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Evaluation of regional climate models performance in simulating rainfall of Lower Awash River Sub-Basin, Gabi Rasu zone of Afar region, Ethiopia

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Abstract

This study evaluated the performance of five RCMs and their skill in simulating daily and monthly precipitation over Lower Awash River Sub-Basin using statistical parameters such as Standard Deviation, BIAS, RMSE and Correlation Coefficient. Reference data was obtained from two selected rain gauges namely Gewane and Awash meteorological stations from the rain gauge network operated by the National Meteorological Institute of Ethiopia. The name of RCMs was Rossby Centre Regional Atmospheric Model (RCA4), Climate Limited-Area Modeling Community (CCLM4-8) High-Resolution Hamburg Climate Model 5 (HIRAM5), Regional model (REMO2009) and the Regional Atmospheric Climate Model (RACMO22T) simulations from Coordinated Regional Climate Downscaling Experiment (CORDEX) Africa program. The simulation period 1981–2005 was evaluated considering how each RCM were simulated the observed daily and monthly rainfall pattern. The results revealed that all RCMs were attained positive correlation with observed daily rainfall at both stations except HIRHAM5 which indicated negative correlation at Gewane station. The findings also indicated that nearly all models were underestimated the daily rainfall amounts of the basin. In addition, each of the models was found best at capturing certain aspects of statistical parameters simulating gauged rainfall. For example, CCLM4 performed best in all performance measures at Gewane station, whereas RACMO22T is best when evaluated in terms of correlation, Bias and SD at Awash station. However, the bias correction algorithm is well improved the systematic errors in all RCMs showing significant improvement between performance of the bias corrected and uncorrected. Overall, these results suggest the need to correct the systematic error of the rainfall extracted from RCMs outputs and choosing an appropriate bias correction algorithm is fundamentally necessary to quantitatively examine climate change impact studies.

Key Words: Bias Correction, Climate Change, Climate Models, CORDEX-Africa, GCM, Lower Awash River Basin, Precipitation

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1 Introduction

Climate models are important tools for improving our understanding and predictability of climate behavior on daily, monthly, seasonal, annual and centennial time scales. The available climate models indicate the changes in average climate and to some extent about extreme events. As a result, the frequency of occurrence of extreme events (i.e., floods, droughts) has increased in recent decades and caused an impact on the socio-economic and environmental sectors at large (Harley et al., 1993, Dale et al., 2001, Parmesan & Yohe, 2003, Zollo et al., 2014). The impacts of the extreme events are becoming even worse and could continue to worsen in the future unless remarkable and proper measures are taken to reduce the current greenhouse gas emissions (Bell et al., 2004, Arora et al., 2011). Climate change will have wide-ranging effects on the environment, and on socio-economic and related sectors, including water resources, agriculture and food security, human health, terrestrial ecosystems and biodiversity. Changes in rainfall pattern are likely to lead to severe water shortages and/or flooding (Dale et al., 2017). As a result of global warming, the type, frequency and intensity of extreme events, such as tropical cyclones (including hurricanes and typhoons), floods, droughts and heavy precipitation events, are expected to rise even with relatively small average temperature increases. Changes in some types of extreme events have already been observed, for example, increases in the frequency and intensity of heavy precipitation events on some parts and on the other hand severe to extreme drought events (Meehl et al., 2007). Nowadays climate change is expected to affect society in a number of ways ranging from food security to water resources Developing country like Ethiopia is vulnerable to climate change since the economy of the country mainly depends on rain-fed agriculture, which is very sensitive to climate change and variability. In Ethiopia, adverse impacts of climate change may worsen existing social and economic challenges of the whole country, particularly where people are dependent on resources that are sensitive to climate change (Tekle, 2015). Currently Ethiopia's agriculture depends on rainfall with limited use of water resources for irrigation. At approximately 50% of the GDP, agriculture, most of it based on rain-fed small -holder systems and livestock, contributes by far the largest part of the economy and is currently growing on average 5% per year. Highly variable rainfall, frequent floods and droughts, and limited storage capacity continue to constrain the ability of the country to produce reliable food supplies in spite of being relatively rich in water and land resources (Taddese et al., 2004).

Climate change impact and adaptation studies can benefit from an enhanced understanding about the performance of individual General Circulation Models (GCMs) as well as ensemble simulations of GCMs when dynamically downscaled using Regional Climate Models (RCMs). Regional climate models (RCMs) driven by the global climate models (GCMs) are increasingly used to access potential changes in climatic states by various studies (Rosenzweig & Parry, 1994, Duffy et al., 2006). The objective of this study is to evaluate the CORDEX-Africa RCM results for historical rainfall over the Lower Awash sub-basin. We are conducting the evaluation of daily time scales and monthly cycles in order to improve our understanding of reliability of dynamically downscaled simulations of RCMs which are part of the Coupled Model Intercomparison Project Phase 5 (CMIP5). Accurate and reliable simulation of the climate over the African continent by means of GCMs and RCMs is a major challenge partly due to the complexity and the diversity of processes to be represented (Laprise et al., 2013).

Regional Climate Models (RCMs) can be used to dynamically downscale GCMs output in order to account for fine-scale forcing and to provide climate change information at the local and regional level needed for impact assessments (Paeth et al., 2008, Philippon et al., 2009). Furthermore, climate models developed and available right now also has a different performance of simulating precipitation variables. In other words, climate models that have been developed with the specified resolution are not consistently predict and simulate the climate variables that are intended to cause climate change (Endris et al., 2013, Dibaba et al., 2019).

2 Materials and methods

2.1 Study area

This study is conducted in the Gabi Rasu zone of Afar regional state. Gabi Rasu, also known as administrative zone 3, is a zone in the Afar Region of Ethiopia. This zone is bordered on the south by the Oromia Region, on the southwest by the Amhara Region, on the west by Hari Rasu zone, on the north by Awsi Rasu zone, and on the east by the Somali Region (Figure 2-1). The elevation in the area ranges from 568 m to 1331m above sea level (Figure 2-2).

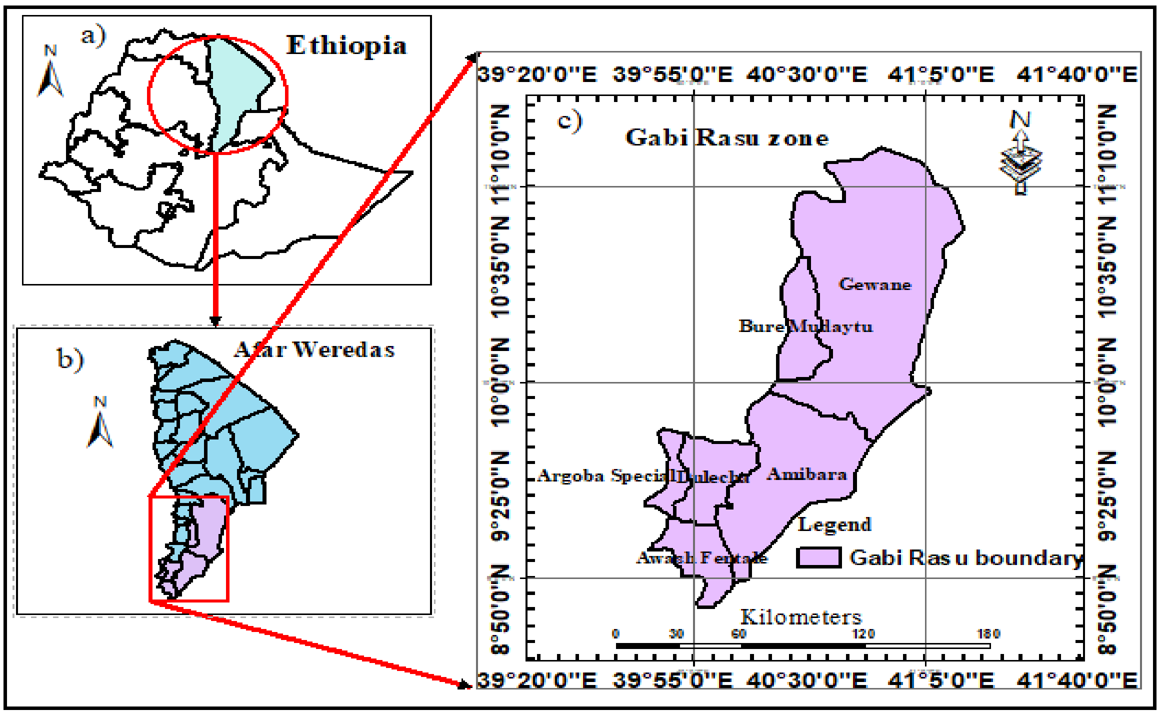

Figure 2-1 (a) the Ethiopia regional states, (b) Afar regional state and Gabi Rasu location, (c) study area districts.

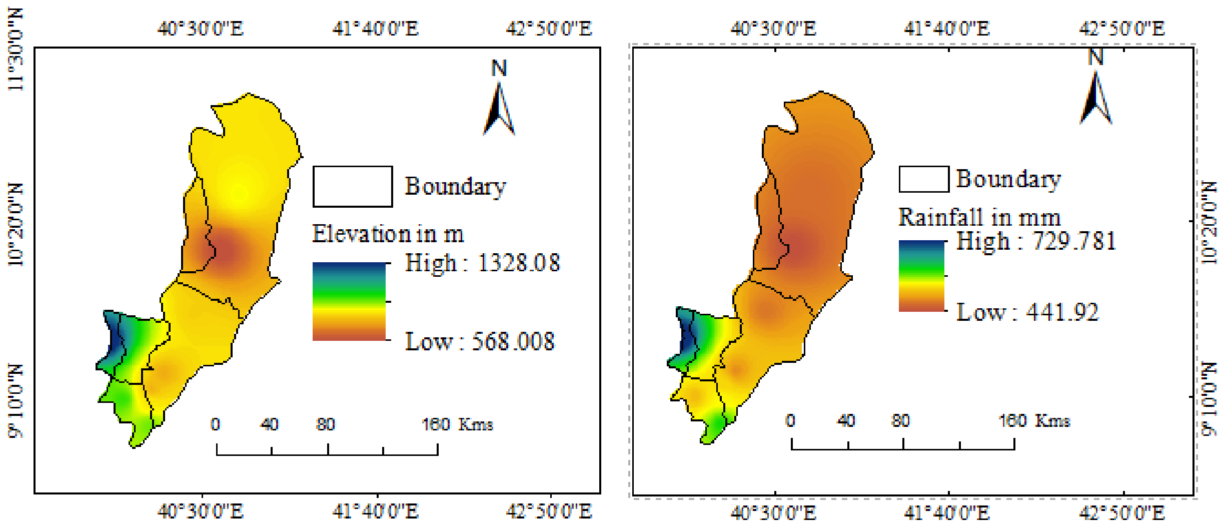

Figure 2-2 Elevation and annual rainfall for Gabi Rasu zone.

2.2 Data description

2.2.1 Meteorological observation

Observed data is used as reference to compare with the simulated data from five RCM models in order to recognize the available deviations that encouraged for estimating their performances. These observed data are collected from the specified location of nine meteorological stations found in the basin and taken from National Meteorological Institute of Ethiopia (NMI). These stations are containing missing data and is filled from CHRIP data set. The daily climate data for precipitation is extracted from CMIP5 GCMs using five regional climate models (RCMs) for Dubti and Awash meteorological stations. The two meteorological stations are selected from existing nine stations network under the study area according to World Climate Data Program (WCDP) and World Meteorological Organization (WCDP, 1986) guideline.

Table 2.1 Available Climatological Stations and their name, geographical location and available percentage of data.

No	Stations	Lat (°)	Lon (°)	Elev (m)	Start year	End year	precp %
1	Awaramelka	9.16	39.98	960	1985	2020	79.02
2	Awash_40	9.14	40.15	826	1981	2020	26.13
3	Awash_7	8.98	40.15	923	1985	2020	81.61

4	Awash sheleko	9.33	40.25	737	1985	2020	55.11
5	Endifo	10.52	40.75	856	1985	2020	9.11
6	Gedamaitu	9.73	40.45	793	1985	2020	12.46
7	Gewane	10.15	40.633	568	1985	2020	85.48
8	Melkasedi	9.23	40.17	749	1985	2020	39.94
9	Argoba	9.55	39.88	1331	2007	2020	15.1

2.2.2 CHIRP Precipitation Data

The CHIRP data set is used to fill missing data in observation and available at[1]. A detailed description of the CHIRP products has been provided in (Funk et al., 2015). The CHIRP product is a new land-only infrared (IR) based climatic precipitation dataset with high spatial resolution (0.05° × 0.05°), long-term records (1981–present) with temporal resolutions of daily, monthly, and yearly (Katsanos et al., 2016, Funk et al., 2015). It is developed by the United States Geological Survey and the University of California. The CHIRP dataset served a number of drought monitoring and evaluation (Tuo et al., 2016, Dinku et al., 2018, Wu et al., 2019, Kebede et al., 2020). It is evaluated over at a regional level for eastern Africa as well as at country level over Ethiopia, Kenya and Tanzania by comparing CHIRP data set with reference rain-gauge data. The result indicated that the CHIRP products performed significantly better (Dinku et al., 2018, Wu et al., 2019).

2.2.1 Homogeneity test

Homogeneity testing is performed by using the Standard Normal Homogeneity Test (SNHT) approach developed by Alexanderson (1986) to detect inhomogeneity in time series (Alexandersson, 1986). The adjusted data should not be considered correct, nor should the original data always be considered wrong. The original data should always be preserved (WMO, 2011). For time series given that Y_i (i is the year from 1 to n) is the testing variable with Y is the mean and s is the standard deviation. A test statistic T(y) compares the mean of the first y years with the last of (n-y) years and written as below:

[1] https://data.chc.ucsb.edu/products/CHIRP/daily/netcdf/

$$\boldsymbol{T_y = y\overline{Z}_1 + (n-y)\overline{Z}_2}, \text{ y=1, 2...n} \qquad 2.1$$

Where

$$\boldsymbol{\overline{Z}_1 = \frac{1}{y}\sum_{i=1}^{n}\frac{(y_i-\overline{y})}{s} \quad and \quad \overline{Z}_2 = \frac{1}{n-y}\sum_{i=y+1}^{n}\frac{(y_i-\overline{y})}{s}} \qquad 2.2$$

The year y consisted of break if value of T is maximum, the test statistic given as the following equation and greater than the critical value, which depends on the sample size.

$$\boldsymbol{T_o = \max_{1\leq y\leq n} T_y} \qquad 2.3$$

A total of 44 stations were tested (36 station were maximum and minimum temperature, and 8 stations only for precipitation) data time series.

2.2.2 Adjustment of inhomogeneity

Detecting and adjusting inhomogeneity is a hard and difficult task, as on most occasions the magnitude of the inhomogeneity is the same or even smaller than that of true climate related variations. Quantile mapping (QM) techniques are among the most important and popular bias correction methods (Thrasher et al., 2012, Maraun, 2013, Zhao et al., 2017, Reiter et al., 2018, & Enayati et al., 2021) and here used to adjust inhomogeneity in gauged data time series.

$$\boldsymbol{x^o = f(x^m)} \qquad 2.4$$

where x^o is adjusted time series x^m is inhomogenoues time series, and $f()$ is transformation function. Given that the QM methods use the quantile-quantile relation to converge the adjusted time series distribution function to the observed one, one should note that with the Cumulative Distribution Functions (CDFs) of both observed and adjusted variables time series, their quantile relation can also be determined, as shown below (Ringard et al., 2017).

$$\boldsymbol{x^o = F_o^{-1}[F_m(x^m)]} \qquad 2.5$$

Where $F_m(x^m)$ is CDF of x^m, and $F_o^{-1}[]$ is inverse form of the CDF of x^o, which is technically referred to as the quantile function.

2.2.3 Bias Correction

The power transformation (PT) algorithm is ued for bias correction (Lenderink et al., 2007). The PT method implements adjusting RCMs and CHRIP daily data output with observation and generate a constant correction factor for each calendar month. This approach is capable of perfectly adjusting the mean, Standard Deviation (STD) and Coefficient of Variation (CV) for RCMs, CHRIP and observation over the same period of the observed time series to get bias corrected data (Teutschbein & Seibert, 2012).

$$\mathbf{P^{cor}\,hst,m,d} = \boldsymbol{P^{b}_{hst,m,d}} * [\frac{\mathbf{u(P_{obs,m})}}{\mathbf{u(P_{hst,m})}}] \qquad 2.6$$

Where $\mathrm{P^{cor}\,hst,m,d}$ denote the corrected precipitation on the $\mathrm{d^{th}}$ day of the $\mathrm{m^{th}}$ month and$\mathrm{P_{hst,m,d}}$denote the precipitation extracted from CHRIPS outputs during the relevant period, the subscripts d and m are specific days and months, respectively and u denotes the mean value, b is a random constant number called correction factor.

2.2.4 Regional climate models (RCMs)

The outputs of regional climate models (RCMs) simulations utilized for this study consists of five RCM models carried out in the framework of the CORDEX-Africa. Their names are Rossby Centre Regional Atmospheric Model (RCA4), Climate Limited-Area Modeling Community (CCLM4-8), High-Resolution Hamburg Climate Model 5 (HIRAM5), Regional model (REMO2009) and the Regional Atmospheric Climate Model (RACMO22T) simulations from Coordinated Regional Climate Downscaling Experiment (CORDEX) Africa program. The simulation period 1981–2005 is evaluated considering how each RCM were simulated the observed daily and monthly rainfall pattern. All RCM models are at 50 × 50-km horizontal resolution over the same Africa domain, and all are available on the Earth System Grid Federation (ESGF) under the CORDEX project[2].

2.3 Methods

RCMs simulated data are in a netCDF4 file format and extracted using python 3 script using gauged locations. The performances of these Regional climate models are evaluated using

[2] (https://esgf-data.dkrz.de/search/cordex-dkrz/)

statistical parameters such as Standard Deviation, BIAS, RMSE and Correlation Coefficient. The smallest the values of Root Mean Square Error (RMSE) close to zero, the good the performance of RCM. Also, the BIAS measure the systematic error between the observed and simulated climate variable and close to zero indicate good performance, while values away from zero show the deviations to observed data. Negative values of absolute bias indicate underestimation while the positive values indicate overestimation. The values closer to zero show minimum difference and best estimation of the climate models (Florida, 2021). Furthermore, the study also incorporates how RCMs are reproducing monthly Precipitation cycle related to the inter-seasonal variability over the basin, the results are presented in tables and figures.

$$\boldsymbol{Bias = 100 * \frac{\sum_{i=1}^{N}(S_i - O_i)}{\sum_{i=1}^{N} O_i}} \qquad 2.7$$

Where, S and O are the simulated and observed values respectively, while $\boldsymbol{i}$ refer to the simulated and observed pairs and N is the total number of such pairs.

Pearson correlation measures the strength (given by the coefficient r between -1 and +1) of a linear relationship between two variables. According to Cohen (1988) an absolute value of r of 0.1 is classified as small, an absolute value of 0.3 is classified as medium and of 0.5 is classified as large (Schmidt & Bohannon, 1988, Pillemer, 1990, Chuan & Penyelidikan, 2006). The Pearson's correlation coefficient formula is given as:

$$\mathbf{r = \frac{\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \overline{x})^2} * \sqrt{\sum_{i=1}^{n}(y_i - \overline{y})^2}}} \qquad 2.8$$

Where r is correlation coefficient, n is number of observations in the correlation equation, $x_i \ and \ y_i$ are data sets or variables of the correlation equation and $\overline{x} \ and \ \overline{y}$ are mean of x and y in the equation. Standard deviation is the average amount of variability in a given data set. It tells how far each values lies from the mean. A high standard deviation means that values are generally far from the mean, while a low standard deviation indicates that values are clustered close to the mean.

$$\boldsymbol{\mu = \frac{1}{n}\sum_{i=1}^{n} x} \qquad 2.9$$

$$\boldsymbol{\sigma} = \sqrt{\frac{\sum(\boldsymbol{x}-\boldsymbol{\mu})^2}{\boldsymbol{n}}} \qquad 2.10$$

Where x is set of numbers, μ is the average of the set of numbers, n is the size of the set and σ is the required standard deviation, respectively.

$$\boldsymbol{RMSE} = \sqrt{\sum_{i=1}^{n}(\boldsymbol{S_i} - \boldsymbol{O_i})^2 * \frac{\mathbf{1}}{\boldsymbol{N}}} \qquad 2.11$$

3 Results

3.1 *Adjustment of inhomogeneity*

In the following plots, the x axis represents time in years and y axis represents daily, dekadal and monthly time series respectively**.** where Red color for breakpoint, black color for base series and blue color for adjusted series, respectively. Taking daily precipitation time series under the confidence level of 0.01, the data set contains more breakpoints for daily data time series than dekadal and monthly. For example at Awash station, a total of 4 breakpoints were found in the daily precipitation time series, 2 breakpoints in the daily series (October 19 and 21, 1999), 1 breakpoint in the dekadal series (third dekad of November 1999) and 1 breakpoint in monthly series (November 1998), respectively **(**Figure 3-1), left side figure depicts inhomogeneous and the right side depicts adjusted.

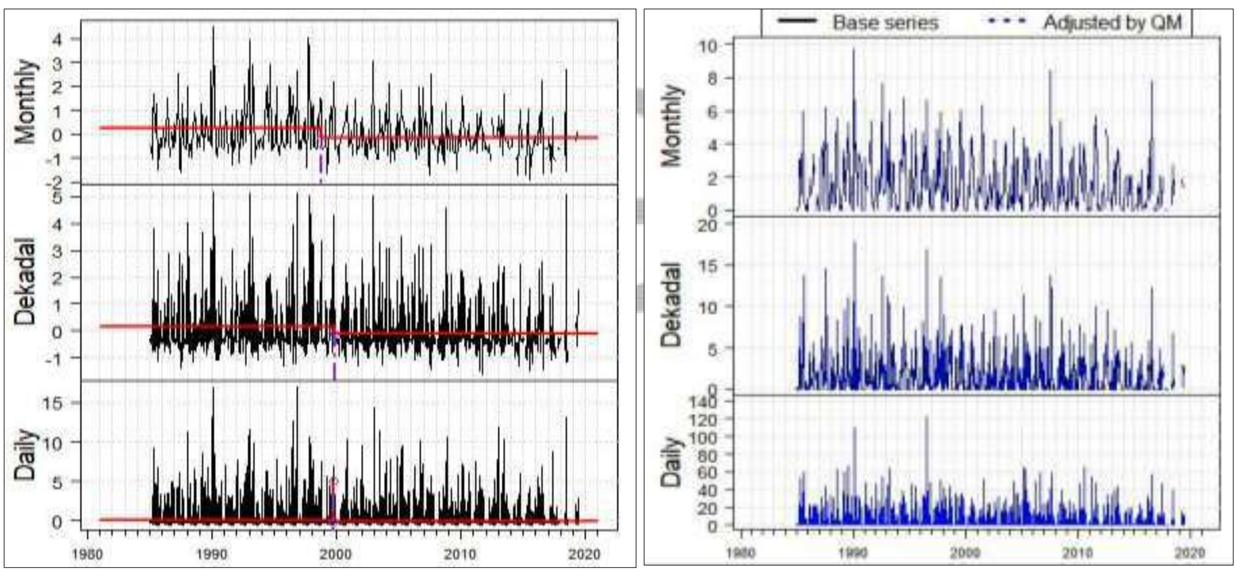

Figure 3-1 Inhomogeneous and adjusted daily precipitation for Awash station.

3.2 *Gauge data*

The seasonal characterization of precipitation over the study area reveals that a wet season with two rainfall peaks, separated by one dry month. Long precipitation period occurs during July to September (JAS) while short precipitation period occurs from the March to May (MAM) (Figure 3-2).

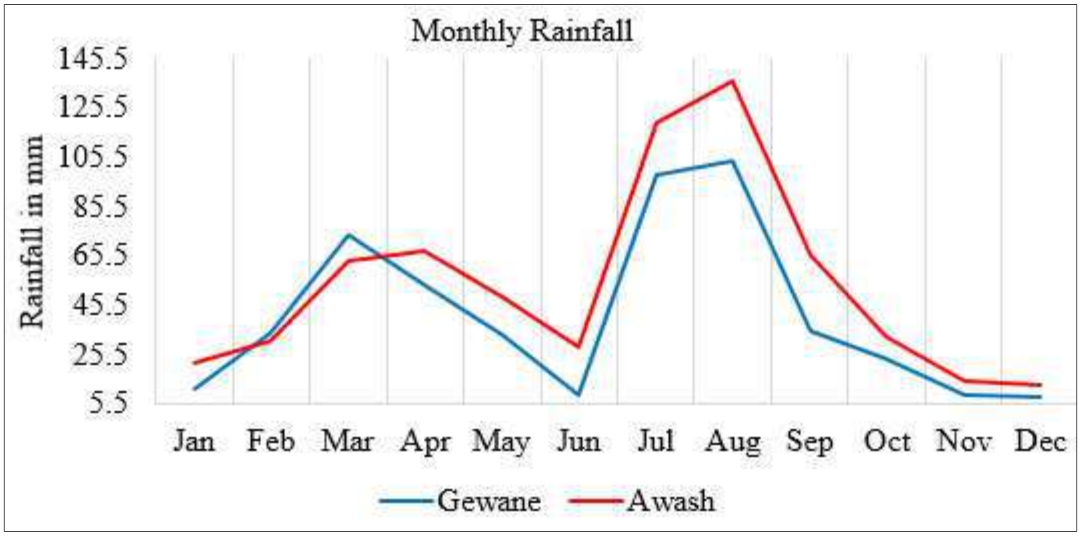

Figure 3-2 Monthly rainfall pattern at Gewane and Awash stations

3.3 RCMs Model Performance

3.3.1 **Daily Precipitation**

The result of Pearson correlation tells that all models were positively correlated for both stations except HIRHAM5 model which showed negatively correlated. The bias corrected data set have strongly correlated against observation (r = 0.79 to 0.81) for Awash station and (r = 0.83 to 0.93) for Gewane station. However, the REMO2009 models was inadequately correlated with observation at Gewane station (r = 0.05) (Table 3.1). The bias corrected data set have showed small underestimation of (-0.71 to -1.35) mm per day for Awash station, which suggests the presence of systematic error in RCMs. At the same station while after bias correction the presence of a systematic error in RCMs became closer to zero, between -0.01 to 0.13 mm/day. Similarly**,** the small underestimation of –0.08 mm for CCLM4, -0.34 for RACMO22T and -1.19 for RCA4, while small overestimation of 0.09 mm for HIRHAM5 model and large overestimation of 333.88 mm for REMO2009 model at Gewane station before bias correction.

The bias correction technique is well adjusted the RCMs at both stations, closer to zero (Table 3.1). Other researchers also concluded that biases of the models can be considered relatively large with values larger than ±10% (Alemseged & Tom, 2015, Haile et al., 2017, Mengistu et al., 2021). In general, all models were found best in capturing the observed rainfall except REMO2009 model which indicated large bias at Gewane station, while after bias correction of all RCMs were well performed against gauged for both stations.

Coming to RMSE, all RCMs relatively shown good performance for all parameters considered in this evaluation. Comparatively REMO2009 and CCLM4 models were performed better than the others with RMSE of 0.71 and 0.91 mm/day before bias correction for Awash station. Similarly, CCLM4, HIRHAM5 and RACMO22T models were well performed than others with RMSE of 0.8, 0.9 and 0.34 mm/day before bias correction for Gewane station (Table 3.1).

Table 3.1 Standard Deviation SD (mm/day), Correlation (r), BIAS (in %) and RMSE (in mm/day) between Observed and RCMs daily rainfall for Gewane and Awash stations.

Stations		Observed	Models	CCLM4	HIRHAM5	RACMO22T	RCA4	REMO2009
Gewane	Mean	1.4	Uncorr	1.3	1.4	1.0	0.2	335.3
			Corr	1.4	1.4	1.3	1.2	3.4
	SD	5.4	Uncorr	6.4	11.0	3.4	1.6	30507.9
			Corr	5.7	5.8	5.2	5.2	94.7
	r		Uncorr	0.01	-0.02	0.01	0.01	0.01
			Corr	0.85	0.83	0.93	0.93	0.05
	Bias (%)		Uncorr	-9.42	3.47	-22.51	-86.5	9892.19
			Corr	-3.8	-2.96	3.27	9.17	-59.69
	RMSE		Uncorr	0.08	0.09	0.34	1.19	333.88
			Corr	0.05	0.04	0.04	0.11	2.00
Awash	Mean	1.74	Uncorr	0.53	0.38	0.34	0.10	0.73
			Corr	1.57	1.52	1.50	1.46	1.54
	SD		Uncorr	2.77	1.71	1.36	0.63	6.39
			Corr	5.54	5.37	5.37	5.35	5.45
	r	5.83	Uncorr	0.06	0.02	0.06	0.04	0.02
			Corr	0.79	0.8	0.8	0.81	0.8
	Bias (%)		Uncorr	-58	-70.34	-73.75	-92.4	-46.2
			Corr	8.02	4.85	3.68	0.95	6.44
	RMSE		Uncorr	0.91	1.07	1.1	1.35	0.71
			Corr	0.13	0.07	0.06	0.01	0.1

Concerning the variability of precipitation, the result of standard deviation showed that RCMs have generated a low standard deviation sufficiently for the majority of RCMs for both locations and closer to the observation after bias correction (Table 3.1).

3.3.2 **Monthly Climatology**

Figure 3-3 and Figure 3-4 show the monthly rainfall cycle for Gewane and Awash meteorological stations before and after bias correction of RCMs and compared against observation.

Comparing RCMs output against gauged data at Gewane station, most models were well performed monthly rainfall patterns with slight underestimation in June-September and February-May months. The REMO2009, RACMO22T and RCA4 models resulted in poor performance capturing the monthly rainfall amount and cycle. The REMO2009 model resulted in the poorest performance indicating overestimation with highest rainfall amount in March-June and September-December months. While RCA4, RACMO22T and HIRHAM5 resulted in underestimation with lowest rainfall amount in February-May and July-August months (Figure 3-3). Note that the left side figure depicts uncorrected and right side depicts bias corrected RCMs and observed data, respectively.

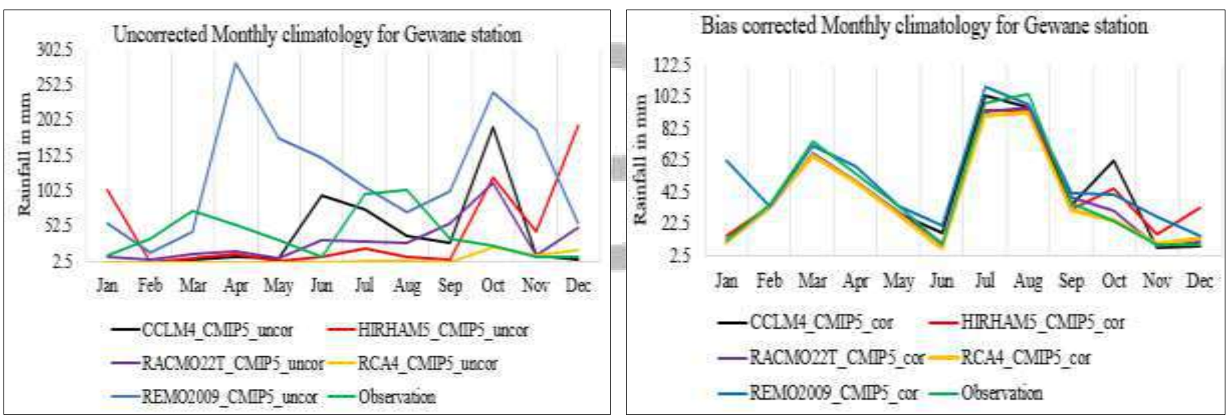

Figure 3-3 Monthly rainfall cycle for RCMs and gauged data at Gewane station.

Similarly, when comparing RCMs output against gauged data for Awash station most models resulted in poor performance capturing the monthly rainfall amount and cycle. The HIRHAM5, RACMO22T and RCA4 models were resulted in underestimation for all months except November and December (Figure 3-4).

However, the result of bias corrected RCMs output showed relatively good representation of monthly rainfall pattern in all models as compared to uncorrected RCMs (right side of Figure 3-3 and Figure 3-4).

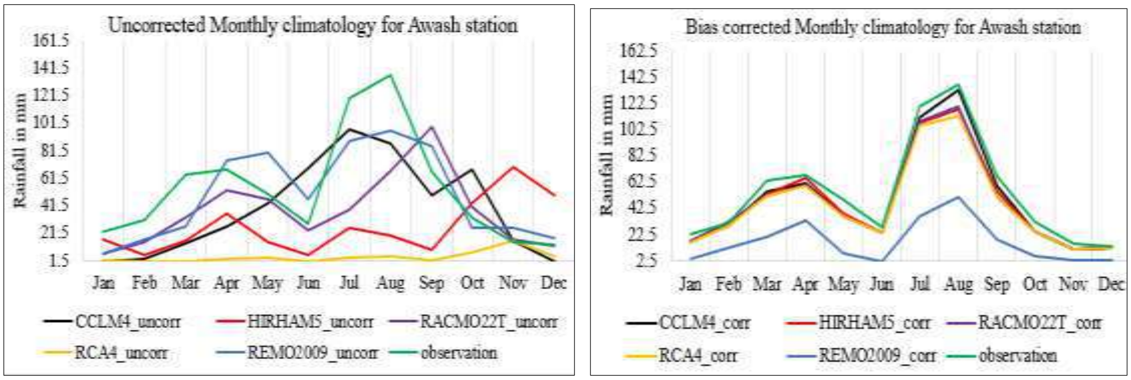

Figure 3-4 Monthly rainfall cycle for RCMs and gauged data at Awash station

A comparison between the bias-corrected RCMs with uncorrected showed that the RCMs bias correction can add value than uncorrected RCMs. All bias corrected RCMs indicated good performance compared to uncorrected, with RMSE of 0.01 to 0.13 mm/day for Awash and 0.04 to 0.11 mm/day for Gewane station. However, REMO2009 model indicated poor performance with RMSE of 2.0 mm/day at Gewane station (Table 3.1).

4 Conclusion

In this study, five RCMs which were part of the Coupled Model Intercomparison Project Phase 5 (CMIP5) data set are evaluated in simulating precipitation over Lower Awash sub-basin. We used a group of performance measures such as Bias, RMSE, correlation coefficient and Standard Deviation of daily rainfall amount to assess performance of climate models. In addition, monthly rainfall plots have been used for the evaluation and to capture and to represent seasonal rainfall pattern over the basin. Reference data was obtained from two selected rain gauges namely Gewane and Awash meteorological stations from the rain gauge network operated by the National Meteorological Institute of Ethiopia.

Before bias correction, all RCMs are attained positive correlation against gauged data set at both stations except HIRHAM5 which indicated negative correlation at Gewane station. The bias corrected RCMs daily data set are strongly correlated at both station in the range of (r = 0.79 to 0.81) at Awash station and (r = 0.83-0.93) at Gewane station, respectively. The findings of this study indicated that nearly all models underestimated the daily rainfall amounts of the basin. Underestimation of daily rainfall is as large as 9% to 86% in the order of (HIRHAM5, RACMO22T and RCA4) at Gewane station. The CCLM4 model slightly overestimated and REMO2009 model is considerably overestimated the observed daily rainfall at the same station. Similarly, all RCMs are underestimated the daily rainfall at Awash station as large as 46% to 92% in the order of (REMO2009, CCLM4, HIRHAM5, RACMO22T and RCA4), respectively. However, the bias correction algorithm is well improved the systematic errors in RCMs at both stations showing significant improvement and differences between performance of the bias corrected and uncorrected RCMs. Overall, these results suggest the need to correct the systematic error of the rainfall amounts from the models before any application.

Each of the models was found best at capturing certain aspects statistical measures of the gauged rainfall. For example, CCLM4 performed best in all performance measures at Gewane station, whereas RACMO22T is best when evaluated in terms of correlation, rainfall Bias and SD at Awash station.

The gauged monthly rainfall pattern showed that the monthly rainfall cycle over the basin has double peak of the rainfall from March to May and July to September. Similarly, the simulated rainfall from RCM output showed double peaks, March to April and July to September but most models are underestimated at both stations. For example, RCA4, RACMO22T and HIRHAM5 resulted in underestimation with lowest rainfall amount in February-May and July-August months at Gewane station. Similarly, the HIRHAM5, RACMO22T and RCA4 models were resulted in underestimation for all months except November and December at Awash station. However, the bias corrected RCMs output revealed good performance in amount and seasonality generating monthly rainfall cycle at both stations.

The results of this study provide insight into the differences among different RCMs in simulating climate change over the basin, which advances our understanding of the applicability of RCMs in assessing climate change impact studies. 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 food security. In addition, the bias correction algorithm was strongly re-scaled, reduced systematic biases in climate models and improved the performance of RCMs output. This suggests that bias correction of RCMs is strongly recommended before using simulated RCMs outputs to quantitatively examine climate change impact studies.

5 Reference

Alemseged, T. H., & Tom, R. (2015). Evaluation of regional climate model simulations of rainfall over the Upper Blue Nile basin. *Atmospheric Research*, *161*, 57–64.

Alexandersson, H. (1986). Alexandersson, Hans. "A homogeneity test applied to precipitation data." Journal of climatology 6.6 (1986): 661-675. *Journal of Climatology, 1986 - Wiley Online Library*.

Bell, J. L., Sloan, L. C., & Snyder, M. A. (2004). Regional changes in extreme climatic events: a future climate scenario. *Journal of Climate*, *17*(1), 81–87.

Chuan, C. L., & Penyelidikan, J. (2006). Sample size estimation using Krejcie and Morgan and Cohen statistical power analysis: A comparison. *Jurnal Penyelidikan IPBL*, *7*(1), 78–86.

Dale, A., Fant, C., Strzepek, K., Lickley, M., & Solomon, S. (2017). Climate model uncertainty in impact assessments for agriculture: A multi-ensemble case study on maize in sub-Saharan Africa. *Earth's Future*, *5*(3), 337–353. https://doi.org/10.1002/2017EF000539

Dibaba, W. T., Miegel, K., & Demissie, T. A. (2019). Evaluation of the CORDEX regional climate models performance in simulating climate conditions of two catchments in Upper Blue Nile Basin. *Dynamics of Atmospheres and Oceans*, *87*, 101104.

Dinku, T., Funk, C., Peterson, P., Maidment, R., Tadesse, T., Gadain, H., & Ceccato, P. (2018). Validation of the CHIRPS satellite rainfall estimates over eastern Africa. *Quarterly Journal of the Royal Meteorological Society*, *144*(August), 292–312. https://doi.org/10.1002/qj.3244

Duffy, P. B., Arritt, R. W., Coquard, J., Gutowski, W., Han, J., Iorio, J., Kim, J., Leung, L.-R., Roads, J., & Zeledon, E. (2006). Simulations of present and future climates in the western United States with four nested regional climate models. *Journal of Climate*, *19*(6), 873–895.

Florida, S. (2021). *Evaluation of Regional Climate Models (RCMs) Using Precipitation and Temperature-Based Climatic Indices : A Case*.

Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., Rowland, J., Harrison, L., Hoell, A., & Michaelsen, J. (2015). The climate hazards infrared precipitation with stations - A new environmental record for monitoring extremes. *Scientific Data*, *2*(December). https://doi.org/10.1038/sdata.2015.66

Haile, G. G., Tang, Q., Hosseini-Moghari, S. M., Liu, X., Gebremicael, T. G., Leng, G., Kebede, A., Xu, X., & Yun, X. (2020). Projected Impacts of Climate Change on Drought Patterns Over East Africa. In *Earth's Future* (Vol. 8, Issue 7). https://doi.org/10.1029/2020EF001502

Kebede, A., Raju, U. J. P., Korecha, D., & Nigussie, M. (2020). Developing new drought indices with and without climate signal information over the Upper Blue Nile. *Modeling Earth Systems and Environment*, *6*(1), 151–161. https://doi.org/10.1007/s40808-019-00667-y

Laprise, R., Hernández-Díaz, L., Tete, K., Sushama, L., Šeparović, L., Martynov, A., Winger, K., & Valin, M. (2013). Climate projections over CORDEX Africa domain using the fifth-generation Canadian Regional Climate Model (CRCM5). *Climate Dynamics*, *41*(11), 3219–3246.

Lenderink, G., Buishand, A., & Deursen, W. van. (2007). Estimates of future discharges of the river Rhine using two scenario methodologies: direct versus delta approach. *Hydrology and Earth System Sciences*, *11*(3), 1145–1159.

Maraun, D. (2013). Bias correction, quantile mapping, and downscaling: Revisiting the inflation issue. *Journal of Climate*, *26*(6), 2137–2143.

Meehl, G. A., Stocker, T. F., Collins, W. D., Friedlingstein, P., Gaye, A. T., Gregory, J. M., Kitoh, A., Knutti, R., Murphy, J. M., & Noda, A. (2007). *Global climate projections. Chapter 10*.

Paeth, H., Capo-Chichi, A., & Endlicher, W. (2008). Climate change and food security in tropical West Africa—a dynamic-statistical modelling approach. *Erdkunde*, 101–115.

Parmesan, C., & Yohe, G. (2003). A globally coherent fingerprint of climate change impacts across natural systems. *Nature*, *421*(6918), 37–42.

Ringard, J., Seyler, F., & Linguet, L. (2017). A quantile mapping bias correction method based on hydroclimatic classification of the Guiana shield. *Sensors*, *17*(6), 1413.

Taddese, G., Sonder, K., & Peden, D. (2004). *The water of the Awash River Basin: A Future*

Challenge to Ethiopia. *January*, 13.

Tekle, A. (2015). Assessment of climate change impact on water availability of Bilate watershed, Ethiopian Rift Valley Basin. *AFRICON 2015*, 1–5.

Teutschbein, C., & Seibert, J. (2012). Bias correction of regional climate model simulations for hydrological climate-change impact studies: Review and evaluation of different methods. *Journal of Hydrology*, *456*, 12–29.

WCDP/WMO. (1986). *Guidelines on the Selection of Reference Climatological Stations (RCSs) from the Existing Climatological Station Network*. *130*, 16. http://books.google.de/books/about/Guidelines_on_the_Selection_of_Reference.html?id=-LjxNAAACAAJ&pgis=1

WMO. (2011). *Guide to Climatological Practices 2011: Weather, Climate, Water* (Issue 100).