	-3.11	-4.11	0.53	-2.33	-1.82	0.52	-1.11	-2.35	1.71	-0.73	-1.24	-1.45
	Rank	7	10	13	14	2	11	9	1	4	12	8	3	5	6
Kulumsa	R	0.93	0.78	0.85	0.82	0.30	0.90	0.81	0.97	0.99	0.82	0.65	0.83	0.84	0.81
	MAE (mm)	30.60	63.00	105.40	150.30	41.20	61.60	85.30	20.60	15.30	110.40	55.20	9.10	18.40	24.80
	RMSE (mm)	45.60	90.50	161.20	213.80	48.20	87.50	117.00	24.10	22.80	152.30	64.70	11.00	25.60	35.40
	PBIAS (mm)	-0.73	-1.22	-1.51	-1.71	0.42	-1.37	-1.10	0.33	-0.51	-1.41	0.88	-0.21	-0.55	-0.66
	Rank	7	10	13	14	3	11	9	2	4	12	8	1	5	6
Ogolcho	R	0.93	0.78	0.85	0.82	0.30	0.90	0.81	0.97	0.99	0.82	0.65	0.83	0.84	0.81
	MAE (mm)	31.90	66.00	110.70	153.30	40.90	66.30	80.90	16.00	7.90	109.60	54.30	18.40	60.00	24.50
	RMSE (mm)	47.00	92.80	163.00	215.50	53.70	91.30	115.70	23.50	11.80	153.90	63.50	25.30	81.30	28.45
	PBIAS (mm)	-0.25	-0.31	-0.45	-0.77	0.06	-0.34	-0.29	-0.18	-0.12	-0.38	0.21	-0.11	-0.27	-0.15
	Rank	7	10	13	14	1	11	9	5	3	12	6	2	8	4



**Table 4** (continued)

Station	Statically indicators	CCLM4-CNRM	CCLM4-ICHEC	CCLM4-MOHC	RCA4-CSIRO	RCA4-ICHEC	RCA4-NOAA-2G	GERICS-ICHEC	GERICS-IPSL	GERICS-MPI	GERICS-NOAA-2M	CCCma-CanESM2	CCCma-CanESM2-2-2	GERICS-MOHE-2-2	CCLM4-NCC-2-2
Sagure	R	0.97	0.85	0.93	0.91	0.32	0.97	0.86	1.00	0.99	0.89	0.80	0.97	0.99	0.80
	MAE (mm)	47.20	234.30	250.30	285.00	58.50	9.20	119.20	2.30	4.60	251.10	67.50	9.20	23.60	39.00
	RMSE (mm)	56.00	303.90	297.60	377.70	79.40	13.10	184.90	3.30	6.50	339.30	76.60	13.10	28.00	51.40
	PBIAS (mm)	-0.37	-0.45	-0.51	-0.61	-0.26	0.22	-0.41	0.14	0.19	-0.58	0.29	0.22	-0.24	-0.31
	Rank	9	11	12	14	6	3	10	1	2	13	7	3	5	8



**Fig. 4** Performance of RCMs in simulating annual rainfall in Katar sub stations

Fig. 5. The result revealed that the individual RCMs were good in representing the yearly pattern of the observed annual maximum and minimum temperature even if some of the simulations were closer to the observed temperature and others were partly different in replicating the annual maximum and minimum temperature. RCM model such as GERICS-MPI was relatively better than the others in replicating the annual pattern of the maximum temperature at Areta, Bokoji, and Ketergenet stations. Similarly, GERICS-IPSL were relatively better in replicating the annual maximum temperature at Assela, and Sagure stations, CCCma-CanESM2-AFR22 at Kulumsa station, and RCA4-ICHEC at Ogolcho station performed well in capturing the observed and simulated annual maximum temperature. Generally, the performance of GERICS-MPI, and GERICS-IPSL were better in capturing annual temperature in most stations. Girma et al. (2022); Yonas et al. (2023) also supported these findings, showing that GERICS-MPI satisfactory captured the maximum and minimum temperature variability.

Most models except RAC4-NOAA-2G, GERICS-IPSL, CCCma-CanESM2-AFR22 at Areta, CCLM4-ICHEC, CCLM4-MOHC, RAC4-NOAA-2G, CCCma-CanESM2-AFR22, GERICS-MOHE-AFR-22, and CCLM4-NCC-AFR-22 at Assela, GERICS-MPI at

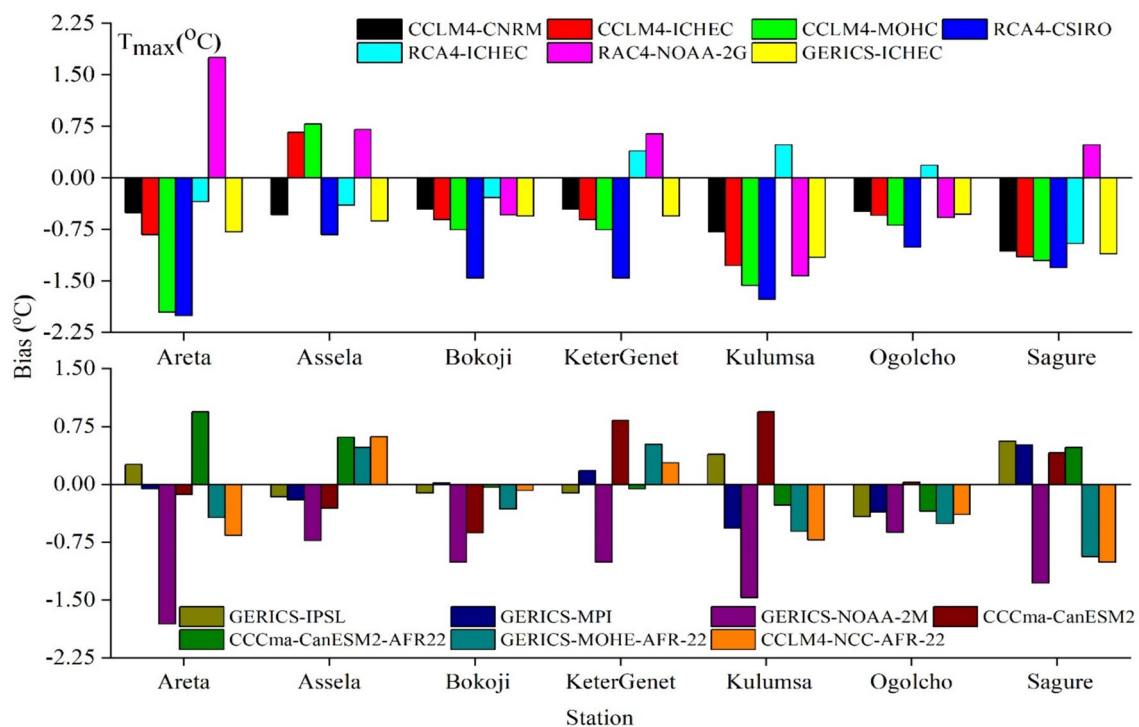
Bokoji, RCA4-ICHEC, RAC4-NOAA-2G, GERICS-MPI, CCCma-CanESM2, GERICS-MOHE-AFR-22, and CCLM4-NCC-AFR-22 at Ketergenet, RCA4-ICHEC, GERICS-IPSL and CCCma-CanESM2 at Kulumsa, RCA4-ICHEC and CCCma-CanESM2 at Ogolcho, RAC4-NOAA-2G, GERICS-IPSL, and GERICS-MPI at Sagure station overestimate the annual maximum temperature. Most of the models overestimate the annual maximum temperature at all stations (above 50%). Similarly, almost 50% of the CORDEX-RCMs simulations showed overestimation of maximum and minimum temperature (Tumsa 2022). This finding is in line with studies conducted in the Blue Nile basin (Gebrekidan et al. 2018; Demessie et al. 2023). In comparison of the current result, the overestimation was lower at most RCM models compared with the result of Meaza et al. (2023) conducted at Zarima sub-basin north-western Ethiopia. The over estimation was high in highland areas and low in lowland area of the sub basin. Similarly, the study conducted in Tanzania the bias was relatively high in highly elevated area and low in low elevated area (Luhunga et al. 2016). The reason behind to the result was the RCMs performance varies based on locations and topography in upper Blue Nile basin (Dibaba et al. 2019).

**Table 5** Statistically performance of RCM models on annual Maximum temperature

Station	Statistical indicators	CCLM4-CNRM	CCLM4-ICHEC	CCLM4-MOHC	RCA4-CSIRO	RCA4-ICHEC	RCA4-NOAA-2G	GERICS-ICHEC	GERICS-IPSL	GERICS-MPI	GERICS-NOAA-2 M	CCCma-CanESM2	CCCma-CanESM2- AFR22	GERICS-MOHE- AFR-22	CCLM4-NCC- AFR-22
Areta	R	0.96	0.85	0.91	0.91	0.49	0.98	0.84	1.01	0.93	0.9	-0.74	0.93	0.99	0.99
	MAE (°C)	1.04	1.33	2.54	2.57	1.10	1.43	1.53	0.37	0.55	1.44	1.13	0.53	0.39	0.48
	RMSE(°C)	1.44	1.73	2.94	2.97	1.50	1.83	1.93	0.77	0.95	1.84	1.53	0.93	0.79	0.88
	PBIAS(°C)	-0.51	-0.83	-1.96	-2.01	-0.35	1.75	-0.79	0.26	-0.06	-1.81	-0.13	0.94	-0.43	-0.66
Assela	Rank	6	10	13	14	4	11	9	2	1	12	3	7	5	8
	R	0.94	0.88	0.88	0.88	0.8	0.95	0.84	0.99	0.98	0.88	0.77	0.97	0.98	0.96
	MAE (°C)	1.03	1.33	1.73	2.07	1.29	1.31	1.37	0.81	0.87	1.53	1.36	0.90	0.84	0.96
	RMSE(°C)	1.44	1.74	2.14	2.48	1.70	1.72	1.78	1.22	1.28	1.94	1.77	1.31	1.25	1.37
Bokoji	PBIAS(°C)	-0.54	0.66	0.78	-0.83	-0.40	0.70	-0.63	-0.16	-0.20	-0.73	-0.31	0.61	0.48	0.62
	Rank	6	10	13	14	4	11	9	1	2	12	3	7	5	8
	R	0.94	0.73	0.79	0.76	0.27	0.86	0.73	0.92	0.68	0.75	-0.71	0.92	0.94	0.92
	MAE (°C)	1.24	1.73	1.64	2.63	1.34	0.86	1.53	0.57	1.03	1.86	1.44	0.53	0.45	0.83
Ketergenet	RMSE(°C)	1.28	1.77	1.68	2.67	1.38	0.90	1.57	0.61	1.07	1.90	1.48	0.57	0.49	0.87
	PBIAS(°C)	-0.46	-0.61	-0.76	-1.46	-0.29	-0.54	-0.56	-0.11	0.02	-1.01	-0.63	-0.04	-0.32	-0.08
	Rank	8	11	12	14	6	7	10	4	1	13	9	3	5	2
	R	0.95	0.85	0.88	0.89	0.49	0.96	0.83	0.85	0.98	0.89	-0.79	0.98	0.98	0.97
Kulumsa	MAE (°C)	1.37	1.55	1.86	2.83	1.38	1.43	1.56	1.18	1.17	1.62	1.41	1.15	1.19	1.21
	RMSE(°C)	1.97	2.15	2.46	3.43	1.98	2.03	2.16	1.78	1.77	2.22	2.01	1.75	1.79	1.81
	PBIAS(°C)	-0.46	-0.61	-0.76	-1.46	0.39	0.64	-0.56	-0.11	0.18	-1.01	0.83	-0.06	0.52	0.28
	Rank	7	10	13	14	2	11	9	4	1	12	8	3	5	6
Ogolcho	R	0.93	0.78	0.85	0.82	0.30	0.90	0.81	0.97	0.99	0.82	-0.65	0.83	0.84	0.81
	MAE (°C)	1.12	1.51	2.07	2.53	1.25	1.49	1.74	1.09	1.04	1.88	1.29	1.11	1.33	1.15
	RMSE(°C)	1.42	1.81	2.37	2.83	1.55	1.79	2.04	1.39	1.34	2.18	1.59	1.41	1.63	1.45
	PBIAS(°C)	-0.49	-0.55	-0.69	-1.01	0.18	-0.58	-0.53	-0.42	-0.36	-0.62	0.03	-0.35	-0.51	-0.39
Rank	7	10	13	14	1	11	9	5	3	12	6	2	8	4	

**Table 5** (continued)

Station	Statistical indicators	CCLM4-CNRM	CCLM4-ICHEC	CCLM4-MOHC	RCA4-CSIRO	RCA4-ICHEC	RAC4-NOAA-2G	GERICS-ICHEC	GERICS-IPSL	GERICS-MPI	GERICS-NOAA-2M	CCMa-CanESM2	CCMa-CanESM2-AMR22	GERICS-MOHE-AMR-22	CCLM4-NCC-AMR-22
Sagure	R	0.97	0.85	0.93	0.91	0.32	0.97	0.86	1.00	0.99	0.89	-0.80	0.97	0.99	0.80
	MAE (°C)	0.89	1.76	1.65	1.98	1.04	0.69	1.14	0.54	0.65	1.84	0.99	0.69	0.76	0.87
	RMSE(°C)	1.20	2.07	1.96	2.29	1.35	1.00	1.45	0.85	0.96	2.15	1.30	1.00	1.07	1.18
	PBIAS(°C)	-1.07	-1.15	-1.21	-1.31	-0.96	0.48	-1.11	0.56	0.51	-1.28	0.41	0.48	-0.94	-1.01
	Rank	9	11	12	14	6	3	10	1	2	13	7	3	5	8



**Fig. 5** Performance of RCMs in simulating annual maximum temperature in Katar sub stations

**Performance of RCMs in simulating yearly minimum temperature in Katar sub stations**

The statistical evaluation of the annual minimum temperature is expressed in Table 6 and Fig. 6. Better performance was observed CCCma-CanESM2-AFR22 at Areta, Assela, and Ketergenet stations, GERICS-MOHE-AFR-22 at Bokoji station, GERICS-MPI at Kulumsa, and Ogolcho stations, RAC4-NOAA-2G at Sagure stations. However, weak performance was observed RCA4-CSIRO at all stations. The result showed that majority of the simulation overestimated the mean annual minimum temperature similar to the annual rainfall and maximum temperature. The annual minimum temperature  $P_{BIAS}$  values range was from (+) 0.02 to (-) 2.57 °C. The lowest and highest bias values are observed at CCCma-CanESM2-AFR22, and RCA4-CSIRO simulation at Ketergenet, and Sagure stations respectively. Whereas the underestimation values were ranged from 0.02 to 0.76 °C which was observed at CCCma-CanESM2-AFR22 of Ketergenet station, RCA4-ICHEC of Bokoji station. Most of the RCM model overestimates the annual minimum temperature at Katar watershed sub stations. Similarly, almost 50% of the CORDEX-RCMs simulations showed overestimation of minimum temperature at most models season (Tumsa 2022).

The minimum MAE value were 0.06 observed at CCCma-CanESM2-AFR22 of Areta station, 0.97 (°C) at

CCCma-CanESM2-AFR22 of Assela station, 0.45 (°C) at GERICS-IPSL, and GERICS-MOHE-AFR-22 of Bokoji station, 0.02 (°C) of CCCma-CanESM2-AFR22 of Ketergenet station, 0.13 (°C) of GERICS-MPI of Kulumsa station, 0.08 (°C) of GERICS-MPI at Ogolcho station, and 0.47 (°C) at RAC4-NOAA-2G of Sagure station. The minimum RMSE were also in the respective MAE values. Whereas, the maximum MAE and RMSE were observed at RCA4-CSIRO at all station of the Katar Sub stations. The performance of the RCM models was also varied in stations. This finding is in line with study conducted in south-western Ethiopia where the CORDEX-AFRICA-RCMs showed low variability of the maximum and minimum temperatures on annual and seasonal time scales (Adugna and Sime 2021).

**Model performance on annual rainfall on Katar watershed**

The model performances of annual rainfall in Katar watershed are shown in Table 7 and Fig. 7. The representative RCMs were selected from fourteen RCM outputs for the catchment based on a statistical comparison of the mean annual rainfall. The catchment mean annual rainfall obtained from ground-observed data was compared with the RCM outputs. The smallest value of  $P_{BIAS}$ , RMSE, and MAE of the models shows good performances and also vice versa. Most of the RCM models overestimate the annual rainfall at Katar watershed with

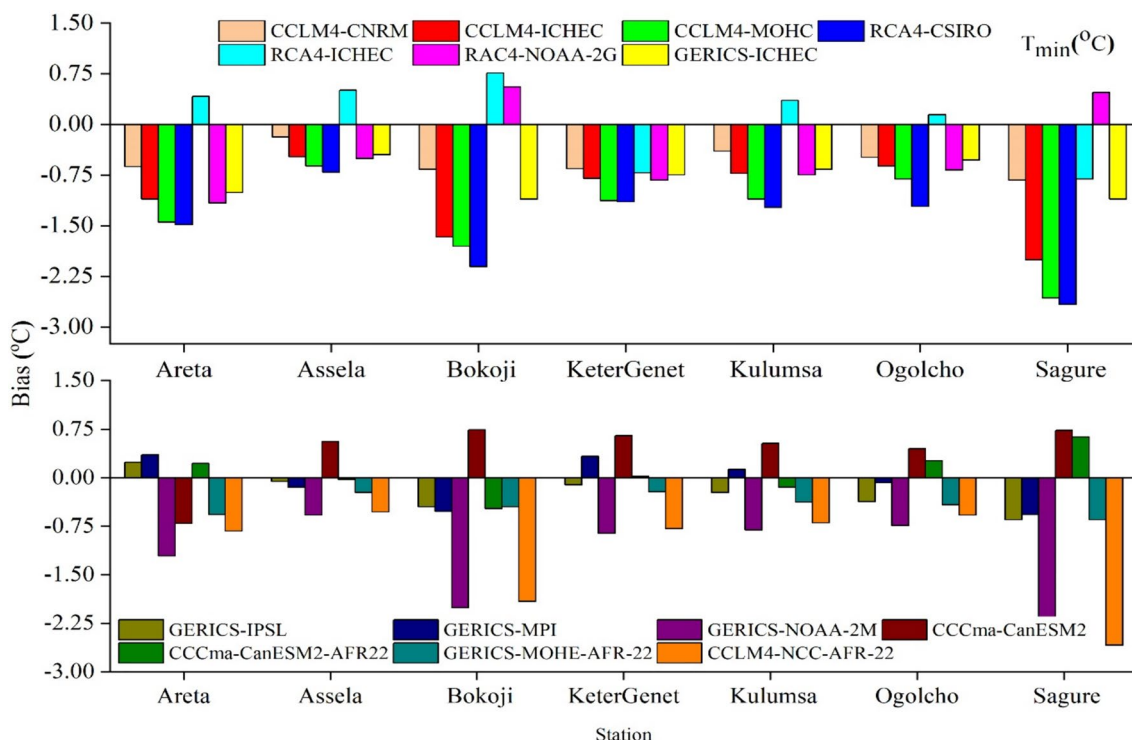


**Table 6** Statistically performance of RCM models on annual minimum temperature

Station	Statistically indicators	CCLM4-CNRM	CCLM4-ICHEC	CCLM4-MOHC	RCA4-CSIRO	RCA4-ICHEC	RCA4-NOAA-2G	GERICS-ICHEC	GERICS-IPSL	GERICS-MPI	GERICS-NOAA-2 M	CCCma-CanESM2	CCCma-CanESM2- AFR22	GERICS-MOHE- AFR-22	CCLM4-NCC- AFR-22
Areta	R	0.73	0.66	0.63	0.75	0.51	0.79	0.62	0.53	0.75	0.61	0.72	0.83	0.81	0.60
	MAE	0.24	0.55	1.14	1.55	0.12	0.64	0.54	0.02	0.06	1.02	0.30	0.00	0.08	0.45
	RMSE	0.35	0.66	1.25	1.66	0.23	0.75	0.65	0.13	0.17	1.13	0.41	0.06	0.19	0.56
	PBIAS	-0.63	-1.11	-1.45	-1.49	0.41	-1.17	-1.01	0.24	0.35	-1.21	-0.71	0.22	-0.57	-0.83
Assela	Rank	6	10	13	14	4	11	9	2	3	12	7	1	5	8
	R	0.71	0.51	0.65	0.47	0.71	0.60	0.27	0.60	0.69	0.52	0.48	0.79	0.69	0.57
	MAE	2.22	4.04	9.55	13.54	4.19	4.50	4.35	1.79	1.89	8.45	6.80	0.82	2.44	4.80
	RMSE	2.37	4.19	9.70	13.69	4.34	4.65	4.50	1.94	2.04	8.60	6.95	0.97	2.59	4.95
Bokoji	PBIAS	-0.19	-0.48	-0.62	-0.71	0.50	-0.51	-0.45	-0.06	-0.15	-0.58	0.56	-0.03	-0.23	-0.53
	Rank	4	7	13	14	8	9	6	2	3	12	11	1	5	10
	R	0.71	0.88	0.58	0.16	0.74	0.63	0.94	0.73	0.76	0.90	0.79	0.81	0.73	0.79
	MAE	4.12	5.13	5.56	5.61	4.83	2.82	4.94	1.24	2.33	5.37	4.86	1.48	1.24	5.35
Ketergenet	RMSE	4.32	5.33	5.76	5.81	5.03	3.02	5.14	1.44	2.53	5.57	5.06	1.68	1.44	5.55
	PBIAS	-0.67	-1.67	-1.81	-1.91	0.76	0.55	-1.11	-0.45	-0.52	-2.01	0.74	-0.48	-0.45	-1.91
	Rank	6	10	11	14	8	5	9	1	4	13	7	3	1	12
	R	0.64	0.98	0.67	0.79	0.53	0.62	0.50	0.95	0.63	0.86	0.61	0.64	0.66	0.62
Kulumsa	MAE	3.84	6.91	12.56	16.93	4.70	7.65	6.63	1.15	2.01	11.56	3.61	1.42	2.69	6.45
	RMSE	4.06	7.13	12.78	17.15	4.92	7.87	6.85	1.37	2.23	11.78	3.83	1.64	2.91	6.67
	PBIAS	-0.66	-0.80	-1.13	-1.15	-0.72	-0.83	-0.75	-0.11	0.33	-0.86	0.65	0.02	-0.22	-0.79
	Rank	6	10	13	14	7	11	8	2	4	12	5	1	3	9
Ogolcho	R	0.86	0.79	0.53	0.63	0.82	0.72	0.62	0.85	0.88	0.67	0.99	0.87	0.57	0.50
	MAE	2.70	6.06	11.87	16.12	2.19	6.86	5.83	0.97	0.97	10.79	4.27	0.83	1.74	5.65
	RMSE	2.87	6.23	12.04	16.29	2.36	7.03	6.00	1.14	1.14	10.96	4.44	1.00	1.91	5.82
	PBIAS	-0.40	-0.73	-1.11	-1.23	0.35	-0.75	-0.67	-0.23	0.13	-0.81	0.53	-0.15	-0.38	-0.70
Ogolcho	Rank	6	10	13	14	4	11	8	3	1	12	7	2	5	9
	R	0.65	0.85	0.67	0.87	0.70	0.62	0.91	0.76	0.61	0.64	0.91	0.69	0.83	0.73
	MAE	4.11	7.12	12.73	17.08	2.52	7.90	6.64	2.06	2.16	11.63	3.89	2.07	3.09	6.61
	RMSE	4.44	7.45	13.06	17.41	2.85	8.23	6.97	2.39	2.49	11.96	4.22	2.40	3.42	6.94
Ogolcho	PBIAS	-0.49	-0.62	-0.81	-1.22	0.14	-0.68	-0.53	-0.37	-0.08	-0.74	0.45	0.26	-0.42	-0.58
	Rank	7	10	13	14	2	11	8	4	1	12	6	3	5	9

**Table 6** (continued)

Station	Statically indicators	CCLM4-CNRM	CCLM4-ICHEC	CCLM4-MOHC	RCA4-CSIRO	RCA4-ICHEC	RCA4-NOAA-2G	GERICS-ICHEC	GERICS-IPSL	GERICS-MPI	GERICS-NOAA-2M	CCMa-CanESM2	CCMa-CanESM2- AFR22	GERICS-MOHE- AFR-22	CCLM4-NCC- AFR-22
Sagure	R	0.96	0.77	0.82	0.61	0.73	0.80	0.82	0.71	0.81	0.73	0.61	0.60	0.60	0.60
	MAE	5.95	2.45	8.03	8.08	3.71	1.95	6.61	2.94	1.92	7.83	3.19	1.88	2.94	7.71
	RMSE	6.35	2.85	8.43	8.48	4.11	2.35	7.01	3.34	2.32	8.23	3.59	2.28	3.34	8.11
	PBIAS	-0.83	-2.01	-2.57	-2.67	-0.81	0.47	-1.11	-0.65	-0.57	-2.65	0.73	0.63	-0.65	-2.59
	Rank	8	10	11	14	7	1	9	4	2	13	6	3	4	12



**Fig. 6** Performance of RCMs in simulating yearly minimum temperature in Katar sub stations

$P_{BIAS}$  ranges between  $-7.5$  and  $-257.93\%$ , RMSE ranges between  $94.1$  and  $2320.25$  mm, MAE between  $81.2$  and  $2336.36$  mm. However, CCLM4-ICHEC and CCLM4-MOHC underestimate the annual mean, with the highest value of  $-432.58$  mm for CCLM4-MOHC at  $P_{BIAS}$ s of  $10.39$  and  $49.97\%$ , respectively. The result of this study, overestimation percentage was lower compared with the result of Meaza et al. (2023) conducted at Zarima sub-basin north-western Ethiopia. The overestimation of rainfall in the highland area may be linked with climate model limitations to resolve topography accurately (Qian, and Zubair 2010; Meaza et al. 2023).

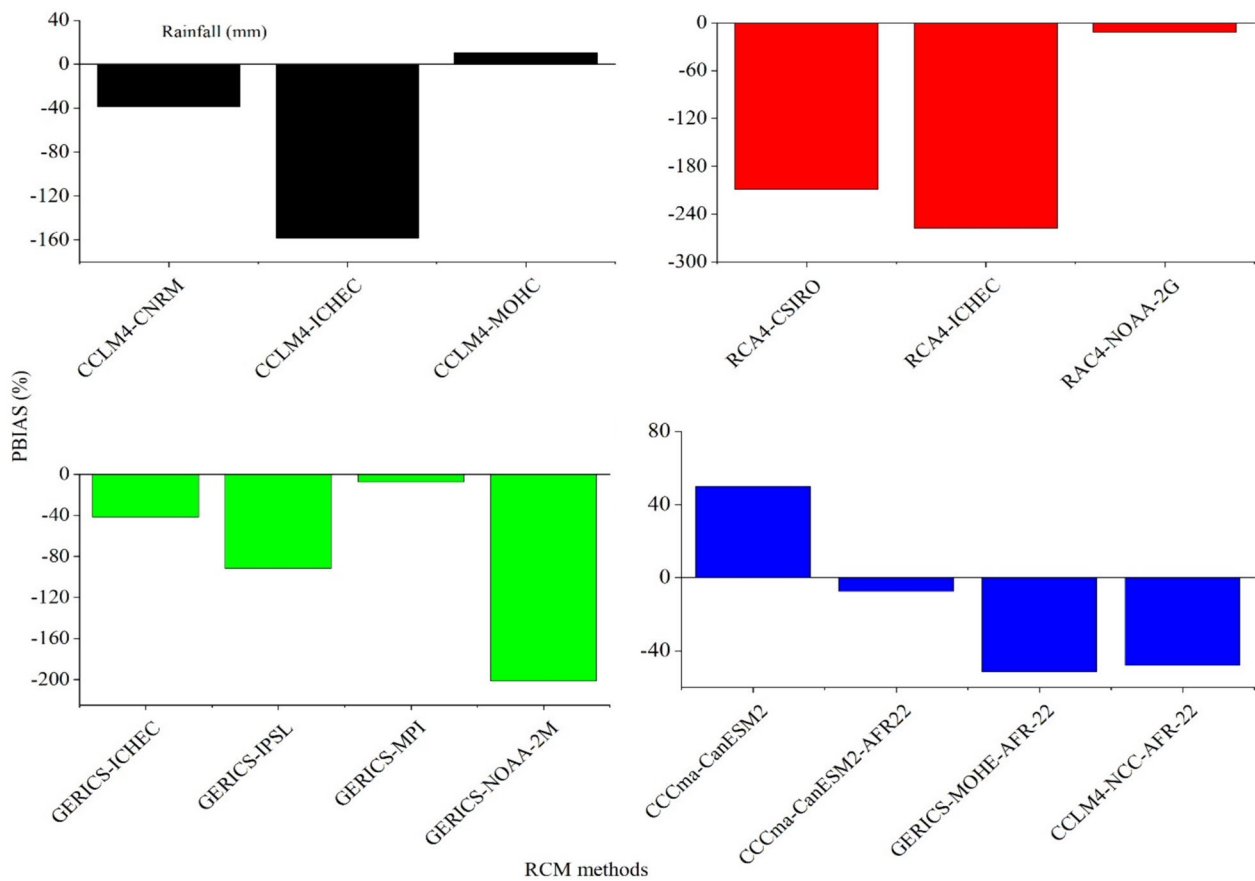
RCM models of GERICS-MPI, and CCLM4-NCC-AFR-22 performed better than the other RCM models for correction of annual rainfall in Katar watershed. However, poor performance was observed at RCA4-ICHEC model on Katar watershed. Most of the models overestimate the observed mean, with the highest value of  $3094.74$  mm for RAC4-ICHEC, followed by GERICS-NOAA-2M, with  $P_{BIAS}$  of  $257.93$  and  $201.52\%$ , respectively. The coefficient of variation was also calculated for the observed and model outputs to compare the inter-annual variability in rainfall in the catchment. The coefficient of variation observed for the 21 years was  $6.86\%$ . Except for RAC4-NOAA-2G and GERICS-ICHEC, all the other models had high CVs compared to the observed

values. RAC4-NOAA-2G exhibited the best performance according to the CV curve, followed by GERICS-MPI and CCLM4-NCCR-AFR-22.

The outputs from the RCM model show a large bias, with the highest bias of over  $100\%$  for four model outputs (CCLM4-CNRM, RCA4-CSIRO, RCA4-ICHEC, and GERICS-NOAA-2M). This indicates that the systematic error in the model accounts for  $100\%$  of the annual rainfall, which suggests that the model was unacceptable. GERICS-MPI has a bias of  $7.5\%$ , which indicates that the model well captures catchment-wide rainfall. Most models have a relatively high bias, with values greater than  $+50\%$ . This value suggested that the observed rainfall was not well captured by the RCM outputs. The GERICS-MPI has the smallest values ( $94.10$  and  $81.20$  mm/year) for the RMSE and MAE efficiency measurements, respectively. Accordingly, the largest  $P_{BIAS}$  ( $-257.93\%$ ), RMSE ( $2320.25$  mm/year) and MAE ( $2336.36$  mm/year) were observed at RAC4-ICHEC which indicates the poor performance of the model. CCLM4-NCCR-AFR-22 has a bias of less than  $10\%$ , and RAC4-NOAA-2G has a bias of  $11.55\%$ , which indicates very good and good simulation results, respectively. Additionally, they showed the minimum RMSE and MEA next to GERICS-MPI. Furthermore, both climate models exhibited better performances

**Table 7** Annual rainfall comparison of dynamically downscaled rainfall from multiple GCM–RCM

Methods	Annual Rainfall (mm)	R	MAE (mm)	RMSE (mm)	P <sub>BIAS</sub> (%)	Rank
Observed	864.6	–	–	–	–	–
CCLM4-CNRM	1198.3	0.72	349.60	386.40	– 38.60	5
CCLM4-ICHEC	2234	0.84	1434.60	1435.70	– 158.40	11
CCLM4-MOHC	861.2	0.95	180.90	202.90	10.40	3
RCA4-CSIRO	2673.6	0.63	1895.20	1893.50	– 209.20	13
RCA4-ICHEC	3094.7	0.63	2336.40	2320.30	– 257.90	14
RAC4-NOAA-2G	964.5	0.90	112.00	131.80	– 11.60	4
GERICS-ICHEC	1227.0	0.87	379.60	383.20	– 41.90	6
GERICS-IPSL	1660.2	0.82	833.50	855.60	– 92.00	10
GERICS-MPI	929.2	0.95	81.20	94.10	– 7.50	1
GERICS-NOAA-2 M	2607.0	0.77	1825.40	1815.60	– 201.50	12
CCCma-CanESM2	432.6	0.67	452.60	462.70	50.00	8
CCCma-CanESM2-AFR22	929.7	0.94	118.80	139.30	– 7.50	1
GERICS-MOHE-AFR-22	1310.9	0.63	467.60	504.80	– 51.60	9
CCLM4-NCC-AFR-22	1280.4	0.68	435.60	515.30	– 48.10	7



**Fig. 7** Performance of RCMs in simulating annual rainfall in Katar watershed

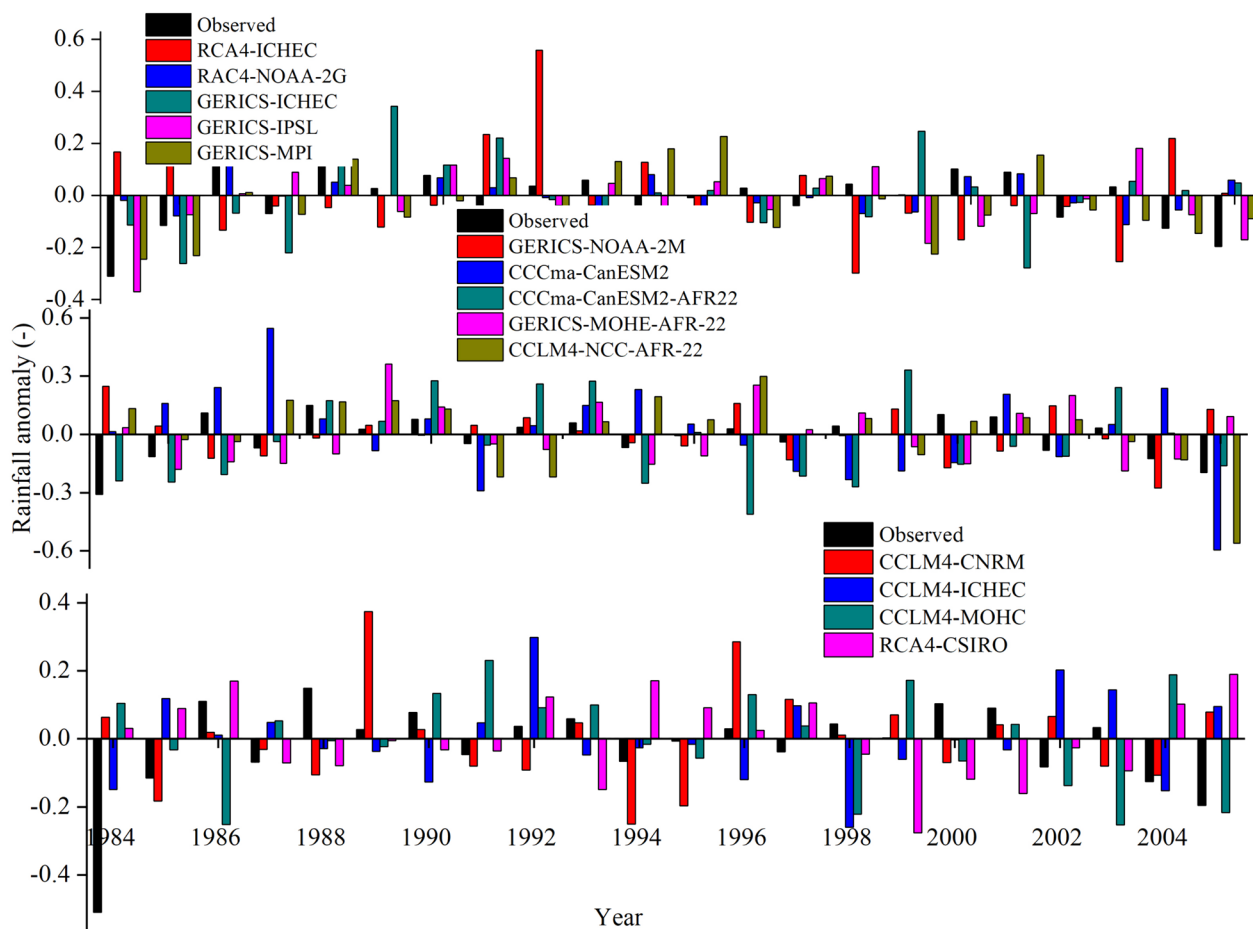
in terms of the mean, CV, and correlation coefficient than did the other climate models.

The results of the annual rainfall comparison of the RCM outputs are also similar to the findings of Alemseged, and Tom, (2015) on the evaluation of regional climate model simulations of rainfall over the Upper Blue Nile basin. According to the findings of Wakjira et al. (2021), the GERICS model performed best in terms of bias, CV and RMSE, which is similar to the findings of this study, as GERIC-MPI, which exhibited the best performance in annual rainfall comparisons. The result contradicts the findings proposed by Tumsa, (2021), who indicated that RACMO22T and RCA4 were better, performed at upper awash catchments. The reason behind the result was the performance of Regional climate models was different at different catchments along with the specified locations and topographies (Tumsa 2021). The performance of RCM models varies with catchment. According to Dibaba et al. (2019), Adugna and Sime (2021), and Amin et al. (2022), all RCMs are not equal when their performance varies within a localized study

area. This result also supported by Dibaba et al. (2019), Mutayoba and Kashaigili (2017), Abraham et al. (2018), Daniel (2023), Yonas et al. (2023), and Meaza et al. (2023), the performance of RCMs was varied on watershed, and location to location.

**Model performance on annual rainfall anomalies**

For the 22-year analysis period, 9 normal, 7 dry and 6 wet years for the Katar catchment were obtained during the analysis period, as shown in Fig. 8. In this analysis, historical climate extremes from 1984 to 2005 were used to assess whether the historical climate year was normal, dry, or wet relative to the reduced regional climate model outputs. A comparison of the three model outputs, which showed better performance in terms of annual rainfall, also showed good results in terms of capturing the occurrence of wet and dry years. The performance of RAC4-NOAA-2G was very good at minimum CV (8.70%),  $P_{BIAS}$  (11.55%) followed by CCLM4-NCC-AFR-22 (CV of 12.53%,  $P_{BIAS}$  of 7.53%) and GERICS-MPI (CV of 9.10%,  $P_{BIAS}$  of 7.50%). However, the RCM models such as



**Fig. 8** Rainfall anomalies in the Katar catchment



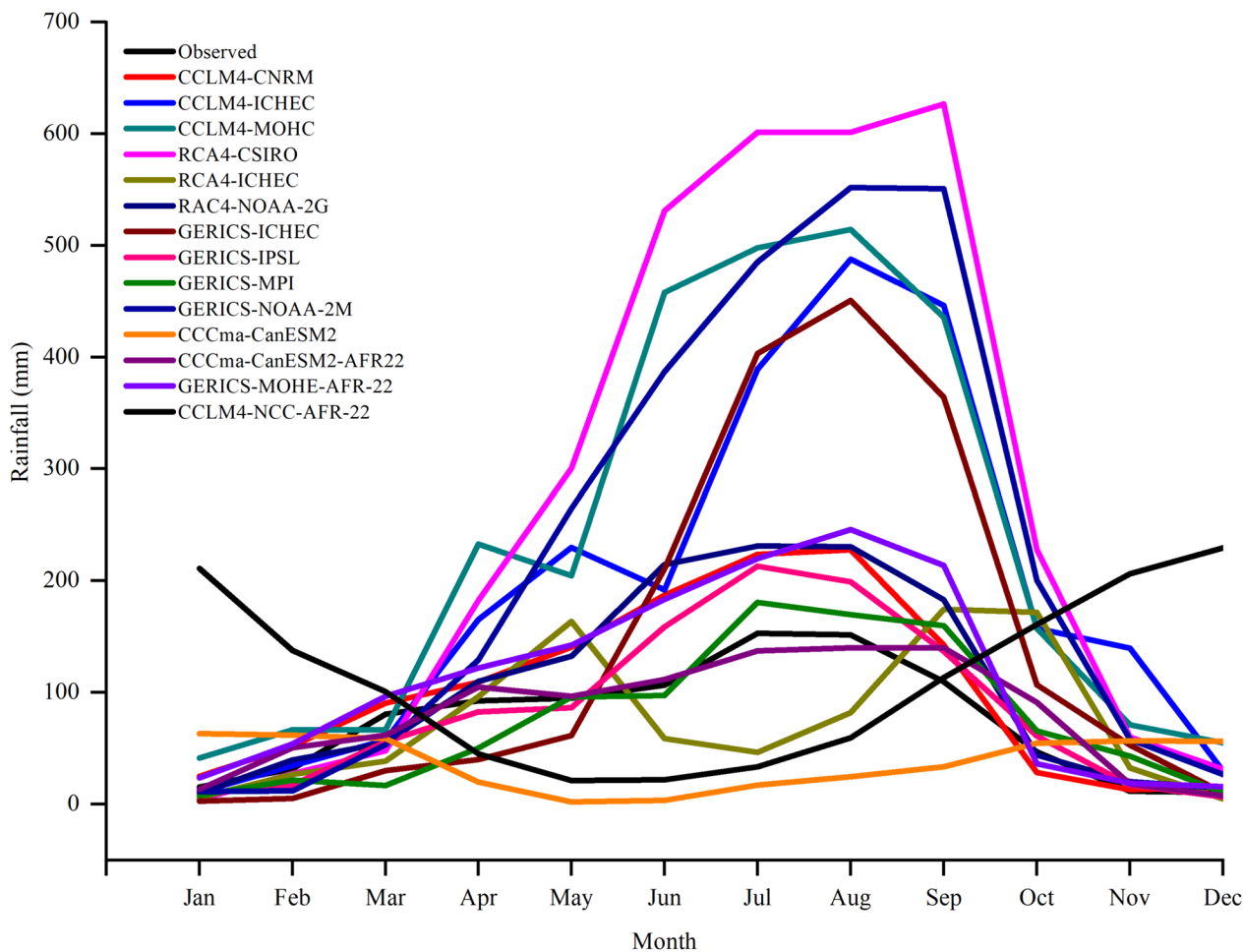
CCLM4-MOHC, HadGEM2-ES-AFR-22, and CCLM4-ICHEC performed poorly compared to the other RCM models. The RCM models of CCLM4-MOHC and CCLM4-ICHEC over estimates the annual rainfall with PBIAS of -49.97, -10.39% respectively. This result contradicts with the finding of Adugna and Sime (2021) and Girma et al. (2022), who evaluated the performance of different RCMs for temperature and precipitation in a river basin in Ethiopia and found that RACMO22T and HIRHAM5 performed well. This may be due to variation of topography, climate (Daniel 2023; Yonas 2022; Mengistu et al. 2021).

**Model performance for monthly rainfall**

The monthly rainfall distributions of the observed rainfall and climate model rainfall over the Katar catchment are shown in Fig. 9. Out of the 14 climate model outputs, two models (HadGM2-ES-AFR-22 and CCLM4-MOHC) failed to completely capture the monthly rainfall trend over the catchment area. CCLM4-MOHC and

CCLM4-ICHCE were unable to capture the annual rainfall pattern over the area for a rainy month. Three models, two from CORDEX-AFR-44 (GERICS-MPI and RAC4-NOAA-2G) and one from CORDEX-AFR-22 (CCLM4-NCCR-AFR-22), display strong monthly rainfall patterns but overestimate annual monthly rainfall. The observed data indicate a weak annual rainfall cycle. The monthly precipitation ranges across a small range of values (100 and 135 mm) between February and October. The catchment average is 29–50 mm per month for the majority of the months, with the lowest amount of rainfall occurring in December. Most climate models consistently overestimate the amount of monthly rainfall.

Based on the above results for CCLM4-CNRM, GERICS-IPSL shows poor performance according to the statistical comparison and thorough visual inspection of the monthly data and from the anomaly index graph. From the graph of the annual monthly rainfall cycle, the above climate models were constructed to capture the wet month and the dry month in the catchment, as



**Fig. 9** Annual monthly rainfall cycle in the Katar catchment

they fully underestimate the wet month rainfall and fully overestimate the dry month rainfall across the catchment. Except for GERICS-MPI, RAC4-NOAA-2G, and CCLM4-NCCR-AFR-22, all the other models highly overestimate the wet month rainfall. This result was in line with Meaza et al. (2023), who suggests Some models overestimated rainfall in dry months while underestimating it in wet months. It was better to use the three models for the Katar catchment that were chosen for any studies pertaining to climate change, employing a multimodal climate for climate impact studies to provide more reliable results, while using the above models for impact and adaptation studies yielded erroneous results. Based on the annual rainfall comparison, annual rainfall anomaly, and monthly rainfall cycle analysis, the three models exhibited the best performances compared with the other models; therefore, it is important to apply a multiclimatic model to the Katar catchment. Three climate models (GERICS-MPI, RAC4-NOAA-2G, and CCLM4-NCCR-AFR-22) were selected for Katar as representative climate models.

#### Model performances on annual mean temperature

A statistical summary of all the models' performances is presented in Table 8 and Figs. 10, 11. The ability of fourteen RCM-CORDEX climate models to simulate the observed minimum and maximum temperatures in the Katar watershed at a seasonal time scale was statistically evaluated using historical time series data from 1984 to 2005. All fifteen RCM-simulated models exhibited relatively better performances in simulating minimum and maximum seasonal temperatures than in simulating seasonal rainfall in the catchment. The GERICS-MPI model performed well. However, poor performance was observed at RCA4-ICHEC on maximum temperature, and GERICS-NOAA-2M on minimum temperature in Katar watershed.

The four RCM models exhibited the largest biases, which were greater than 20%. The three selected models (GERICS-MPI, RAC4-NOAA-2G, and CCLM4-NCCR-AFR22) performed better at correlation coefficient ( $R^2$ ) values, indicating the reproduction of the maximum and minimum seasonal temperatures. The three models also exhibited a small bias of less than  $\pm 5\%$ , which indicated that the model exhibited a perfect fit. According to the annual maximum and minimum temperature comparisons, the bias in the minimum temperature was less than the bias in the maximum temperature for all the down-scaled climate model outputs. Only two models (GERICS-IPSL and GERICS-NOAA-2M) overestimate the catchment annual maximum temperature, and the rest of the models underestimate it slightly. Many studies have also indicated that climate models may overestimate

or underestimate the observed maximum temperature (Demissie et al. 2016). This is likely because rainfall and temperature vary spatially with elevation among the considered meteorological stations. This implies that the best-performing RCMs vary within the study basin; thus, site-specific evaluation of RCMs is indispensable (Mengistu et al. 2021).

#### Model performances on the mean monthly temperature

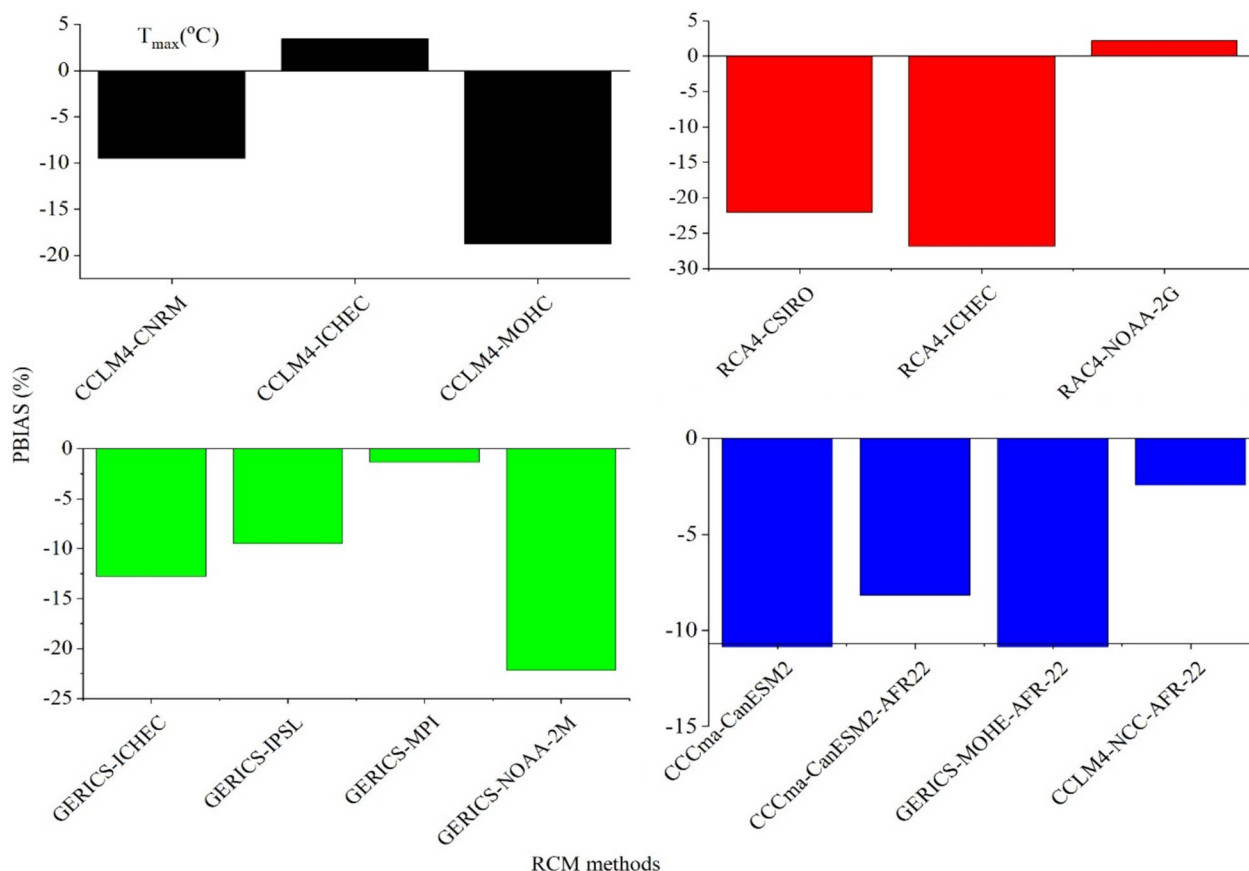
A graph of the mean maximum monthly temperature of the observed and simulated RCM models is shown in Fig. 12. Most of these simulations have not been able to capture the maximum and minimum mean monthly temperatures. Six models completely underestimate the mean monthly temperature in the catchment area. RAC4-ICHEC reveals the worst trend in the simulation of the average monthly high temperature. Moreover, the GERICS-MPI, RAC4-NOAA-2G, and CCLM4-NCCR-AFR-22 models exhibited better efficiency; thus, these three models could be used for climate effect studies in the Katar catchment area. For the mean monthly temperature, the GERICS-MPI, RAC4-NOAA-2G, and CCLM4-NCCR-AFR-22 models also exhibited better performances than did the other models.

#### Conclusion

In this study, the performance of the CORDEX Africa RCM in reproducing rainfall and temperature was evaluated using observed data as a reference for the baseline period from 1980 to 2005. The performance of the RCM was found variable at both spatial and temporal scales. The findings indicated that GERICS-MPI was better performed in representing Areta, and Bokoji station, GERICS-IPSL was better representing in Assela, Katergenet, and Sagure station, CCCma-CanESM2-AFR22, and RCA4-ICHEC performed relatively better in representing the mean annual observed rainfall at the Kulumsa, and Ogolcho station respectively. The performance of RCM models varied at each station. However, RCA4-CSIRO performed weakly in estimation of annual rainfall at all stations. Most of the RCM models overestimated the annual rainfall with bias of  $-0.23$  mm to  $-2.21$  mm except RAC4-NOAA-2G, GERICS-MPI, and CCCma-CanESM2-AFR22 at Areta station with bias of 1.55, 0.06, and 0.74 mm respectively. Similarly most of the models overestimated the annual rainfall except CCLM4-ICHEC, CCLM4-MOHC, RAC4-NOAA-2G, CCCma-CanESM2-AFR22, GERICS-MOHE-AFR-22, CCLM4-NCCR-AFR-22 with bias of 0.53% to 0.83% at Assela station. Models such as RAC4-NOAA-2G, CCCma-CanESM2, GERICS-MOHE-AFR-22, and CCLM4-NCCR-AFR-22 with bias of 0.08 mm to 0.63 mm at Bokoji, RCA4-ICHEC, GERICS-IPSL, and CCCma-CanESM2 with

**Table 8** Model performance for annual minimum and maximum temperatures

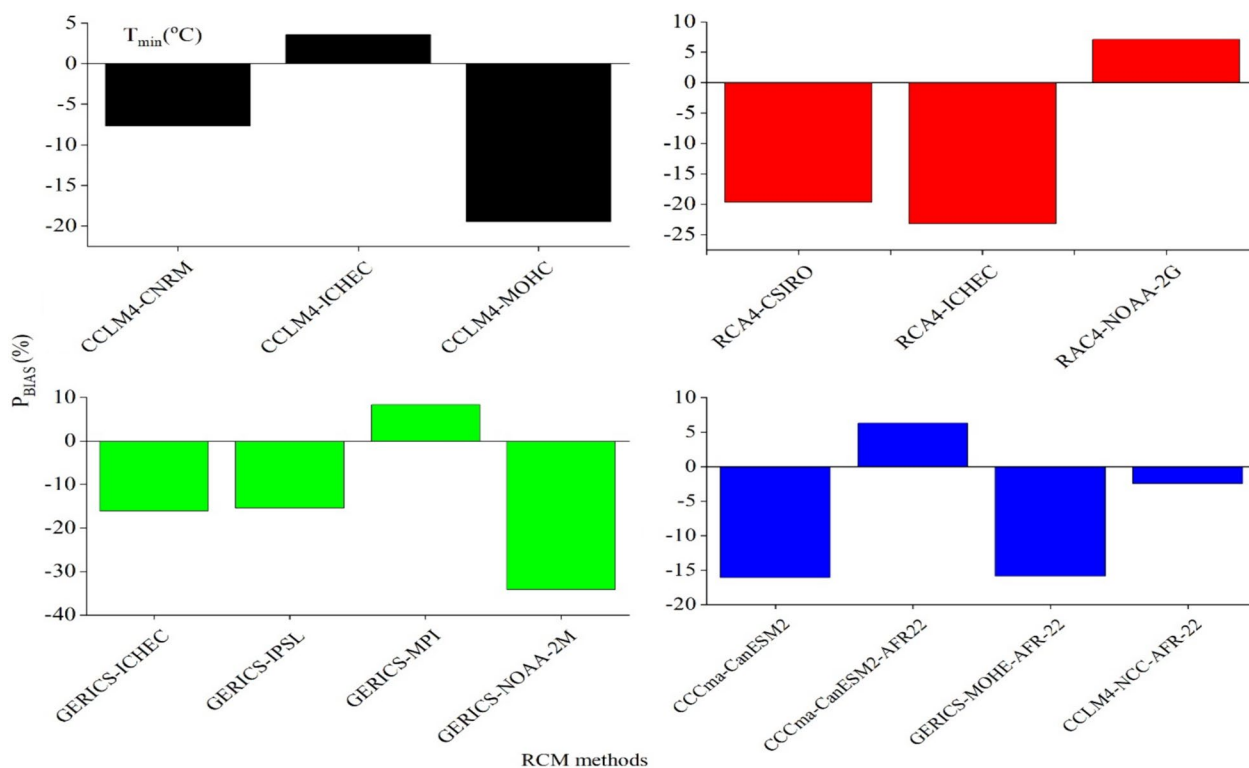
Model	Tmax						Tmin					
	Mean (mm)	R	MAE(°C)	RMSE MAE(°C)	P <sub>BIAS</sub> (%)	Rank	Mean (mm)	R	MAE(°C)	RMSE MAE(°C)	P <sub>BIAS</sub> (%)	Rank
	Observed	24.96	–	–	–	–	–	10.89	–	–	–	–
CCLM4-CNRM	22.59	0.76	2.37	2.46	–9.50	6	11.57	0.76	0.90	1.08	–7.66	6
CCLM4-ICHEC	25.82	0.81	1.00	1.17	3.45	4	11.27	0.88	0.66	0.88	3.53	4
CCLM4-MOHC	20.29	0.66	5.08	5.36	–18.73	11	8.76	0.67	2.12	2.23	–19.49	11
RCA4-CSIRO	19.46	0.66	5.50	5.54	–22.05	12	8.75	0.66	2.14	2.28	–19.66	12
RCA4-ICHEC	18.27	0.62	6.69	6.72	–26.82	14	8.36	0.61	2.52	2.62	–23.19	13
RAC4-NOAA-2G	25.5	0.86	2.37	2.46	2.17	2	11.66	0.89	0.87	1.04	7.07	2
GERICS-ICHEC	21.77	0.68	3.19	3.24	–12.77	10	9.14	0.68	7.15	1.93	–16.06	9
GERICS-IPSL	22.59	0.76	0.80	1.00	–9.50	6	9.21	0.76	0.68	0.86	–15.43	7
GERICS-MPI	24.63	0.90	0.61	0.81	–1.34	1	11.80	0.93	1.05	1.28	8.40	1
GERICS-NOAA-2 M	19.42	0.53	5.54	5.57	–22.21	13	7.42	0.55	6.46	6.43	–34.21	14
CCCma-CanESM2	22.25	0.74	2.71	2.78	–10.86	8	9.14	0.68	1.79	1.93	–16.06	9
CCCma-CanESM2-AFR22	22.92	0.79	2.04	2.14	–8.17	5	10.62	0.86	0.59	0.74	6.30	5
GERICS-MOHE-AFR-22	22.25	0.74	2.71	2.78	–10.86	8	9.16	0.76	0.97	1.91	–15.85	8
CCLM4-NCC-AFR-22	24.35	0.82	1.30	1.52	–2.44	3	10.05	0.89	0.66	1.11	–2.42	3



**Fig. 10** Performance of RCMs in simulating annual maximum temperature in Katar watershed

bias of 0.52 mm to 1.71 mm at Ketergenet station, and 0.33 mm to 0.88 mm at Kulumsa station, RCA4-ICHEC (bias=0.06 mm), CCCma-CanESM2 (bias=0.21 mm) at Ogolcho station, RCA4-NOAA-2G, GERICS-IPSL, GERICS-MPI, CCCma-CanESM2, and CCCma-CanESM2-AFR22 with bias of 0.14 mm to 0.29 mm at Sagure station under estimate the annual rainfall rather than the other RCM models. RCM model such as GERICS-MPI was relatively better than the others in replicating the annual pattern of the maximum temperature at Areta, Bokoji, and Ketergenet stations. Similarly, GERICS-IPSL were relatively better in replicating the annual maximum temperature at Assela, and Sagure stations, CCCma-CanESM2-AFR22 at Kulumsa station, and RCA4-ICHEC at Ogolcho station performed well in capturing the observed and simulated annual maximum temperature. Generally, the performance of GERICS-MPI, and GERICS-IPSL were better in capturing annual temperature

in most stations. Most models except RCA4-NOAA-2G, GERICS-IPSL, CCCma-CanESM2-AFR22 at Areta, CCLM4-ICHEC, CCLM4-MOHC, RCA4-NOAA-2G, CCCma-CanESM2-AFR22, GERICS-MOHE-AFR-22, and CCLM4-NCC-AFR-22 at Assela, GERICS-MPI at Bokoji, RCA4-ICHEC, RCA4-NOAA-2G, GERICS-MPI, CCCma-CanESM2, GERICS-MOHE-AFR-22, and CCLM4-NCC-AFR-22 at Ketergenet, RCA4-ICHEC, GERICS-IPSL and CCCma-CanESM2 at Kulumsa, RCA4-ICHEC and CCCma-CanESM2 at Ogolcho, RCA4-NOAA-2G, GERICS-IPSL, and GERICS-MPI at Sagure station overestimate the annual maximum temperature. The minimum MAE value were 0.06 observed at CCCma-CanESM2-AFR22 of Areta station, 0.97 (°C) at CCCma-CanESM2-AFR22 of Assela station, 0.45 (°C) at GERICS-IPSL, and GERICS-MOHE-AFR-22 of Bokoji station, 0.02 (°C) of CCCma-CanESM2-AFR22 of Ketergenet station, 0.13 (°C) of GERICS-MPI of Kulumsa



**Fig. 11** Performance of RCMs in simulating annual minimum temperature in Katar watershed

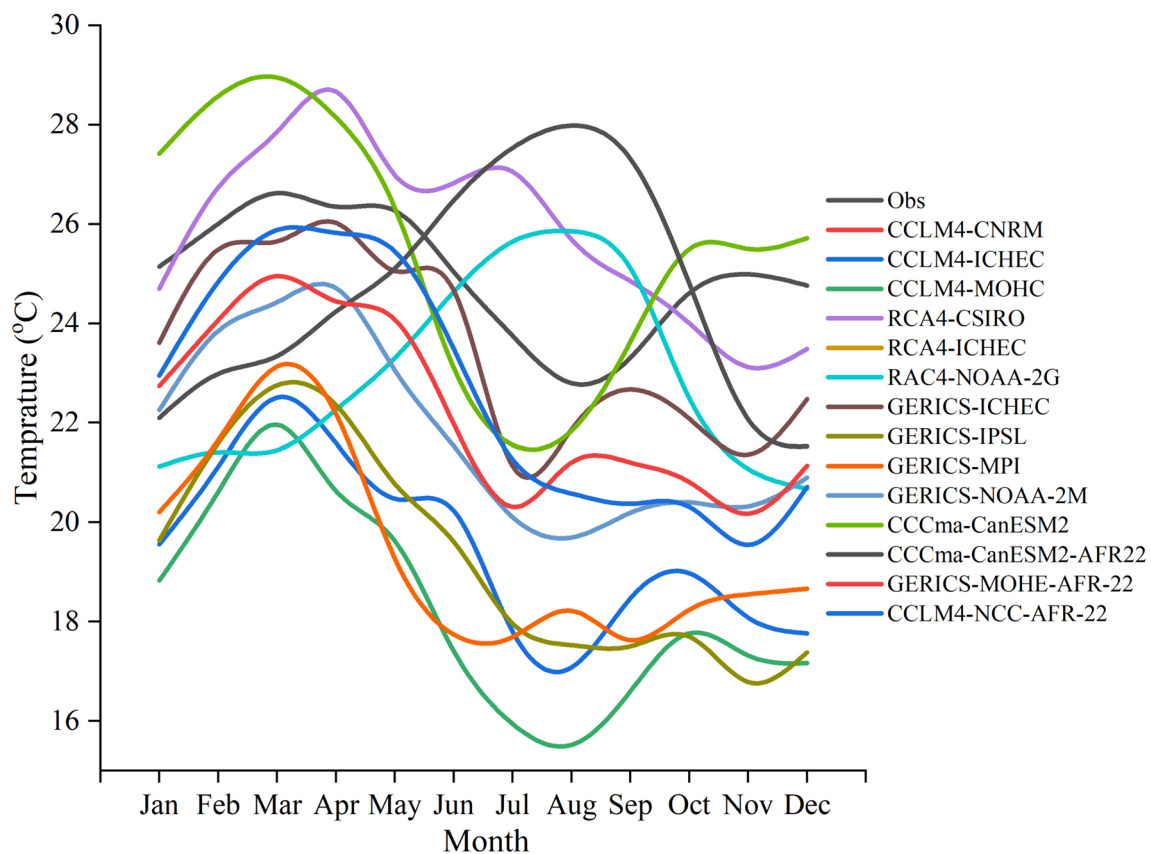
station, 0.08 (°C) of GERICS-MPI at Ogolcho station, and 0.47 (°C) at RAC4-NOAA-2G of Sagure station. The minimum RMSE were also in the respective MAE values. Whereas, the maximum MAE and RMSE were observed at RCA4-CSIRO at all station of the Katar Sub stations. The performance of the RCM models was also varied in stations. RCM models of GERICS-MPI, and CCLM4-NCC-AFR-22 performed better than the other RCM models for correction of annual rainfall in Katar watershed. However, poor performance was observed at RCA4-ICHEC model on Katar watershed. The GERICS-MPI model performed well. However, poor performance was observed at RCA4-ICHEC on maximum temperature, and GERICS-NOAA-2M on minimum temperature in Katar watershed. The models had different performance in different statistical metrics in different catchments of Katar sub stations.

The study examines the effects of climate change on groundwater and surface water resources, agricultural production, soil loss estimation, reservoir operation,

and hydropower production. Furthermore, it promotes the development of a reliable climate service evaluation, enabling well-informed decisions for climate adaptation. Ultimately, these endeavours aim to maximize the benefits of addressing climate change impacts. The variability in RCM performance underscores the importance of bias adjustments in RCM simulation results before utilizing them for climate change impact and adaptation studies.

RCMs have their own inherent biases and uncertainties, which could affect the accuracy of the evaluation. Another limitation is the focus on a specific watershed, which may not be representative of broader regional or global climate trends. Moreover, the study may lack consideration of other important factors such as land use changes, socioeconomic dynamics, and adaptation measures, which could influence the performance of climate models. Finally, the study may not account for future climate scenarios and projections, limiting its applicability for long-term planning and adaptation strategies.





**Fig. 12** Monthly cycle of observed and RCM-simulated mean maximum temperatures

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#### Author contributions

Babur Tesfaye Yersaw conceived the Conceptualization, Methodology, Data Collection and Analysis. Babur Tesfaye Yersaw, Mulusew Bezabih Chane, and Natnael Andualem Yitayew participated on model Implementation, Result Interpretation, participated on Writing—Original Draft Preparation, and Writing—Review and Editing.

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#### Availability of data and materials

The datasets used and analyzed during the current study are available from the corresponding author on reasonable request.

#### Declarations

#### Ethics approval and consent to participate

Not applicable.

#### Competing interests

The authors declare no competing interests.

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