



Research article

Assessment of the performance of CORDEX regional climate models in simulating rainfall and air temperature over southwest Ethiopia

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ABSTRACT

This study analyzed the performance of four (REgional Model (REMO2009), High-Resolution Hamburg Climate Model 5 (HIRAM5), Climate Limited-Area Modeling Community (CCLM4-8) and Rossby Centre Regional Atmospheric Model (RCA4)) Regional Climate Models (RCMs) simulations from Coordinated Regional Climate Downscaling Experiment (CORDEX) Africa program. The simulation period of 1985–2005 was evaluated considering how each RCM simulated the observed rainfall and air temperature over southwest Ethiopia. It was found that all the RCMs simulated the seasonal rainfall, but not the peak rainfall, with all models including their ensemble underestimating the peak rainfall. However, the ensemble was better than the individual RCMs in simulating both rainfall and air temperature. All models were slightly biased around a warm climate zone in simulating maximum air temperature when compared to the simulation of air minimum temperature. Of the four RCMs, REMO2009 performed well in simulating the maximum and minimum air temperatures. The interseasonal variation in rainfall was greater than the seasonal variation in air temperature. In terms of cumulative distribution, the HIRAM5 captured more extreme rainfall events and overestimated the return period. Overall, the differences in performance among the RCMs provided strong evidence for the use of regional-scale data at the local scale in climate impact assessments being controversial. In relation to the spatial pattern of the rainfall, most of the models simulated the observed minimum rainfall in the north and northeast, medium rainfall in the central region, and maximum rainfall in the south and southwest of the study area. The overall results indicate that choosing a reliable RCM is fundamentally necessary to delivering a strong basis for any climate-change impact study.

1. Introduction

The impacts of climate change are becoming severe in developing countries due to their low adaptive capacity (Dessalegn and Akalu, 2015; Warnatzsch and Reay, 2019; Asfaw et al., 2021). An increase in air temperature and variations in the rainfall are threatening agriculture, water security and socioeconomic development in Africa. Agricultural expansion, in tandem with poor watershed management practices, is further aggravating the impacts of climate change in the region (Francisco and Camargo, 2020). In Africa, Sub-Saharan countries are the most vulnerable to the intensifying impacts of climate change (Kotir, 2010; Kula et al., 2013; Adenuga et al., 2021).

In the Ethiopian economy, agriculture accounts for around 45% of the gross domestic product, 60% of the foreign exchange, and is a food source for 85% of the population (Ministry of Finance and Economic Development, 2010). However, 90% of the agricultural productivity

depends on rainfall (Araya et al., 2010). Variability in the rainfall and air temperature are having a significant impact on the agricultural sector (Asseng et al., 2014). The agricultural production system is simplistic and extremely susceptible to climatic variation, with the country regularly being exposed to famine (Seleshi and Zanke, 2004; Moges, 2013). For example, in Ethiopia in the mid-1980s, as a result of climate change, a drought in the northern part of the country caused significant loss of animal and human life (Gray and Mueller, 2012).

Some developed countries, such as the United Kingdom and Canada, have developed nation-specific tools for examining local-scale climate change impacts (Warnatzsch and Reay, 2019). However, African countries have no such tools. To address this omission, and to effectively quantify the impacts of climate change at the local scale, it is necessary to select appropriate regional climate models (RCMs). General Circulation Models (GCM) have been used since 1950 by different climate research institutes for projecting future climate for the entire globe. However,

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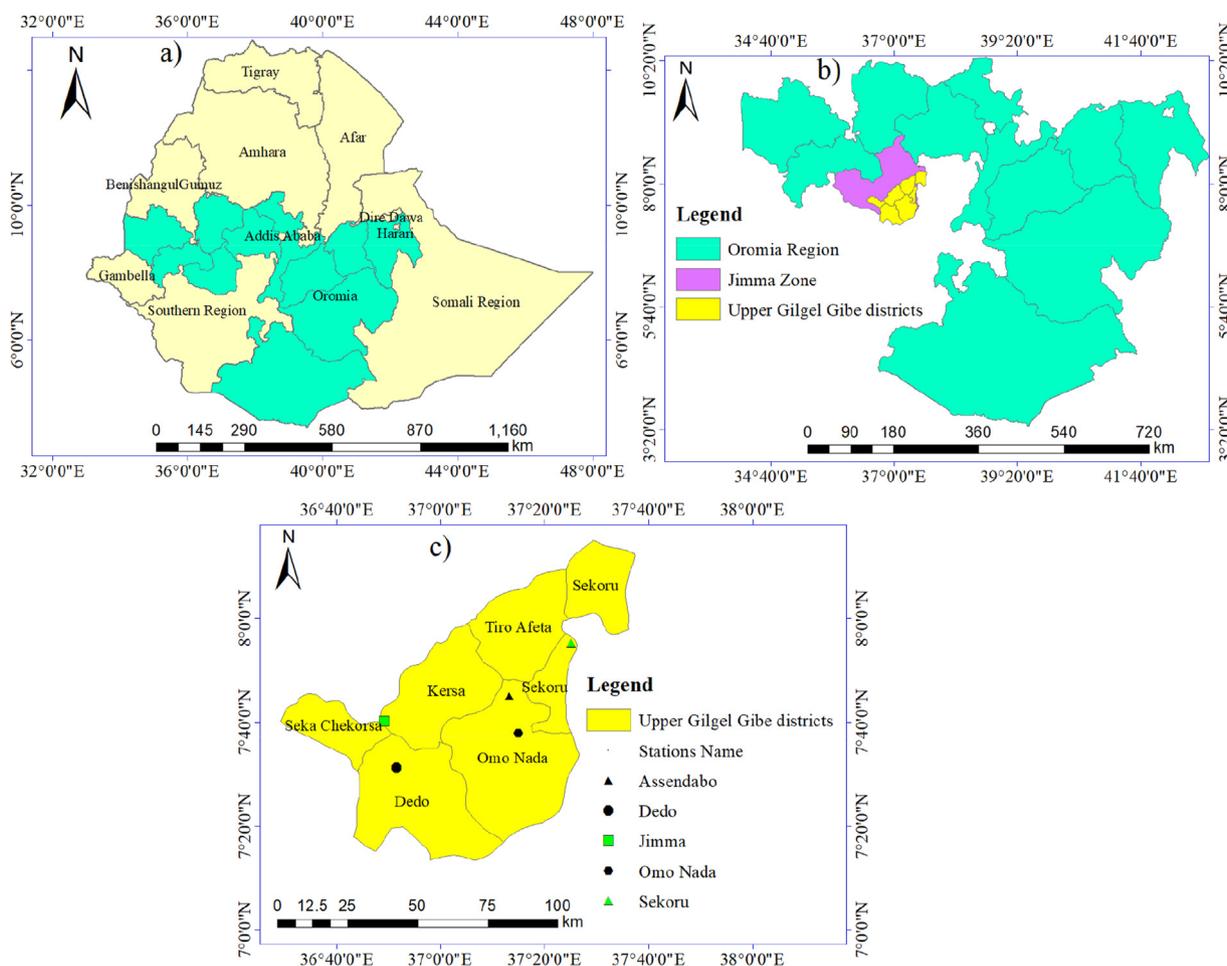


Figure 1. (a) The Ethiopian regional states, (b) Oromia regional state and Jimma zone, (c) the upper Gilgel Gibe districts and the meteorological stations.

Table 1. Statistical indices in mean annual rainfall simulation.

Stations	Performance Statistic	RCMs				
		RCA4	REMO2009	HIRHAM5	CCLM4-8	Ensemble
Asendabo	RMSE	1.39	0.97	0.89	0.88	0.77
	PBIAS	24.41	-10.53	-4.02	-5.96	0.98
	r	-0.07	-0.14	-0.34	-0.20	-0.31
Jimma	RMSE	1.02	1.55	1.72	1.23	1.05
	PBIAS	5.12	-17.41	-22.96	4.27	-7.75
	r	-0.12	-0.11	0.35	-0.26	-0.10
Dedo	RMSE	0.87	1.20	1.71	0.96	0.96
	PBIAS	2.75	-0.13	-27.96	-3.38	-7.18
	r	0.29	-0.09	-0.24	-0.01	-0.02
Omo Nada	RMSE	1.11	1.33	1.35	1.36	1.04
	PBIAS	6.95	-16.98	-19.01	-8.66	-9.43
	r	-0.19	-0.05	-0.19	-0.05	-0.24
Sekoru	RMSE	0.66	1.28	0.68	0.77	0.61
	PBIAS	0.97	-29.94	-0.15	0.66	-7.13
	r	-0.10	0.24	0.03	-0.07	0.02

these have limitations when projecting climate change at the local scale owing to their low spatial resolution (Giorgi et al., 2009; Dibaba et al., 2019). Thus, the World Climate Research Program (WCRP) introduced the Coordinated Regional Climate Downscaling Experiment (CORDEX) initiative in 2009 to provide a harmonised framework for assessing and refining Regional Climate Downscaling (RCD) methods. CORDEX

provides local-scale information for the climate-modelling community and climate-information end-users (Nikulin et al., 2012; Hernández-Díaz et al., 2012; Gutowski et al., 2016). CORDEX Africa is a CORDEX domain, experimentally developed specifically for climate impact studies over Africa. It was designed using multiple RCMs to provide rationalised, predictable variations in local climates and to evaluate any basis for

Table 2. Statistical indices in mean annual maximum air temperature simulation.

Stations	Performance Statistic	RCMs				
		RCA4	REMO2009	HIRHAM5	CCLM4-8	Ensemble
Asendabo	RMSE	4.43	2.20	4.74	7.98	4.82
	PBIAS	-4.39	-2.09	-4.72	-7.96	-4.79
	r	0.03	-0.03	0.39	0.05	0.12
Jimma	RMSE	6.63	4.29	6.81	9.05	6.68
	PBIAS	-6.60	-4.21	-6.78	-9.01	-6.65
	r	0.30	-0.07	0.43	-0.11	0.16
Dedo	RMSE	0.95	2.47	1.00	2.273	0.93
	PBIAS	-0.21	2.22	-0.59	-2.03	-0.15
	r	0.13	-0.13	0.38	-0.094	0.06
Omo Nada	RMSE	4.26	1.82	4.72	6.33	4.22
	PBIAS	-4.08	-1.29	-4.54	-6.19	-4.02
	r	0.33	0.24	0.18	0.12	0.28
Sekoru	RMSE	3.96	2.48	5.09	6.55	4.49
	PBIAS	-5.04	-2.23	-5.04	-6.47	-4.40
	r	-0.33	-0.60	0.23	-0.49	-0.45

Table 3. Statistical indices in mean annual minimum air temperature simulation.

Stations	Performance Statistic	RCMs				
		RCA4	REMO2009	HIRHAM5	CCLM4-8	Ensemble
Asendabo	RMSE	0.64	0.85	1.72	1.30	0.89
	PBIAS	-0.00	-0.34	1.57	1.10	0.54
	r	0.56	0.14	0.45	0.41	0.52
Jimma	RMSE	0.61	0.58	1.58	1.51	0.95
	PBIAS	0.33	0.00	1.46	1.463	0.81
	r	0.49	0.20	0.17	0.46	0.45
Dedo	RMSE	2.98	2.35	3.79	4.26	3.297
	PBIAS	2.47	1.55	3.44	3.90	2.84
	r	0.08	-0.30	0.27	-0.07	-0.002
Omo Nada	RMSE	1.40	1.82	2.54	2.66	2.09
	PBIAS	1.31	1.75	2.49	2.63	2.04
	r	0.40	0.20	0.14	0.44	0.38
Sekoru	RMSE	0.83	1.72	0.81	0.98	0.70
	PBIAS	-0.43	-1.6	0.28	0.75	-0.25
	r	0.14	0.32	-0.16	0.32	0.20

uncertainty in the projection (Kim et al., 2013). To deliver adequate information on climate adaptation, climate-change projection, at high spatial and temporal resolutions, are essential at the local scale. RCMs are being used to examine projections of the climate at the local level (Laprise et al., 2013). Previous studies have shown that RCMs simulate the most reliable annual and seasonal rainfall and air temperature estimations, and are also preferable in analysing extreme rainfall distributions and frequency (Dosio et al., 2014; Worku et al., 2018).

The RCMs covering East Africa such as REgional MOdel (REMO2009), High-Resolution Hamburg Climate Model 5 (HIRHAM5), Ross by Centre Regional Atmospheric Model (RCA4), and Climate Limited-Area Modeling Community (CCLM4-8) and Canadian Regional Climate Model (CanRCM4-8), Regional atmospheric climate model version 2.2 (RECMO22T) have performed well in simulating air temperature, but poorly in simulating precipitation (Warnatzsch and Reay, 2019). A study by Mutayoba and Kashaigili (2017) on Africa indicated that the ensemble fit the observed data better than the single RCMs. Some studies on Ethiopia have indicated that the RCMs show bias at higher elevations, but work well for low-elevation regions (Workua et al., 2018; Dibaba et al., 2019; van Vooren et al., 2019). Most of the previous studies on Ethiopia have concentrated on climate-change vulnerability and mitigation measures (Eshetu et al., 2020; Etana et al., 2020). Some

studies that have focused on the impact of climate change using single RCMs should perhaps re-assess these based on multiple model ensemble. According to Endris et al. (2013), Mutayoba and Kashaigili (2017) and Dibaba et al. (2019), all RCMs are not equal when it comes to their performance in a localised study area. RCMs that achieve good results in some areas may fail in other places. Hence, in order to select the appropriate RCMs for a specific location, evaluating the performance of multiple available RCMs is necessary.

The aim of this study was to evaluate how well the CORDEX Africa RCMs simulate the rainfall and air temperature over southwest Ethiopia. Our main intention was not to evaluate *all* available RCMs, but to evaluate selected RCMs that have been frequently used in climate-impact studies over East Africa at the local-scale level. The selected RCM were evaluated on the basis of annual and seasonal temperatures and rainfall. In addition, we developed a spatial rainfall distribution for the study area, considered the cumulative distribution of the areal extreme rainfall, and analysed the extreme rainfall frequency. The analysis and inter-comparison of the individual RCMs and their ensemble will help us to better understand how the RCMs perform in areas with complex topography, as is the case in southwest Ethiopia. This is an important step in any climate-impact assessment, as the uncertainties in RCMs are characterised.

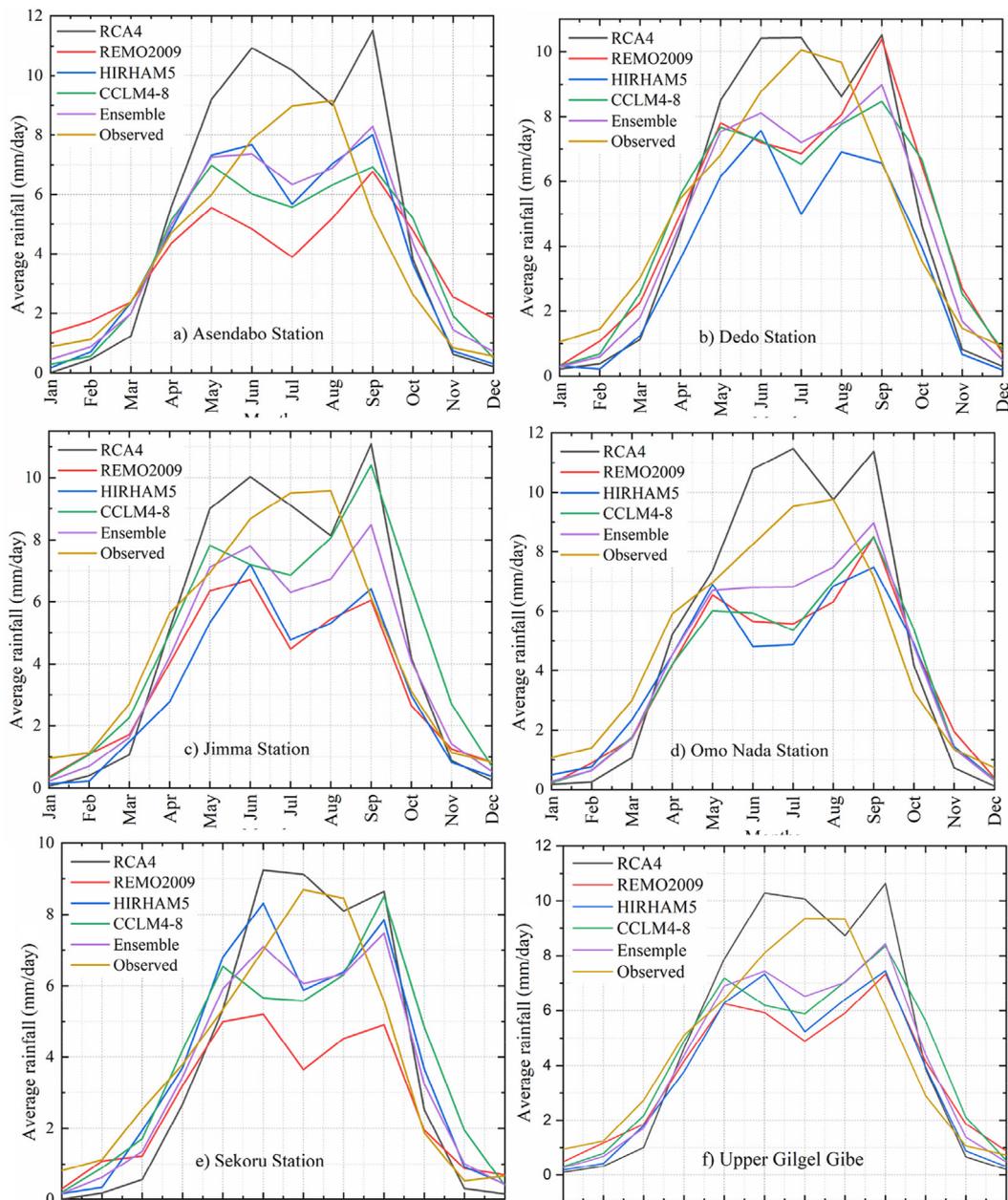


Figure 2. Mean monthly cycle of rainfall.

2. Materials and methods

2.1. Description of the study area

This study was conducted to cover the upper Gilgel Gibe districts in the Jimma zone of the regional state of Oromia, southwest Ethiopia. These districts are bordered to the south by the Southern Nations, Nationalities and Peoples' Region, to the north by the western Welega zone, to the northwest by the Illubabor zone and to the northeast by the West Shewa zone. The upper Gilgel Gibe districts include Dedo, Kersa, Omo Nada, Tiro Afata, Seka Chekorsa and Sekoru, which have an area of about 6448 km². Figure 1 (a) shows the Federal Democratic Republic of Ethiopia Regional states. Figure 1 (b) shows the Oromia Regional State and Jimma Zone. Figure 1 (c) shows the upper Gilgel Gibe Districts and the selected meteorological stations.

2.2. Climate of the study area

Ethiopia has a wide diversity of landscapes, with notable differences in relief and elevations ranging from 155 m to 3354 m. This exposes the country to a wide variation in air temperature and rainfall. The climate of Ethiopia is predominantly controlled by the multifaceted landscape of the country and seasonal variations in the Intertropical Convergence Zone (Fazzini et al., 2015). The study area receives annual rainfall of between 1107.83 and 2428.80 mm, while the average air temperature is in the range of 28.00 to 8.50 °C.

2.3. Observed data

In Ethiopia, there are no long meteorological time-series data available, although the country did expand the number of meteorological stations following the drought of the mid-1980s. Therefore, for this

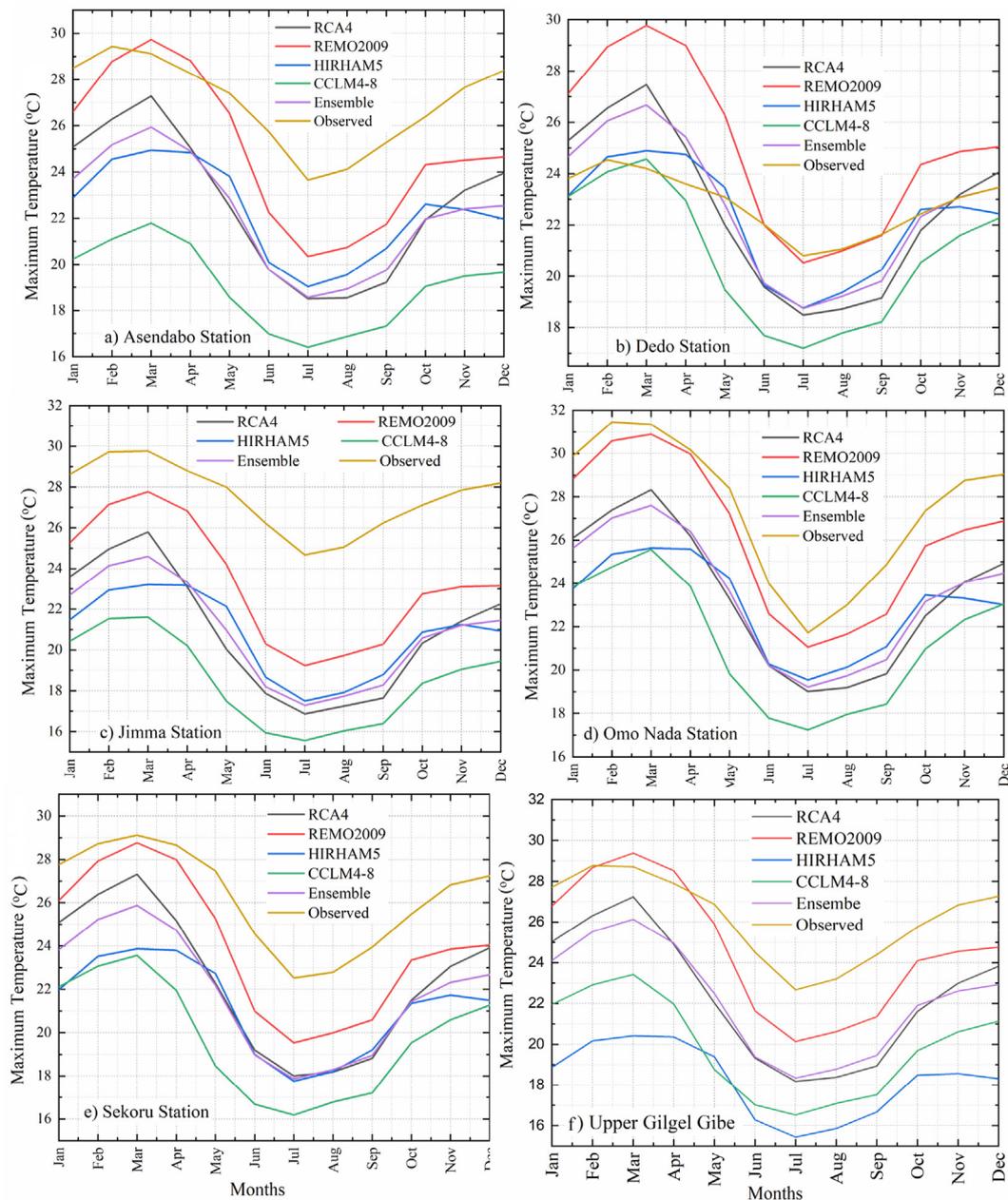


Figure 3. Mean monthly cycle of maximum air temperature.

study, daily air temperature and rainfall data obtained from the National Meteorological Service Agency of Ethiopia were used, which cover the 21 years from 1985 to 2005. Five meteorological stations Jimma, Asendabo, Sekoru, Dedo and Omo Nada were considered in order to adequately represent the study area. The continuity of a record may be broken with missing data due to the absence of the observer and failed instrument. Therefore, it is necessary to estimate and complete the missing data before using for hydrological analysis. The specific technique to fill the missing data is called data imputation. The choice of the methods is based on percentage of data missed and choice of neighboring stations. When the amount of the data filled are less than 5%, linear regression can be used by identifying the relationship between the observed data of neighboring stations and that of reference station (Aieb et al., 2019). In this study, the recorded data had missed values randomly and the percentage of the missing data were less than 4%. Hence linear regression was used to fill the missing rainfall data while simple average method was used to fill the temperature data. Missing data were filled in using XLSTAT 2018 software. It is statistical software which have been used for

examining relationships of multiple variables simultaneously (Vidal et al., 2020).

Homogeneity tests allow checking the quality and reliability of the data. In this study, the data homogeneity was checked using Standard Normal Homogeneity Test (SNHT). This method has been used to identify a variation in a time series of rainfall data by comparing the mean of the first k years of the record with the last $n-k$ years (Elzeiny et al., 2019; Agha et al., 2017). The homogeneity of the data was checked using the standard homogeneity test in XLSTAT, with the data from all of the considered stations being found to be homogeneous.

2.4. Regional climate models (RCMs) data

The RCMs simulated daily rainfall and air temperature for the period 1985–2005 were taken from the CORDEX forced by Irish Centre for High-End Computing Ireland European Centre Earth global climate model system (ICHEC-EC-EARTH). It is CORDEX project under Africa domain with spatial resolution of $0.440^{\circ} \times 0.44^{\circ}$. The selected CORDEX Africa

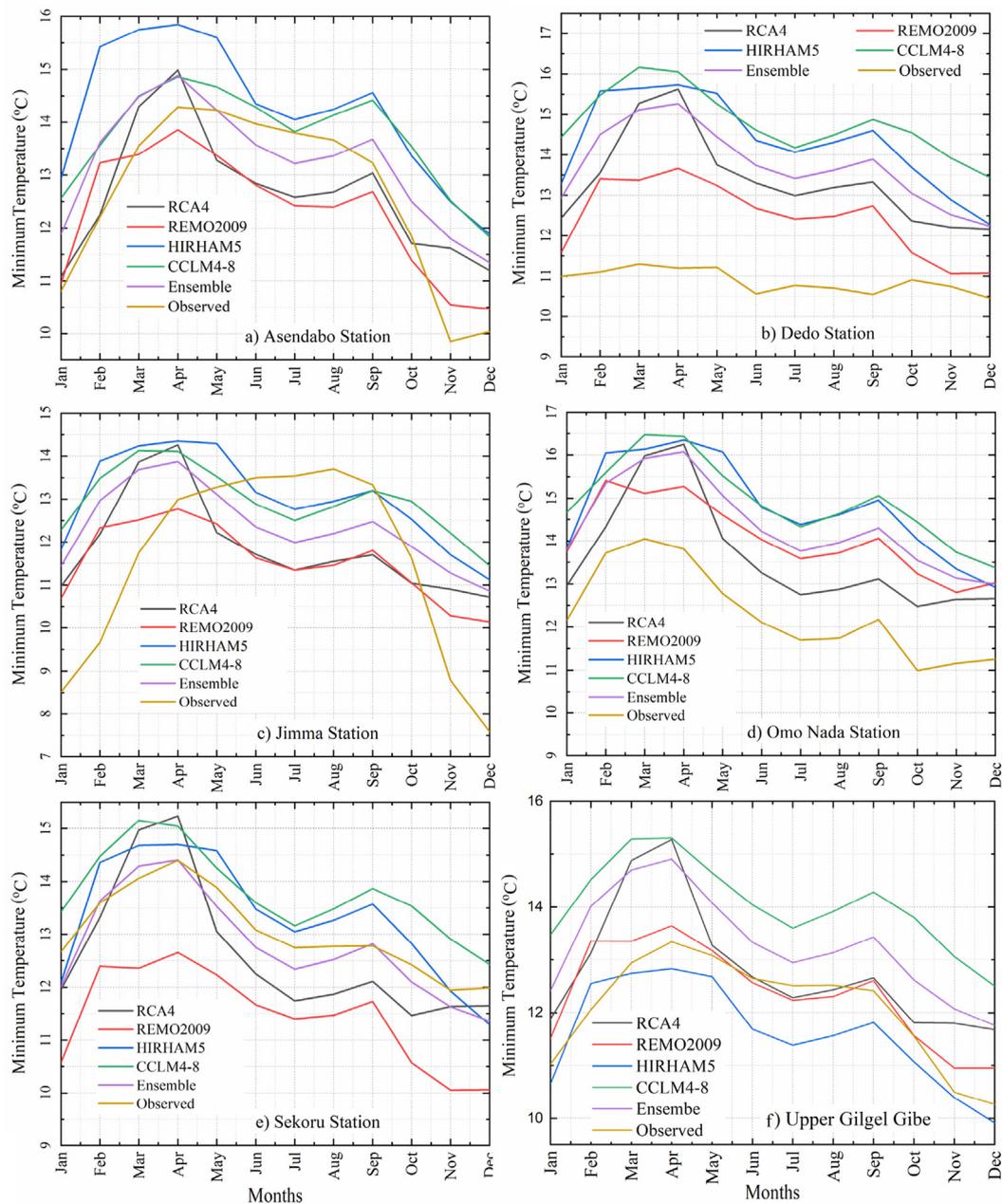


Figure 4. Mean monthly cycle of minimum air temperature.

domains, RCMs included the HIRHAM5, REMO2009, RCA4, and CCLM4-8. The simulated historical period is available from 1950 to 2005. These models have been evaluated in multiple studies on Africa, and have been found to perform well in simulating rainfall and air temperature (Worku et al., 2018; Dibaba et al., 2019). For the upper Gilgel Gibe districts of southwest Ethiopia, the performance of the CORDEX Africa domains has not previously been evaluated using different RCMs. The RCM rainfall and air temperature data were downloaded from a public website, with the required data for each station being extracted using the latitude and longitude of the station in ArcGIS.

2.5. Methodology

2.5.1. Model performance criteria

The systematic and dynamic behaviour of the models was visualised by plotting the simulated and observed data on the same coordinate system. All of the models were not equally able to simulate the climate data because it is influenced by factors such as land features. To assess the

performance of the RCMs in simulating mean annual precipitation and air temperature, the mean Percentage of Bias (PBIAS), the Root Means Square Error (RMSE) and Pearson's correlation (r) have been commonly used in multiple studies (Ongoma et al., 2018; Dibaba et al., 2019; Mendez et al., 2020).

2.5.2. Variations in rainfall and air temperature

The coefficient of variation (CV) was used to analyse the seasonal and annual variations in the rainfall data. The higher the CV value, the more variable the data, with values less than 20 indicating low variability, values between 20 and 30 showing moderate variability, and values greater than 30 indicating high variability in the recorded data (Mekonen and Berlie, 2019).

2.5.3. Spatial analysis of the rainfall data

The spatial pattern of the rainfall was obtained by interpolating rainfall of the five stations using the inverse distance weight (IDW). This is a suitable method for interpolating average rainfall using latitude,

Table 4. Coefficient of variation (CV) for the seasonal and annual rainfall and air temperature.

Climate Parameters	Seasons	CCLM4-8	HIRHAM5	REMO2009	RCA4	Ensemble	Observed
Rainfall	Spring	13.35	13.28	15.68	20.07	11.16	16.48
	Summer	15.65	12.06	17.94	8.70	7.72	18.38
	Autumn	15.78	12.52	21.68	15.21	12.78	26.43
	Annual	8.22	7.40	10.22	6.42	5.02	14.28
Maximum Temperature	Spring	1.48	0.87	1.09	1.21	0.89	0.99
	Summer	2.87	2.69	4.85	2.56	2.44	2.37
	Autumn	4.45	2.49	3.58	3.08	2.40	2.23
	Winter	3.25	2.43	2.68	2.02	1.71	3.72
	Annual	2.20	1.90	2.20	1.97	1.50	2.28
Minimum Temperature	Spring	0.91	0.93	0.94	1.05	0.67	1.59
	Summer	1.73	1.85	2.88	3.04	1.93	5.22
	Autumn	2.94	3.31	3.79	3.96	2.34	5.54
	Winter	5.51	4.75	4.70	7.17	3.75	9.46
	Annual	1.91	2.09	1.90	3.16	1.65	4.63

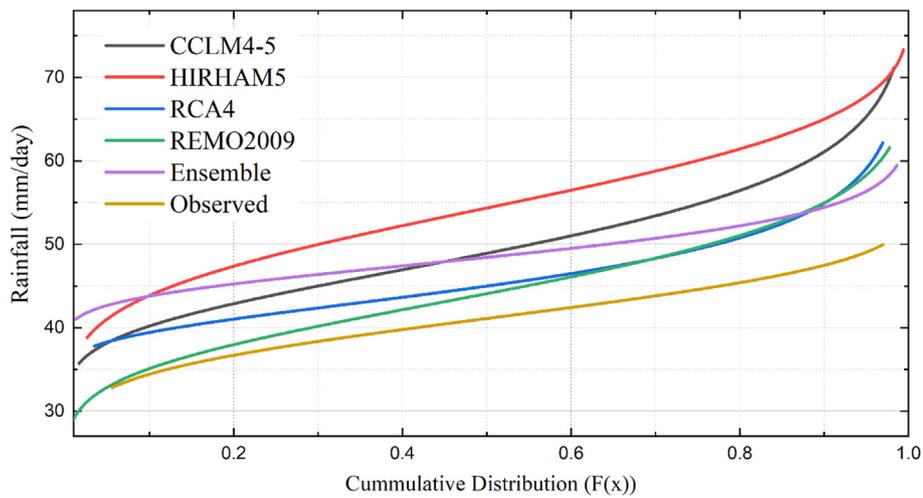


Figure 5. Cumulative distribution of areal rainfall over the study area.

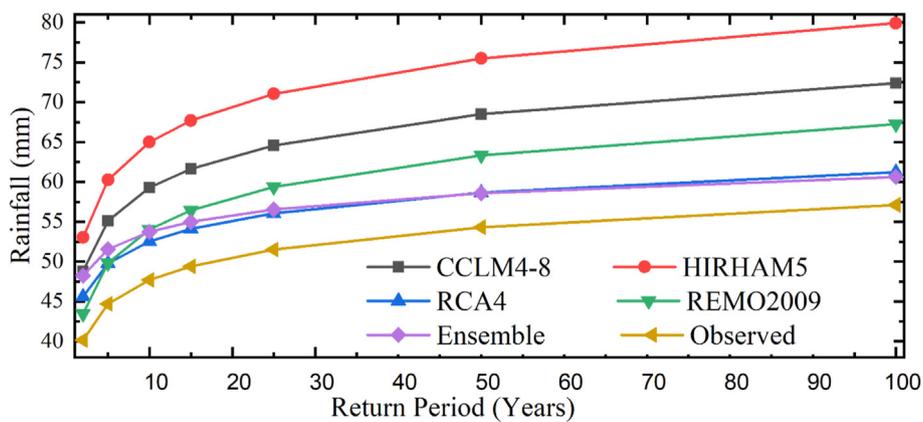


Figure 6. Annual extreme areal rainfall and return periods over the study area.

longitude and the average rainfall recorded at a gauging station. IDW interpolation gives accurate results with a reasonable calculation based on the temporal and spatial structure (Maleika, 2020; Ryu et al., 2020; Yang et al., 2020). The spatial interpolation of the extreme rainfall data, using IDW algorithms, has given good results (Edalat et al., 2019; Tsangaratos et al., 2019). The IDW interpolation for estimating precipitation is given in Eqs. (1), (2), and (3) (Chang et al., 2005).

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

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

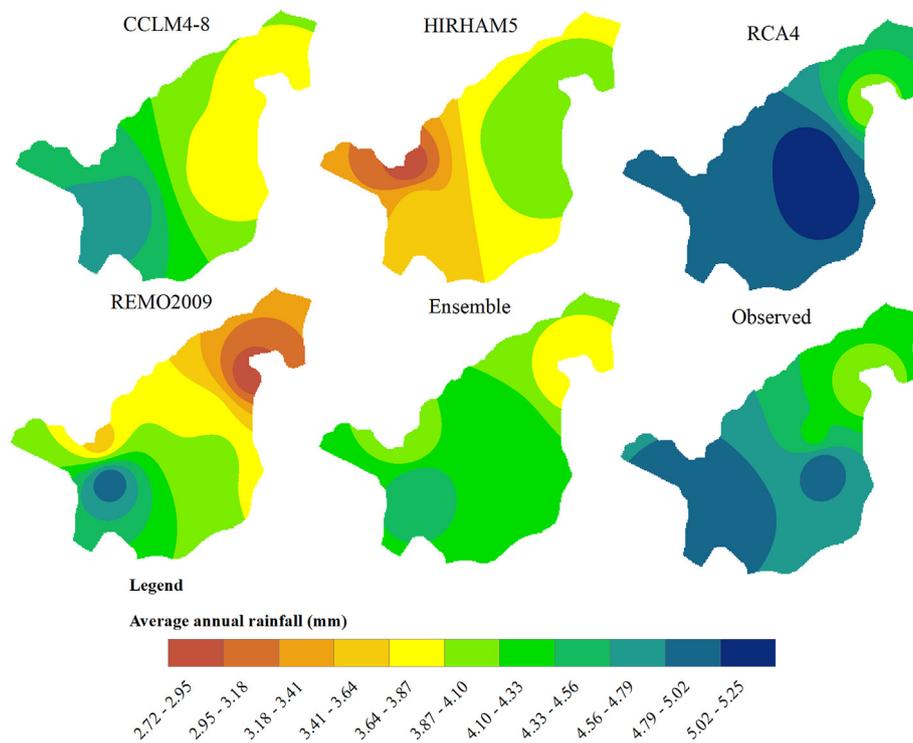


Figure 7. The spatial distribution of mean annual rainfall (1985–2005) over the study area.

$$P_p = \frac{\sum_{i=1}^N P_i d_{pi}^{-m}}{\sum_{i=1}^N d_{pi}^{-m}} \quad (3)$$

where P_p is the required rainfall data in mm, P_i is the rainfall data from the gauging station in mm, W_i is the weighting of individual rainfall stations, w_i is a weighting factor representing the relative importance of the individual rainfall station, N is the number of gauging stations, d_{pi} is the distance from each station to the required point, m is the exponent and the controlling factor fixed by the user (Bartier and Keller, 1996), usually assumed to be 2 (Chen and Liu, 2012), and d is calculated using the Haversine formula (Ingole and Nichat, 2013).

3. Results and discussion

3.1. Mean annual rainfall climate

The REMO2009 and HIRHAM5 models underestimated the mean annual rainfall in the upper Gilgel Gibe districts, whereas the RCA4 overestimated the mean annual rainfall in the study area. In terms of PBIAS, only in four out of twenty possibilities the relative biases exceeded $\pm 20\%$, which is an acceptable range of relative bias for precipitation (Table 1). In terms of the RMSE, systematic errors occurred at the Sekoru station, followed by the Asendabo station. The highest values of RMSE were 1.72 and 1.71 at the Jimma and Dedo stations, respectively, using the HIRHAM5 model. A minor systematic error occurred using the ensemble at most stations, as opposed to the individual RCMs. In terms of r , the CCLM4-8 simulated mean annual rainfall data negatively correlated with the observed data at all the stations. The higher positive and negative values of r were $r = 0.35$ and $r = -0.34$, using the HIRHAM5 at the Jimma and Asendabo stations, respectively. Table 1. Statistical indices in mean annual rainfall simulation.

3.2. Mean annual air temperature climate

3.2.1. Maximum mean annual air temperature climate

The REMO2009 performed better over the study area than the other RCMs considered in this study. Almost all the models underestimated the

maximum mean annual air temperature in the study area. The minimum bias observed was 0.21°C at Asendabo station with RCA4. However, the maximum bias observed was 8.61°C at Jimma station with CCLM4-8. There were high negative values of bias at the Jimma and Sekoru stations, indicating that the models were highly biased around these areas. This was also shown by the high RMSE values at the Jimma and Sekoru stations. There was a positive correlation between the observed and simulated mean annual maximum temperatures at the Omo Nada station, while HIRAM5 gave a positive correlation in the maximum mean annual air temperature simulations at all stations (Table 2).

3.2.2. Minimum mean annual air temperature climate

In the minimum mean annual air temperature simulation, all the models performed fairly well in the hot to warm sub-humid valleys around Sekoru and Asendabo stations, but were biased in the cool sub-humid mountainous areas around the Omo Nada and Dedo stations. The REMO2009 performed better than all the individual RCMs in most stations. The large bias and RMSE values observed were 3.90°C and 4.26% , respectively, at the Dedo station using CCLM4-8. The CCLM4-8 overestimated the minimum mean annual air temperature. Almost all models overestimated the minimum mean annual air temperature when compared with the observed data. At the Asendabo, Jimma and Omo Nada stations, a positive correlation were observed (Table 3).

3.3. Mean monthly cycles

3.3.1. Mean monthly rainfall cycle

Figure 2a–e shows the station-based mean monthly rainfall cycle, while Figure 2f shows the mean monthly rainfall cycle over the entire study area. A common error in all RCMs is to simulate a double peak of the rainfall from May to September, while the observation shows only one peak in August. Some models overestimated the rainfall in the dry months and underestimated it in the wet months. The RCA4 showed high interannual variation, estimating relatively very high rainfall in the wet months and too-low rainfall in the dry months. The REMO2009 simulated lower rainfall values in the wet months than all the other models.

All the model-simulated rainfall were better in the dry months than the wet months.

3.3.2. Mean monthly air temperature cycle

a) Mean monthly maximum air temperature cycle

Figure 3a–e shows the station-based mean monthly maximum air temperature cycle, with Figure 3f illustrating the mean annual maximum air temperature cycle over the entire study area. The RCMs underestimated the maximum air temperature in all months. The CCLM4-8 and HIRHAM5 failed to simulate the maximum air temperature, while the REMO2009 simulated it fairly accurately in the study area (Figure 3f). All the models simulated the maximum monthly air temperatures from January to April and August to December. The maximum air temperatures decreased between May and September, and the minimum fell in July.

b) Mean monthly maximum air temperature cycle

Figure 4a–e shows the station-based mean monthly minimum air temperature cycle and Figure 4f shows mean monthly minimum air temperature cycle over the entire study area. The CCLM4-8 overestimated the monthly minimum air temperature, while the HIRHAM5 underestimated the minimum air temperature in all months. The REMO2009 simulated the air temperatures in all the months fairly well. The models estimated high values between January and April, and October and September, with the minimum air temperature gradually increasing from January to May, but decreasing from September to October (Figure 4).

3.4. Annual and seasonal climate variability

3.4.1. Annual and seasonal rainfall variability

The CV values for variability in the annual and seasonal rainfall were in the low (less than 20%) to moderate (20–30%) categories (Table 4). The RCMs underestimate the observed interannual and seasonal variability of precipitation, except RCA4 in spring. There was moderate variability in the rainfall in the autumn and spring under the REMO2009 and RCA4, respectively.

3.4.2. Mean annual and seasonal air temperature variability

The mean annual and seasonal maximum and minimum air temperatures variability were in the low-variability range. The variability in the minimum and maximum air temperatures in autumn and spring were slightly high when compared with other seasons. The variability in the maximum air temperature was slightly high when compared with the minimum air temperature. Table 4 illustrates coefficient of variation (CV) for the seasonal and annual rainfall and air temperature.

The simulated rainfall showed considerable variability in spring and autumn. The rainfall variability in the summer season was relatively low. The ensemble data was in agreement with the observed data throughout the considered years, and agreed with the findings of (Endris et al., 2013; Gadissa et al., 2018; Dibaba et al., 2019).

The annual and seasonal maximum air temperature anomalies indicated an increase in air temperature between 1985 and 2005. In simulating the maximum air temperature, the HIRHAM5 showed significant variation compared to the other RCMs. In 1991 and 1998, there was high variability in the maximum air temperature in spring. The maximum air temperature variation produced positive anomalies between 1998 and 2005 in most seasons. In autumn and summer, the variation given by RCM simulation was somewhat related to the observed variation.

The RCM-based variations in minimum air temperature slightly diverged from the observed values in 1986–1988. In summer, all the RCMs simulated the minimum air temperature better. The seasonal

variation in minimum air temperature continuously increased from 1994 to 2005 in spring, summer and annually.

3.5. RCM event characteristics

The areal rainfall over the study area for the period 1985–2005 was used for analysis of the extreme rainfall. The Gumbel (maximum extreme value type I) cumulative distribution was used. The REMO2009 simulated the distribution of extreme rainfall well compared to the other models (Figure 5). The probability of the occurrence of heavy rainfall was high in all the models. From the observed data, there was no probability of the occurrence of very extreme rainfall greater than 50 mm/day. The HIRHAM5 estimated very high extreme rainfall (Figure 5). All the RCMs overestimated the return period (Figure 6). The ensemble and RCA4 estimated the return period relatively well. The HIRHAM5 best estimated the return period, followed by the CCLM4-8 (Figure 6).

3.6. Spatial analysis of mean annual rainfall

The RCM and observed rainfall data simulated for 1985–2005 was used to examine the spatial variation in rainfall over the study area (Figure 7). The mean annual minimum simulated value was 2.72 mm/day at the Asendabo station by REMO2009. The HIRHAM5 and RCA4 simulated the maximum rainfall around the Omo Nada and Asendabo stations. The CCLM4-8, ensemble, REMO2009 and observed data gave high rainfall values around the Dedo station (Figure 7). Maximum rainfall was simulated for the southwest and central parts of the study area. Almost all the models simulated minimum rainfall in the northeast and moderate rainfall in the south. The ensemble and observed models gave similar average rainfall distributions. Figure 7 shows the spatial mean annual rainfall distribution (1985–2005) over the study area.

4. Conclusions

In this study, the performance of the CORDEX Africa RCMs in simulating rainfall and air temperature was evaluated using observed data as a reference for the baseline period 1985–2005. The performance of the RCMs was found to be variable on the spatial and temporal scales. The RCMs performed better at simulating maximum air temperature than minimum air temperature. They overestimated the minimum air temperature and underestimated the maximum average in the study area. Rainfall was simulated well in the dry months, but was underestimated in the wet months. In both the rainfall and air temperature simulations, the ensemble data fit relatively well to the observed data in comparison to the individual RCMs. The variations in both rainfall and air temperature were relatively low, interannually and seasonally, in the study area. All the RCMs, including the ensemble, overestimated the extreme areal rainfall and return periods. These findings clearly indicate why the use of climate-change evidence, from the regional to local scale, is important for assessing climate-change impacts in southwest Ethiopia.

In general, the RCMs showed systematic deviations in model performance, and it is therefore necessary to be aware of these limitations before using models to investigate the impacts of climate change on water resources, agriculture and hydropower generation. The differences in the biases of the RCMs strongly indicated the importance of corrections to the RCMs before using RCM outputs for climate-impact studies.

Declarations

Author contribution statement

Tamene Adugna Demissie, Chala Hailu Sime: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

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Data availability statement

The data that has been used is confidential.

Declaration of interests statement

The authors declare no conflict of interest.

Additional information

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