Reliability of NASA NEX-GDDP Dataset in Reproducing Climatological Mean Temperature and Precipitation over the Gibe III Watershed, Omo-Gibe Basin, Ethiopia

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Abstract

Background: The challenge of climate variability is a major problem for developing and using water resources. Scarcity of climate data compounds the problem and undermines the efforts to acquire updated information for predicting climate change and reduce its risks.
Objective: The objective of the study was to evaluate and select the best climate models having NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP) dataset for Gibe III watershed. **Material and Methods:** NEX-GDDP data of precipitation and temperature with spatial resolution of 0.25º x 0.25º of ten CMIP5 models was, evaluated against observed data of eight stations distributed in the Watershed.
Results: The models showed a consistent and reasonable pattern for mean monthly total precipitation and mean temperature (max and min). The mean monthly precipitation of all models against observation also resulted to R^2 of 0.71 to 0.99 and the Nash–Sutcliffe efficiency (NSE) value of 0.66 to 0.99. Mean annual precipitation of model ensemble mean over the watershed against observation spatially varied between –100 and 100 mm underestimating at the northern and southern tips of watershed while overestimating at central and northeastern parts. The mean maximum and minimum temperature varied from –1.6 ºC to +2.9 ºC and 0.4 ºC to 3.8 ºC, respectively.
Conclusion: The result indicates that, selecting climate models' ensemble mean could provide higher confidence in climate change projection than choosing a specific model for an entire watershed. Based on evaluation metrics and long-term mean annual rainfall, NEX-GDDP dataset of CSIRO-MK3-6-0, MIROC5, MPI-ESM-MR, NorESM1-M, MIROC5 and GFDL-ESM2M models reasonably simulated the mean annual rainfall at Shebe, Sodo, Jimma, Hosaina, Sokoru and Woliso stations respectively for uses of climate change projection in the Watershed. The reliability of NEX-GDDP dataset for the climate models need seasonal basis study in the future at the Watershed since this study did not conduct seasonal data analysis.

Keywords: Bias corrected; Climatological mean; Model ensemble mean; Statistically downscaled

1. Introduction

Studies on climate change impact on water resources require the use of climate models with higher resolution at local condition that could simulate the present day climate and give increased confidence on future climate scenarios (Ramirez-Villegas *et al*., 2013). These GCM projections have a spatial resolution (0.5º x 0.5º or more) (Chu *et al*., 2010) that affect its application for climate change impact assessment at a local scale (IPCC, 2013). Downscaling (Jones *et al*., 2004; Pervez and Henebry, 2015) and bias correction of climate simulation models (Ho *et al*., 2012) are major procedures when working with climate simulation models. Dynamical downscaling technique (Boé *et al*., 2006; Christensen *et al*., 2006; Jacob *et al*., 2014) and statistical downscaling technique (Hewitson and Crane, 2006; Bosshard *et al*., 2013; Maraun and Widmann, 2018) were applied to downscale the GCM output to finer local climate conditions (Dibike and

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Coulibaly, 2005; Frei *et al*., 2006; Shimelis Gebriye *et al*., 2010; Wayne, 2013).

Gibe watershed has potential water resources for electric power generation at cascades of Gibe I, II, III, and IV dam whose construction targeted before fifteen years (EEPCo, 2009). However, scarcity in climate data and the challenge of climate variability is a major problem for the Gibe watershed hydrological resource basis which otherwise will not achieve its development goal (UNEP, 2013). The area needs updated information on the climate change impacts to reduce risks of climate change. Downscaling of global-scale climatic variables to local-scale hydrologic variables is an important procedure before perusing impact studies for climate change.

However, as Shimelis Gebriye *et al*. (2010) explained, the limitation of downscaling procedure for getting climate model output is that it requires high computing resource capacity, high human knowledge and skill as well as time. In response to this problem, NASA produced Earth Exchange Global Daily Downscaled Projection (NEX-GDDP) dataset of Coupled Model Inter-comparison fifth Project (CMIP5) with resolution of 0.25° x 0.25° for climate models (Thrasher *et al*., 2012; Thrasher *et al*., 2015). Chen *et al*. (2017) and Jain *et al*. (2019) justified that the near and long-term climate study using the datasets was proved to be robust in regions with complex topography like the study region, Gibe watershed, Ethiopia. Since Gibe watershed is a source of hydroelectric power energy for the country, it needs a critical attention to sustain its service as planned. One of the information for such action is analysis of future climate state specially the rainfall and maximum and minimum temperature.

On the other hand, studies on future climate condition and the prediction require use of climate models, which could show us plausible future climate. In this regard, it is important to compare some climate model outputs with existing observational dataset with historical data and use the best model that could represent the station climate data for future climate change as well as impact study. In this case, a comparative evaluation and selection of best climate models at Omo-Gibe basin in general and at Gibe III in particular was, not conducted. Therefore, it is important to select best and high-resolution model type with NEX-GDDP dataset for the watershed through model reliability evaluation. Accordingly, this study is signifies the importance of overcoming climate data scarcity and solve the uncertainty expected during climate change studies for sustainable management of water resources. The result will be of benefit to stakeholders who manage hydroelectric dams and its water sources as well as the scientific community for further research. The research question was, 'Is the existing bias corrected statistically downscaled high-resolution climate models with NEX-GDDP dataset applicable for use in Gibe watershed'. Therefore, the objective of the study was to evaluate the reliability of the NEX-GDDP datasets in reproducing climatological means of rainfall and temperature over Gibe III Watershed

2. Materials and Methods

2.1. Description of the Study Area

Gibe III watershed is located within the Omo-Gibe River Basin, in the middle reach of the Omo river. It is located between the latitude of 6.6°–9.4°N and longitude of 35.78°–38.42°E. The catchment area is about 34,154.16 km^2 with the Hydropower scheme comprising a 243 m high dam creating a reservoir of surface area spanning 200 km^2 and creating storage of some 11,750 million m^3 of water (EEPCO, 2009). Gibe III dam has the capacity to generate about 1870 MW (Negash Teklu *et al.,* 2016) hydroelectric power. The area experiences hot arid to tropical humid and sub humid climatic conditions. The rainfall pattern is uni-modal for the northern and central parts of the Watershed and bimodal for the southern part. The average annual rainfall calculated over the whole Gibe III watershed where the dam is located is 1,426 mm with major distribution occurring from May to September. The mean annual temperature varies from 16 °C to over 29 °C (EEPCO, 2009). The study area has a topography characterized by mountainous to hilly terrain and flat alluvial plain punctuated by hilly areas. The Watershed has an altitude range of 681–3570 m a.s.l. (EEPCO, 2009).

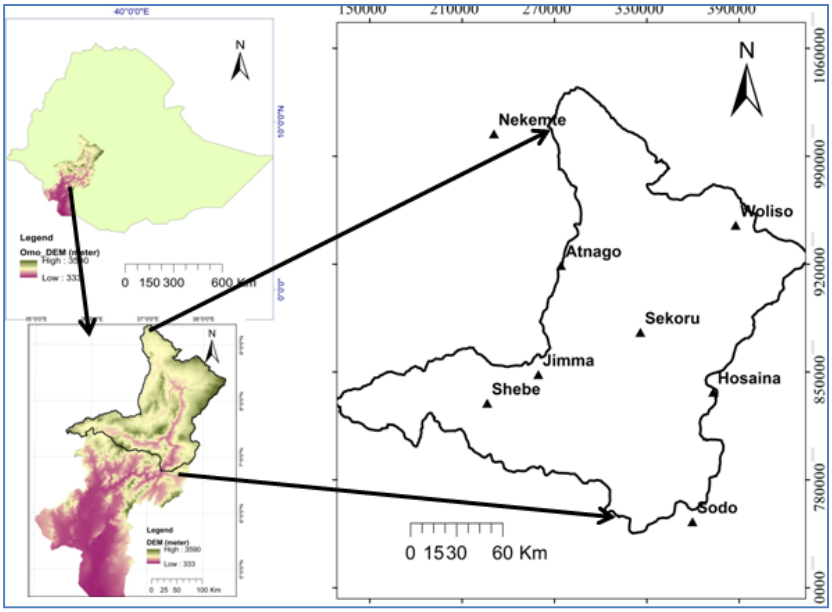


Figure 1. Location of the Gibe-III watershed and weather stations (Ethio-GIS database).

2.2. Data Type and Source

The National Aeronautics and Space Administration (NASA) Earth Exchange Global Daily Downscaled Projections (NEX-GDDP) dataset contains downscaled climate scenarios derived from the GCM simulations of the Coupled Model Inter-comparison Project Phase 5 (CMIP5). The spatial resolution of the dataset is 0.25° (~ 25 km × ~ 25 km). These datasets provide a set of global, high-resolution, bias- corrected climate change projections that can be, used to evaluate climate change impacts on finer scales. Each of the climate projections includes mean maximum and minimum temperatures and precipitation for the periods from 1950 to 2005 (retrospective run) and from 2006 to 2099 (prospective run) on a daily scale available at https://dataserver.nccs.nasa.gov/thredds/catalog/bypass/NEX-GDDP/bcsd/catalog.html. The bias corrected statistically downscaled climate model output data of GCMs with data range of 1976–2005 was, downloaded from NASA data portal (ftp://ftp.nccs.nasa.gov/). For comparative analysis, observed daily rainfall and maximum and minimum temperature data from 1976–2005 was, obtained from National Meteorological Agency (NMA) of Ethiopia. Eight climate stations in and around the Watershed having full data similar to the selected model historical data period (1976–2005) were selected (Table 1).

Table 1. Data obtained from National Meteorological Agency for selected stations.

Stations	Lat. (degree)	Long. (degree)	Elev. (m.a.s.l)	Number of year	Period	Data type
Sokoru	7.92	37.42	1928	30	1976–2005	Daily precipitation; daily maximum and minimum temperature
Atnago	8.31	36.95	1804	30	1976–2005	
Hosaina	7.57	37.85	2349	30	1976–2005	
Jimma	7.67	36.82	1718	30	1976–2005	
Nekemte	9.08	36.55	2108	30	1976–2005	
Shebe	7.50	36.52	1772	30	1976–2005	
Sodo	6.81	37.73	2032	30	1976–2005	
Woliso	8.55	37.98	2464	30	1976–2005	

2.3. Methods

2.3.1. Climate model selection

The following table indicates the list of selected CMIP5 climate models for this study (Table 2). However, due to limitation of time for analysis of each variable on a station basis, from twenty-one models developed in different countries at different institutions, the study selected only about ten models. The researcher downloaded historical daily precipitation and maximum and minimum temperature data for each point-station from NASA web page.

Table 2. Information about the selected 10 Coupled Model Inter-comparison fifth Project (CMIP5) general circulation models (GCMs).

Number	Model	Country and institution
01	ACCESS1-0 1	Commonwealth Scientific and Industrial Research Organization and Bureau of Meteorology, Australia
02	CanESM2	Canadian Centre for Climate Modelling and Analysis, Canada
03	CNRM-CM5	Centre Europeen de Recherche et Formation AvanceesenCalculScientifique, France
04	CSIRO-Mk3-6-0	Commonwealth Scientific and Industrial Research Organization Queensland Climate Change Centre of Excellence, Australia
05	GFDL-ESM2M	Geophysical Fluid Dynamics Laboratory, America
06	IPSL-CM5A-LR	Institute Pierre-Simon Laplace, France
07	MIROC5	Atmosphere and Ocean Research Institute, Japan
08	MPI-ESM-MR	Max Planck Institute for Meteorology, Germany
09	MRI-CGCM3	Max Planck Institute for Meteorology, Germany
10	NorESM1-M	Norway Consumer Council, Norway

In order to analyze the data on a Watershed basis, area weighted data were prepared for average annual precipitation and temperature using Inverse Distance Weight (IDW), the method recommended by Chen and Liu (2012) for spatial interpolation using ArcGIS version 10.1. IDW is a common and simple way of spatial interpolation, where observations are weighted based on their distance to a given point by a non-linear relationship expressed by an exponent (typically equal to 2). The method is widely used due to its simplicity and its applicability to even sparse and irregular datasets (Ahrens, 2006; Yang *et al*., 2015). IDW uses the distances from the target neighbor gauge stations with more weight given to data of nearest station as justified by different authors (Longley *et al*., 2001; De Silva *et al*., 2007; Achilleos, 2011; Chen and Liu, 2012; Moeletsi *et al*., 2016). Monthly patterns of precipitation and temperature were plotted against the observation for the monthly long-term mean data of the selected models.

2.3.2. Performance metrics for evaluation of models

The performance Metrices, such as the root mean squared error (RMSE), coefficient of determination (R^2), and Nash–Sutcliffe efficiency (NSE) of the Annual Mean Precipitation (MA-P), the mean monthly temperature (MM-T- both max. and min) as well as mean monthly precipitation (MM-P) (Nash and Sutcliffe, 1970; MacLean, 2005) were applied during statistical analysis (Equations 1-3). In addition, Absolute (AE) and relative errors (RE) were used to identify models that could reasonably reproduce the mean annual precipitation (MA-P) at each station so that the station would get one representative model. The smaller the AE or RE, the better is the model to reproduce the observation (Equations 4 and 5). These metrics were used as the indicators for the performance comparison of each model with observed data. R^2 shows the degree of the linear relation between model output and observed data; R^2 of 0 denotes no relation whereas 1 represents strong relation. RMSE represents the errors between two variables; the smaller the RMSE, the better the results. The specific performance metrics including mean annual precipitation (Mean-P) and mean annual temperature (Mean-T) were also used during the evaluation.

$$R^2 = \left[\frac{\frac{1}{n}\sum_{m=1}^{n}(X_o-\mu_o)(X_m-\mu_m)}{\sigma_{X_o} \, X \, \sigma_{X_m}}\right]^2 \quad \text{Eq. 1}$$

$$RMSE = \sqrt{\frac{\sum_{m=1}^{n}(X_o-X_m)^2}{n}} \quad \text{Eq. 2}$$

$$NSE = 1 - \left[\frac{\sum_{i=1}^{n}(Y_i^{obs}-Y_i^{sim})^2}{\sum_{i=1}^{n}(Y_i^{obs}-Y^{mean})^2}\right] \quad \text{Eq. 3}$$

Where, X, μ and σ show the raw data, mean and variance, respectively, while o and m show the observed and model, respectively, and n is the number of events.

$$Absolute\ Error\ (AE) = |y_{mean}{}^{obs} - y_{mean}{}^{model}| \quad \text{Eq. 4}$$

$$Relative\ Error\ (RE) = \frac{|y_{mean}{}^{obs}-y_{mean}{}^{model}|}{y_{mean}{}^{obs}} x100 \quad \text{Eq. 5}$$

Where, ${y_{mean}}^{obs}$ = long-term mean (1976-2005) of the observation of annual precipitation at station and ${y_{mean}}^{model}$ = long-term mean (1976-2005) of the model of annual precipitation at station

3. Results

Knowledge of historical climate condition compared to model outputs from different sources of data has an important role to play in building confidence in the knowledge of future climate change simulated by such models. Although GCMs are a very important source of information to know the future climate, uncertainty due to their inherent characteristics, the complexity of variables (parameters) producing atmospheric and land system interaction requires evaluation of their output based on observation data. Thus, precipitation and temperature analyses for ten models, ensemble mean of the models and observation data were, carried out and the results are discussed below.

3.1. Performance of NEX-GDDP Dataset for Simulating Mean Monthly Temperature

The mean monthly maximum and minimum temperatures of each model and ensemble mean as well as for observation in selected weather stations are shown in Figure 2.

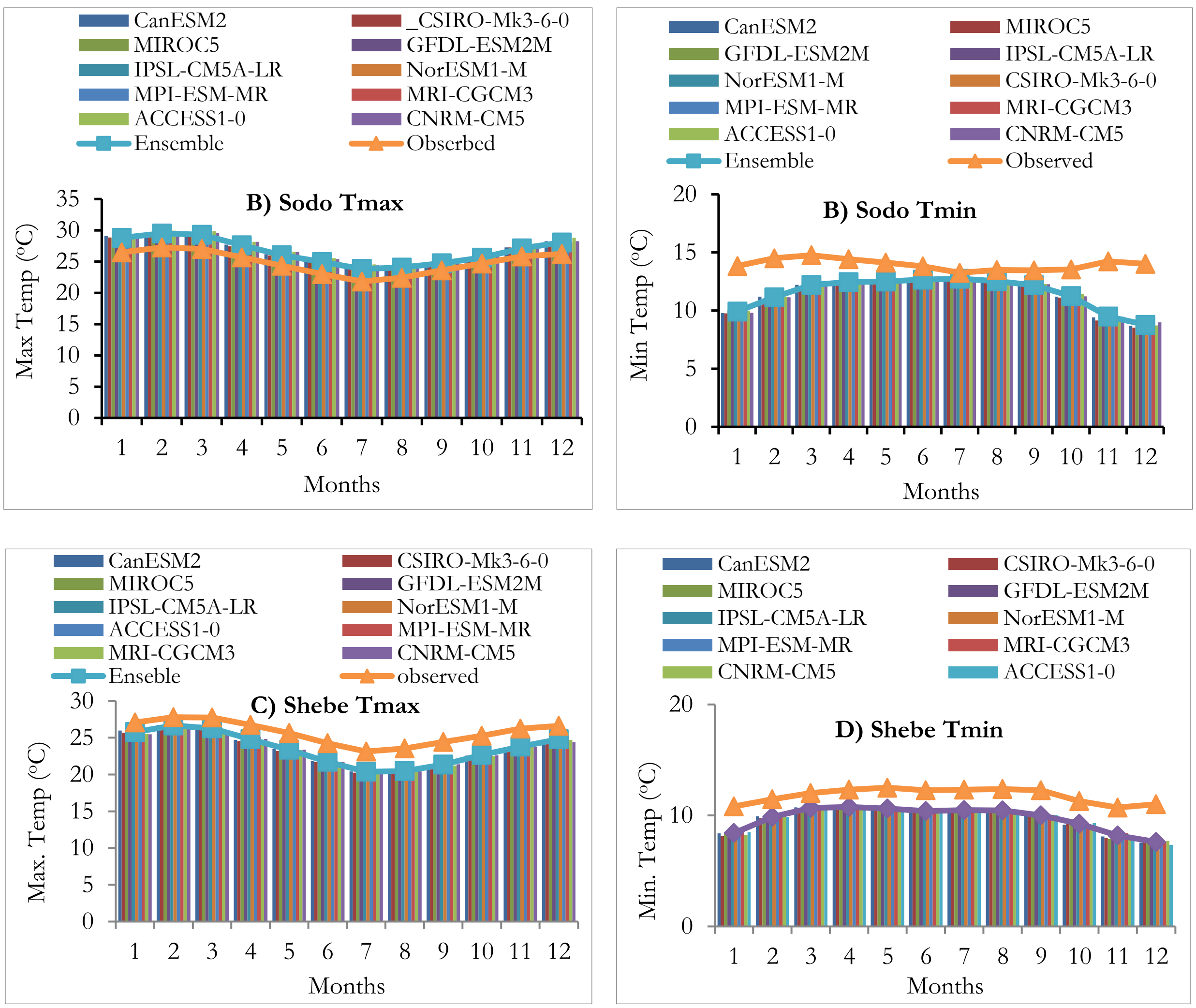


Figure 2. Climatological (1976–2005) annual cycle (monthly mean) of surface temperature (maximum (left) and minimum (right) of NEX GDDP model historical and observed data (A-P).

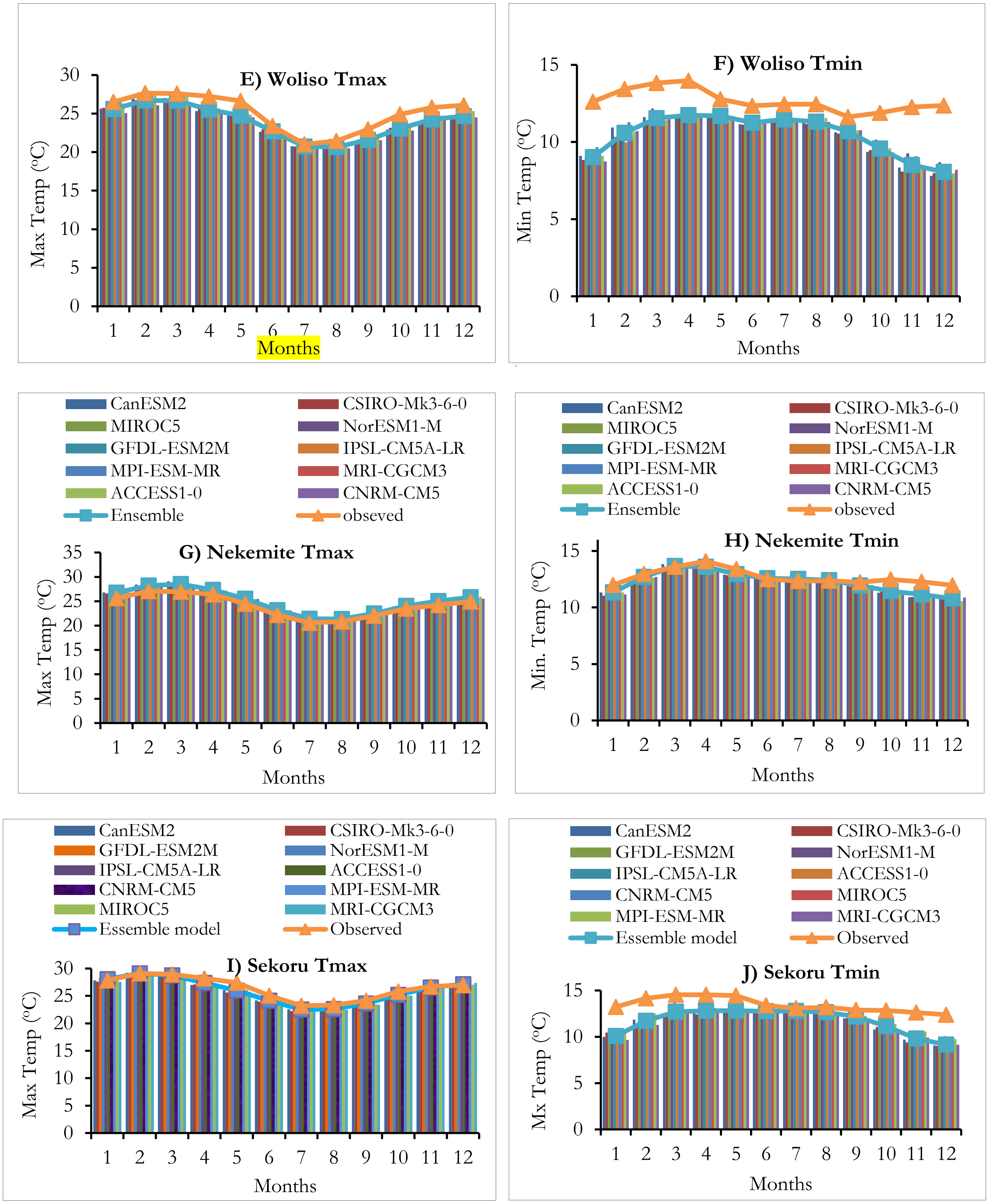


Figure 2. Continued.

3.2. Performance of NEX-GDDP Dataset for Simulating Mean Monthly Distribution Pattern of Precipitation

The results of comparing the ten CMIP5 models with NEX-GDDP dataset outputs, their ensemble mean and observed data of monthly distribution from (1976–2005) of rainfall data for eight weather stations is shown in Figure 3 below. As in the case of temperature, the precipitation pattern was similar among ten models and the ensemble mean. Although bar graphs show the magnitude of precipitation for all ten models, to make the document simple to readers, only model ensemble mean and observed value were, made visible by line graph overlay.

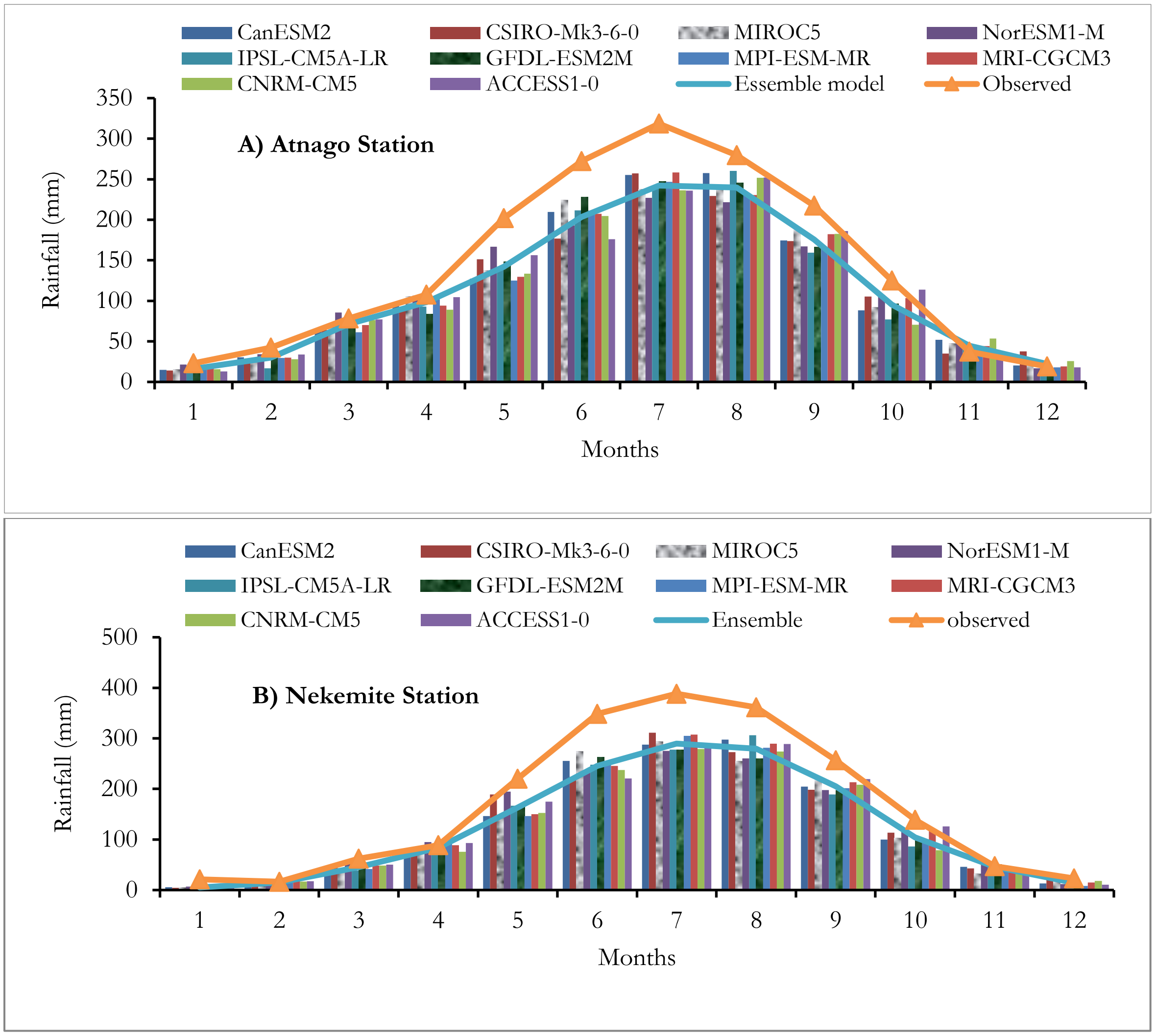
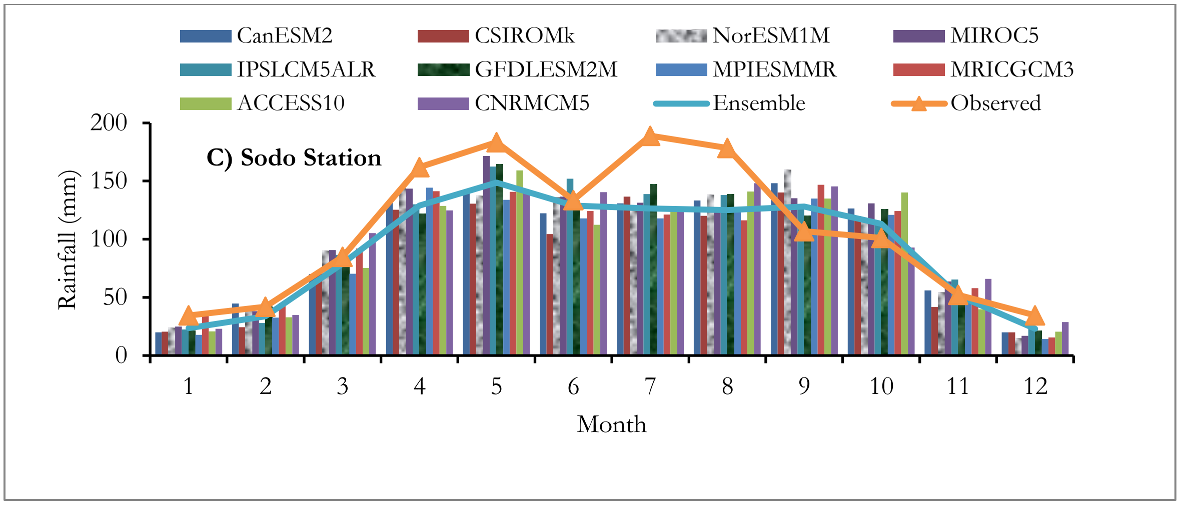
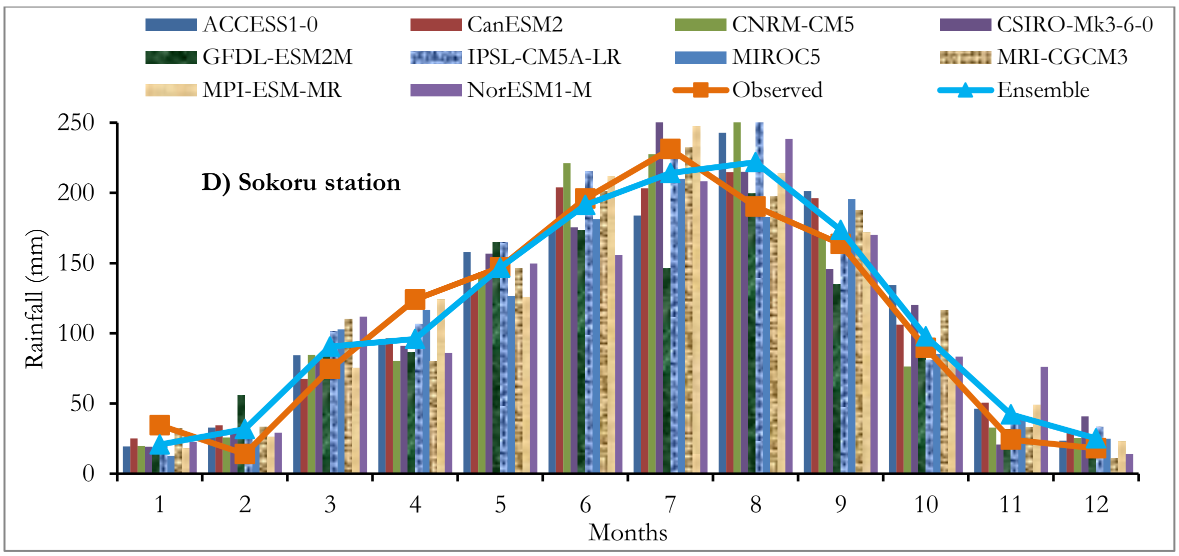


Figure 3. Climatological (1976–2005) mean monthly total precipitation at each station for NEX_GDDP dataset, the ensemble mean of 10 models and observed data





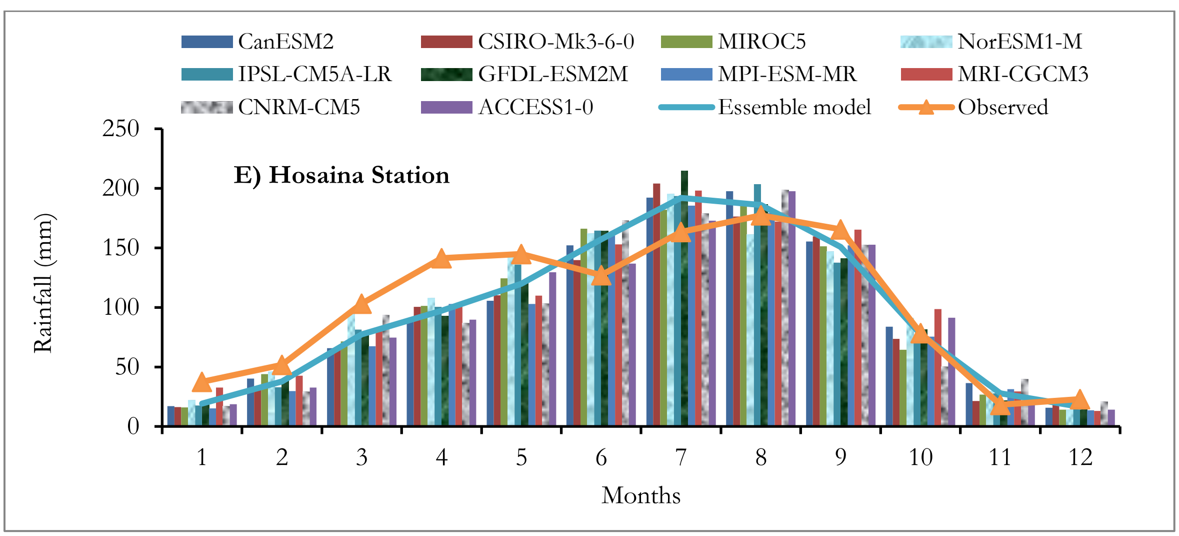


Figure 3. Continued

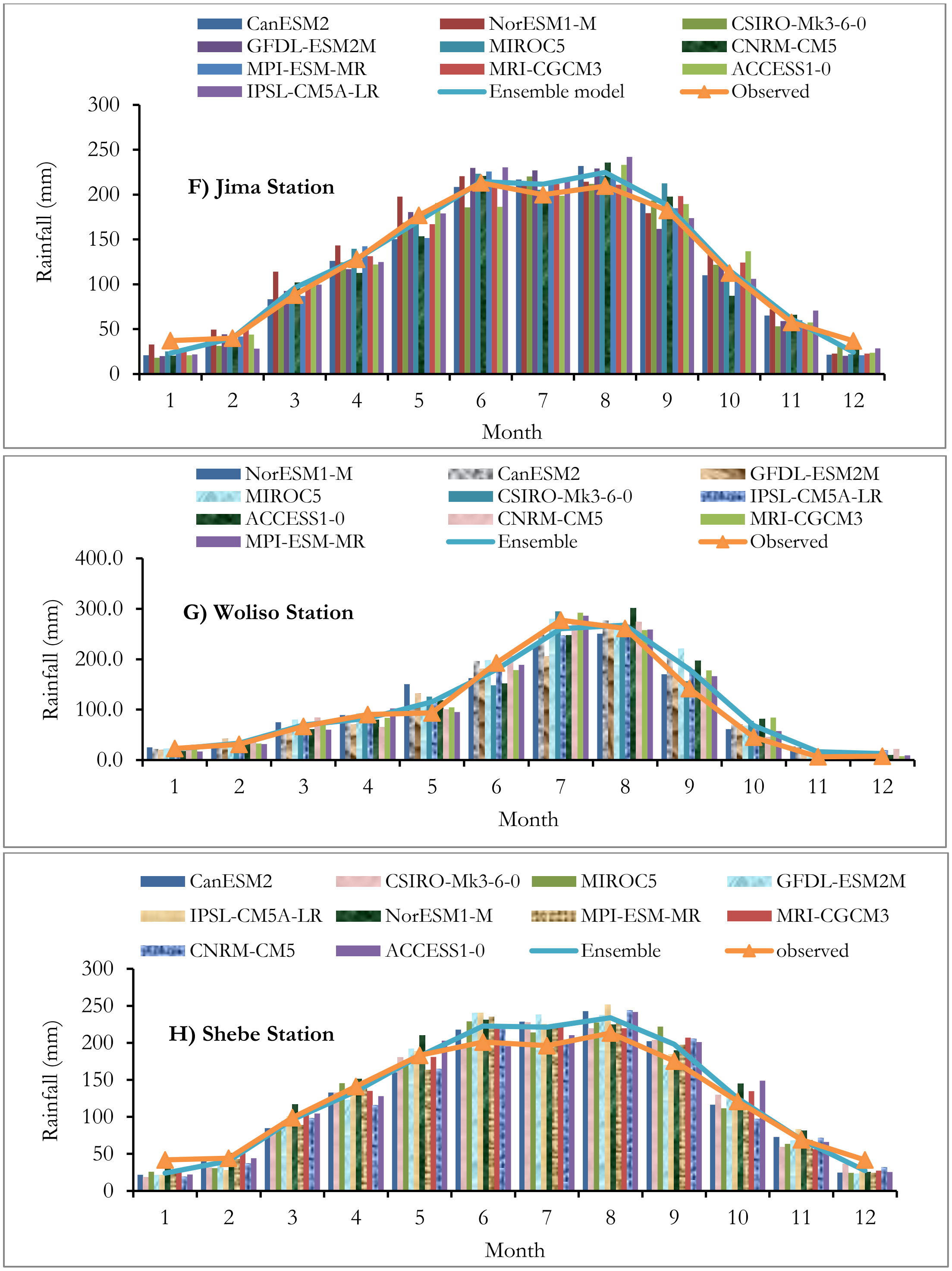


Figure 3. Continued.

The Climatological (1976–2005) mean monthly model outputs of precipitation was also subjected evaluation metrics such as RMSE, R^2 and NSE and the result is indicated in Table 3

Table 3. Performance metrics for climatological mean monthly precipitation total models outputs relative to observation at the station.

Metrics	CanESM2	CSIRO-Mk3-6-0	MIROC5	IPSL-CM5A-LR	GFDL-ESM2M	NorESM1-M	MPI-ESM-MR	MRI-CGCM3	ACCESS1-0	CNRM-CM5	Ensemble	Max	min	mean
Sokoru station														
RMSE	20.75	20.53	17.95	24.38	32.63	29.57	15.12	20.60	30.61	25.63	16.84	32.63	15.12	23.2
R^2	0.92	0.93	0.94	0.93	0.83	0.84	0.97	0.93	0.84	0.91	0.95	0.97	0.83	0.91
NSE	0.95	0.95	0.96	0.93	0.87	0.89	0.97	0.95	0.89	0.92	0.97	0.97	0.87	0.93
Atnago station														
RMSE	38.72	42.29	37.65	41.41	35.79	43.16	42.52	38.28	41.02	42.66	39.47	43.16	35.79	40.3
R^2	0.96	0.97	0.97	0.96	0.99	0.98	0.98	0.98	0.95	0.95	0.98	0.99	0.95	0.97
NSE	0.86	0.84	0.87	0.84	0.88	0.83	0.84	0.87	0.85	0.83	0.86	0.88	0.83	0.85
Hosaina station														
RMSE	26.52	24.15	22.53	23.98	27.16	19.75	25.07	22.12	21.31	28.78	22.21	28.78	19.75	23.9
R^2	0.83	0.88	0.88	0.87	0.84	0.89	0.86	0.86	0.9	0.81	0.88	0.9	0.81	0.86
NSE	0.78	0.82	0.84	0.82	0.77	0.88	0.8	0.85	0.86	0.74	0.84	0.88	0.74	0.82
Jima station														
RMSE	13.54	12.74	12.64	14.45	15.12	14.51	11.97	10.45	15.17	16.12	8.64	16.12	8.64	13.2
R^2	0.97	0.97	0.98	0.98	0.97	0.97	0.98	0.98	0.96	0.96	0.99	0.99	0.96	0.9
NSE	0.96	0.96	0.97	0.95	0.95	0.95	0.97	0.98	0.95	0.94	0.98	0.98	0.94	0.96
Nekemte station														
RMSE	52.84	54.04	53.84	55.43	57.06	58.63	52.77	49.97	55.61	59.82	53.88	59.82	49.97	54.9
R^2	0.99	0.98	0.98	0.98	0.97	0.98	0.99	0.99	0.97	0.99	0.99	0.99	0.97	0.98
NSE	0.85	0.85	0.85	0.84	0.83	0.82	0.85	0.87	0.84	0.81	0.85	0.87	0.81	0.84
Sodo station														
RMSE	19.34	16.03	19.43	20.59	20.98	18.31	17.72	16.05	17.62	19.54	14.9	20.98	14.9	18.2
R^2	0.96	0.97	0.97	0.98	0.97	0.98	0.97	0.98	0.97	0.95	0.99	0.99	0.95	0.97
NSE	0.91	0.94	0.91	0.9	0.89	0.92	0.92	0.94	0.92	0.91	0.95	0.95	0.89	0.92
Shebe station														
RMSE	30.78	33.71	31.38	24.19	23.21	27.11	33.32	33.4	29.99	29.75	28.92	33.71	23.21	29.6
R^2	0.77	0.79	0.73	0.85	0.88	0.8	0.78	0.71	0.79	0.77	0.84	0.88	0.71	0.79
NSE	0.71	0.66	0.7	0.82	0.84	0.78	0.66	0.66	0.73	0.73	0.75	0.84	0.66	0.73
Woliso station														
RMSE	23.36	20.64	24.79	17.28	26.68	26.11	9.63	17.22	28.13	13.29	16.33	28.13	9.63	20.3
R^2	0.95	0.95	0.95	0.97	0.92	0.93	0.99	0.97	0.91	0.98	0.97	0.99	0.91	0.95
NSE	0.86	0.95	0.93	0.96	0.91	0.92	0.99	0.96	0.9	0.98	0.97	0.99	0.86	0.94

Note: *This table is the output of statistical analysis of selected model climatological mean monthly values relative to observed values for each station. Sample analysis for Sokoru station was shown in Appendix Table 2.*

3.3. Performance of NEX-GDDP Dataset for Simulating Climatological Mean Annual Precipitation Distribution and Magnitude

The annual precipitation result for ten models, the ensemble mean and observed data over selected eight stations of the watershed is demonstrated in Figure 4.

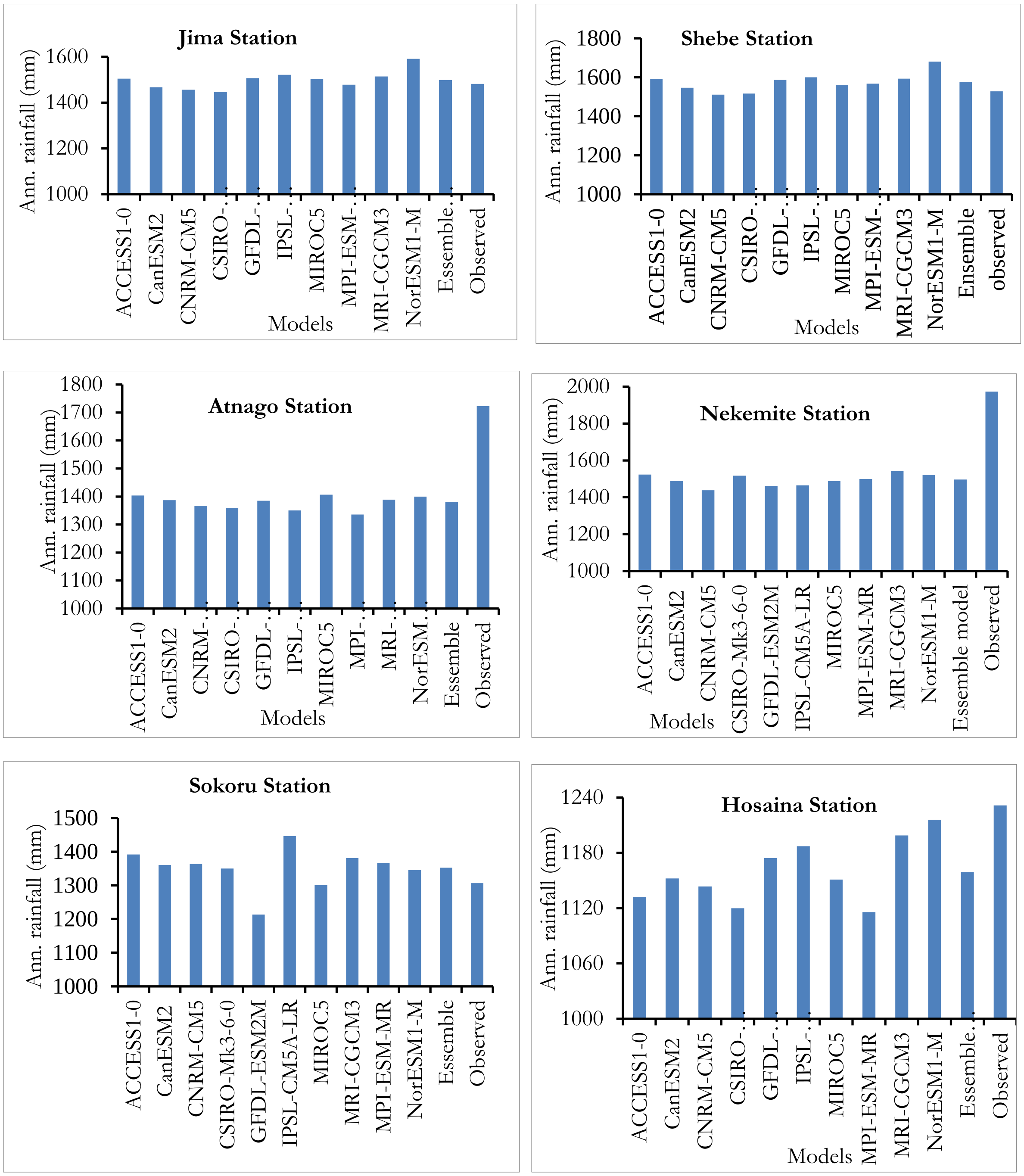
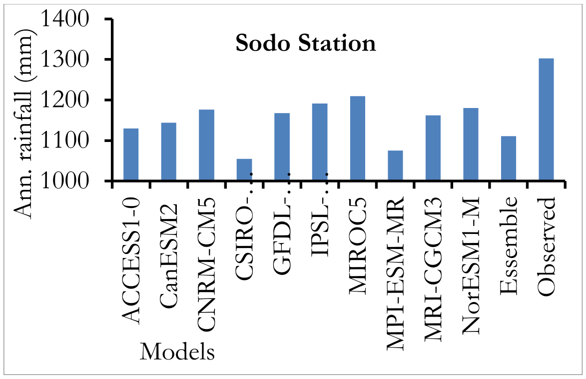


Figure 4. Climatological mean annual rainfall distribution for models and observation.



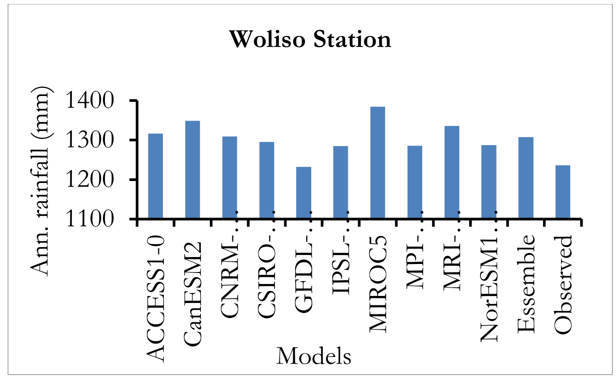


Figure 4. Continued.

The mean standard deviation and coefficient of variation indicated in Table 4 was obtained for each variables (mean annual precipitation and mean maximum and minimum temperture for each station. The analysis is to identify the variability between models and observation in eneral.

Table 4. The Mean, standard deviation (SD) and coefficient of variation (CV) for climatological means of models and observation at each station.

Station	Mean annual precipitation for models and observation			Mean annual maximum temperature for models and observation			Mean annual minimum temperature for models and observation		
	Mean	SD	CV (%)	Mean	SD	CV (%)	Mean	SD	CV (%)
Atnago	1394.59	86.66	6.21	26.59	0.32	1.22	12.98	0.22	1.66
Nekemte	1407.07	101.54	7.22	24.88	0.29	1.17	12.28	0.16	1.33
Sodo	1165.09	37.09	3.18	26.77	0.64	2.38	11.70	0.72	6.15
Shebe	1497.15	37.71	2.52	23.68	0.65	2.73	10.01	0.99	9.91
Hosaina	1534.36	41.25	9.21	23.91	0.51	2.13	9.76	0.34	3.46
Jimma	1571.40	45.91	2.92	25.54	0.57	2.24	11.22	0.16	1.42
Woliso	1158.60	65.04	5.61	23.99	0.39	1.64	10.64	0.66	6.21
Sokoru	1348.44	56.85	4.22	24.45	0.87	3.56	10.28	0.62	5.99

Tables 5 and 6 show absolute error and relative error of each model at each station. The climatological mean annual precipitation indicated in Appendix Table 3 and equations 4 and 5 was the source of data for caluculation of AE and RE. Shaded values indicate the minimum values of the model at respective station and it shows the model to be selected at the station.

Table 5. The absolute error for climatological mean annual precipitation of models relative to observation at each station.

Name of station	CanESM2	CSIRO-Mk3-6-0	MIROC5	IPSL-CM5A-LR	GFDL-ESM2M	NorESM1-M	MPI-ESM-MR	MRI-CGCM3	ACCESS1-0	CNRM-CM5
Sokoru	54.0	43.7	6.2	139.8	93.3	39.0	59.7	74.3	85.1	57.3
Atnago	335.5	362.4	316.0	337.1	371.9	322.6	386.7	333.6	318.8	354.5
Hosan	79.3	111.7	80.4	44.3	57.3	15.6	115.7	32.6	99.2	88.1
Jimma	15.2	35.9	20.1	39.1	24.9	108.9	3.9	31.9	22.6	26.1
Nekemte	484.1	456.0	485.9	508.2	511.3	451.0	473.6	431.1	449.5	535.4
Shebe	18.7	10.8	31.8	73.3	60.3	152.8	39.5	65.5	63.8	15.9
Sodo	159.3	248.6	93.2	111.8	135.3	122.6	227.7	141.0	172.9	126.9
Woliso	111.8	58.5	147.9	47.8	4.7	50.8	49.3	98.9	79.8	72.4

Table 6. The Relative error (%) for long-term mean annual precipitation of models relative to observation at each station.

Station	CanESM2	CSIRO-Mk3-6-0	MIROC5	IPSL-CM5A-LR	GFDL-ESM2M	NorESM1-M	MPI-ESM-MR	MRI-CGCM3	ACCESS1-0	CNRM-CM5
Sokoru	4.1	3.3	0.5	10.7	7.1	3.0	4.6	5.7	6.5	4.4
Atnago	19.5	21.0	18.4	19.6	21.6	18.7	22.5	19.4	18.5	20.6
Hosain	6.4	9.1	6.5	3.6	4.7	1.3	9.4	2.7	8.1	7.2
Jimma	1.0	2.4	1.4	2.6	1.7	7.3	0.3	2.2	1.5	1.8
Nekemte	24.5	23.1	24.6	25.8	25.9	22.9	24.0	21.8	22.8	27.1
Shebe	1.2	0.7	2.1	4.8	4.0	10.0	2.6	4.3	4.2	1.0
Sodo	12.2	19.1	7.2	8.6	10.4	9.4	17.5	10.8	13.3	9.7
Woliso	9.0	4.7	12.0	3.9	0.4	4.1	4.0	8.0	6.5	5.9

3.4. Performance of NEX-GDDP Dataset for Simulating Spatial Variability of Mean Annual Precipitation and Temperature

The model ensemble mean annual rainfall was spatially, interpolated to the watershed area for comparative analysis with the observed values. Spatial basis distributions of the NASA dataset (1976–2005) mean annual precipitation and temperature are displayed in Figure 5.

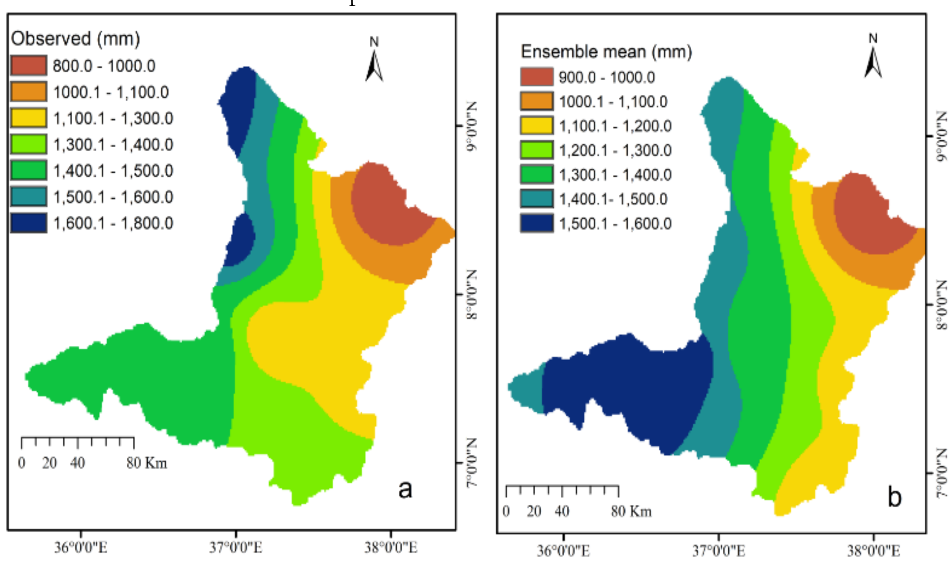


Figure 5. Spatial distributions of the climatological mean annual precipitation (1976–2005) (a) Observed, (b) Ensemble mean of 10 models for the watershed.

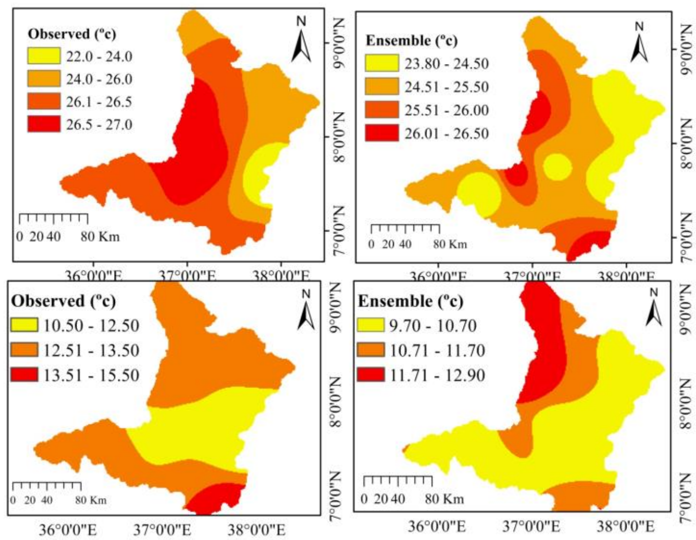


Figure 6. Spatial distributions of the climatological mean annual surface temperatures (1976–2005) for observed and the ensemble mean of 10 models for mean maximum temperature (A and B) and minimum temperature (C and D) of the watershed.

4. Discussion

4.1. Performance of NEX-GDDP Dataset for Simulating Mean Monthly Temperature

The mean monthly maximum and minimum temperatures of the models were not significantly different to each other in the respective stations (Figure 2). However, the difference was, obviously observed between observation and ensemble mean. In all stations, mean maximum temperature of ten models and ensemble mean had a similar pattern of observation. However, the mean minimum temperature had a similar pattern of observation only at Sokoru, Jimma, Shebe, Nekemte, and Atnago. During the months from October to March, mean minimum temperatures at Sodo, Hosaina and Woliso stations were not captured by all models and indicating the underestimation of mean minimum temperature. Dyer *et al.* (2019) justified that, cold biases from November–March are a common characteristic of almost all of the coupled model climatology in some parts of Ethiopia. The author explained that if the models cannot reproduce higher temperatures in the months of dry season, they might not be a useful tool for using in such event prediction. The best fit of the lines (pattern) among the models and their ensemble mean for mean maximum and minimum temperature at the remaining stations indicates the possibility of using one of the models data or ensemble mean data for further studies in this Watershed.

The climatological mean monthly maximum temperature was little overestimated at Sodo and Hosaina while it was underestimated at Shebe, Jima and Sokoru stations. According to Randall *et al.* (2007), the local topography, existing surface condition and the weather events can make variations among stations. Regions with sharp elevation changes that could come from mismatches between the smoothed model topography and the actual topography of area can result in larger errors. This situation is in agreement with justification of Dyer *et al.* (2019) who stated that the highland in general is cooler so that the models may not be able to capture the spatial heterogeneity in regional temperature. The climatological mean monthly temperature patterns in Figure 2 clearly indicates how well the NEX-GDDP model runs and reproduces observed annual cycle. Generally, five out of eight stations shown at Figure 2 indicated good simulation ability of NEX-GDDP model datasets for Gibe Watershed to reproduce the observed temperature.

4.2. Performance of NEX-GDDP Dataset for Simulating Mean Monthly Distribution Pattern of Precipitation

There was a good match of mean monthly precipitation total (climatological mean monthly precipitations) pattern in all cases between models, their ensemble means and observed values. In stations such as Atnago (Figure 3A), Nekemte (Figure 3B), and Sodo (Figure 3C), the models failed to capture the higher magnitude of the observations during the months of May to September so that, the mean was underestimated. This situation was explained by to Randall *et al.* (2007) since the models continue to have significant limitations in their representation of clouds that could lead to uncertainties in the magnitude and timing of precipitation. Though NEX-GDDP dataset is bias-corrected, it underestimates rainfall observation which might result in uncertainties especially from high discrepancies in the extreme values of precipitation (Bao and Wen, 2017; Raghavan *et al.*, 2018). However, Dettinger *et al.* (2004) and Wilby *et al.* (2000) agreed that, the performance of model outputs with NEX-GDDP data were applicable in hydro-climatology studies under data scarce conditions. The peak and trough for the magnitude of the annual cycle were kept in a similar trend for all models against the observation though there could be a limitation in the inherent uncertainties in the models. The result is supported by the findings of Dyer *et al.* (2019), Raghavan *et al.* (2018) and Tierney *et al.* (2015) that NEX-GDDP reproduced the observed patterns except for some marginal differences in the rainfall magnitude during wet months. The result indicates that NEX-GDDP dataset can be applicable with better confidence during station based climate change impact study as the NEX-GDDP data represents well the mean states of temperature and precipitation on a monthly scale. Several studies adopted the Bias Correction and Spatial Disaggregation (BCSD) method to assess the hydrological impacts of climate change (Payne *et al.*, 2004; VanRheenen *et al.*, 2004; Hayhoe *et al.*, 2006).

4.3. Performance Metrics for Climatological Mean Monthly Precipitation Total

From Table 3, it is clear that, the selected models of the NEX-GDDP dataset reproduced the observed mean monthly total precipitation better based on the acceptance level of metrics used in evaluation. The evaluation metrics resulted in R^2 of 0.71–0.99; NSE of 0.66-0.99 and RMSE of 8.64–59.82mm for different models at eight stations. In eight stations, NSE value ranged from 0.66 at Shebe station for the CSIRO-Mk3-6-0 model to 0.99 at Woliso station for the MPI-ESM-MR model indicating strong relation to the observed value since a value of NSE greater than 0.5 is generally at acceptable level of performance (Nash and Sutcliffe, 1970). The higher RMSE (59.82 mm) was obtained from CNRM-CM5 model (Nekemte station) while the lower RMSE (8.64 mm) was observed at the model ensemble at Jimma station.

Multi Model ensemble of these ten models (Figure 3) shows that mean monthly observations for June, July, August and September were highly underestimated at Atnago, Nekemte and Sodo stations with maximum difference at July by about 80–100mm of rainfall. These stations are at boundary divide of Watershed (Sodo and Atnago) and outside the Watershed (Nekemte) at high elevation (Figure 1). On the other hand, at Hosaina station, March April and May were, underestimated while June, July and August were, overestimated slightly. On the contrary, all models captured dry periods in all stations correctly. It can be justified that the models well captured rainfall pattern at Shebe, Jimma, Sokoru and Woliso stations for all selected models. It could be argued that the detail agricultural water management requires NEX-GDDP dataset selection on seasonal bases because obvious biases were observed in the seasonal values, which are also not uniform in space amongst models. The justification by Kug *et al.* (2008), Sengupta and Rajeevan (2013) and Jain *et al.* (2019) supports this argument. The result indicates that the NASA dataset of monthly scale could help during the prediction of the rainfall simulation in the future. According to Alo and Wang (2010), the statistical downscaling with bias correction is an effective tool to derive fine resolution predictions directly from coarse resolution GCMs' outputs.

4.4. Performance of NEX-GDDP Dataset for Simulating Mean Annual Precipitation Distribution and Magnitude

Station based comparision indicated that the observed mean annual rainfall was reproduced for Jimma and Shebe stations except for the case of NorESM1-M which is overestimated by about 100 mm per year. Generally, the mean annual precipitation showed high mismatch at stations such as Hosaina, Sodo, Nekemte and Atnago resulting to underestimation of observation by 100–300 mm annual rainfall. On the contrary, overestimation was observed at Sokoru and Woliso by 50–80 mm per year. Underestimations of the mean annual precipitation by the models were observed for northern (Atnago and Nekemte) tip of the study area and overestimations were observed for central (Sokoru and Woliso) areas of the study. However, unpredictable condition of mean annual precipitation was seen among the models in south-east (Hosaina and Sodo) of study Watershed. The results agree with the findings of McMahon *et al.* (2015) who reported that, the performance statistics comparing CMIP5 GCM outputs and observed mean annual precipitation showed that the high mean annual precipitation was underestimated and the low mean annual precipitation was overestimated. According to Ahmed *et al.* (2013), the drawback of the models, however, is that many wet days are set to no-rain days, which leads to a slight underestimation of the amount of rain. It was also justifed by Raghavan *et al.* (2018) that the magnitude of precipitation in the inter-annual variability is underestimated by NEX-GDDP compared to the observation. This is because the frequency and mangnitude of annual daily maximum events in obsevations may be higher than that of the model. Precipitation is one of the ckimate varaibles that is the mist challengimng for modelling due to the low predictability especially a topographically complex region (Wilby and Dawson, 2007). Acoording to Jain *et al.* (2019), the NEX-GDDP information biases with observed data at 25 km horizontal resolution could be due to the lack of ability of the model parameterization schemes to deal with mountainous regions.

Atnago and Nekemte stationss overall variability or mean annual precipitation was high among models including observation with SD of 86.66 and 101.54 respectively. In addition, the mean monthly and annual precipitation of all models tested at these two stations did not reasonably capture the observation. Tables 5 and 6 also confirm the condition that the absolute error for all models is above 300 mm. The cause may be the microclimate effect, which was not parameterized in the models. Based on the performance metrics (Tables 3, 4, 5 and 6) as well as the magnitude of the station based long-term mean annual precipitation (Figure 4) Atnago and Nekemte stations could be out of stations to use NEX-GDDP dataset. The results shown in Tables 5 and 6 indicated that NEX-GDDP dataset of CSIRO-MK3-6-0, MIROC5, MPI-ESM-MR, NorESM1-M, MIROC5 and GFDL-ESM2M models reasonably simulated the mean annual rainfall at Shebe, Sodo, Jimma, Hosaina, Sokoru and Woliso stations, respectively.

4.5. Performance of NEX-GDDP Dataset for Simulating Spatial Variability of Annual Precipitation and Temperature

The results of maps from NEX-GDDP data showed a similar trend of distribution against the observation in the catchment with small variation in magnitude. From Figure 5, it is observed that, the major coverage of variability of observed data from model output is in the range of -100 to 100 mm per year. From the spatial information, the NEX-GDDP could capture the pattern of precipitation but not the magnitude of precipitation. The result indicates underestimation of the annual precipitation by the models at the Northern and southern tips of the Watershed while overestimation at Sokoru (Central watershed) and Woliso (Northeast tip) of the study area. Given the complexity of variables in modeling precipitation, existence of limitations in downscaling technique, data scarcity problem in the region (Thrasher *et al.*, 2015) and topographic effect of the microclimate in the study area, the results obtained can be tolerable and could be used to evaluate the impact of climate change on water resource in the study area.

The spatial distribution of the mean annual maximum and minimum temperatures for the Watershed (Figure 6) was observed not to be consistent with the variations in the rainfall of selected stations. The maximum temperature is overestimated by the model at the Northern tip, southern tip, and the southeastern tip of the watershed while it was underestimated by 1.2–2.9 ºC at the central and towards the western part of the study area. However, the magnitude of the difference is very small (-0.6–1.2 ºC) for major coverage of the area. The minimum values were overestimated while the maximum values were underestimated. Regarding the minimum temperature (Figure 6), small coverage of land showed underestimation by about 2.4–3.8 ºC difference at the southern tip and the western tip. A larger portion of the watershed got little variation from 0.4–2.4 ºC difference (mean 1.4 ºC).

5. Conclusion and Recommendation

Study of the impact of climate change on water resource at local scale requires reliable and bias corrected high resolution, climate model output. BCSD NEX-GDDP dataset of daily precipitation and temperature having spatial resolution of 25km was released by NASA for use in data scarce regions. Accordingly, these dataset were not evaluated for their reliability for application in Gibe III Watershed. Thus, the climatological means of precipitation and temperature (1976–2005) from ten climate models were comparatively evaluated with observed data at selected representative stations of Gibe III Watershed. The NEX-GDDP dataset of the most of the stations reasonably reproduced the pattern of the climatological annual cycles (monthly means) for temperature and precipitation. However, the climatological mean monthly minimum temperature at Sokoru, Shebe and Woliso showed underestimation while the mean monthly precipitation at Atnago, Nekemte and Sodo also resulted to underestimation. Although different metrics were applied to evaluate and select the relative model that could capture the observation at each station, R^2 value greater than 0.71; NSE value more than 0.66 and RMSE lower than 59.82 mm were recorded by the different models at each station for climatological mean monthly total values. From all models in the eight stations, the lowest NSE value of 0.66 at Shebe station for CSIRO-Mk3-6-0 model and the higher NSE of 0.99 at Woliso station for the MPI-ESM-MR model indicated the strong relation of the models to observed values. The highest RMSE (59.82 mm) was obtained at the CNRM-CM5 model (Nekemte station) while the lower RMSE (8.64mm) was observed at ensemble mean at Jimma station which indicate NEX-GDDP dataset of one single model may not be applicable for different locations. The findings indicted that the six stations had likely representative model that simulated climatological mean monthly and mean annual rainfall as well as temperature (max. and min). Accordingly, based on evaluation metrics and long-term mean annual rainfall, NEX-GDDP dataset of CSIRO-MK3-6-0, MIROC5, MPI-ESM-MR, NorESM1-M, MIROC5 and GFDL-ESM2M models reasonably simulated the mean annual rainfall at Shebe, Sodo, Jimma, Hosaina, Sokoru and Woliso stations respectively. The implication of finding was that, any model dataset requires proper evaluation an interpretation before use as a decision tool for water resource management and planning at local level. It was also found that, higher resolution data does not mean quality and representative but the model type and local microclimate also play great role. Therefore, water resource experts, the country's dam authorities, environmentalists or the climate modelers should evaluate climate model reliability before making use it. Similarly, those who are working in Gibe III Watershed can use the selected model dataset as a source of data for water resource management and modeling works at the Watershed. Since the data used for this study did not include seasonal evaluations of precipitation and temperature, future studies should focus on reliability study of NEX-GDDP dataset for the climate models on seasonal basis in this Watershed.

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Appendix Table 1. Information about the selected 21 Coupled Model Inter-comparison fifth Project (CMIP5) general circulation models (GCMs) with NASA NEX-GDDP dataset.

Number	Model	Country and institution
01	ACCESS1-0 1	Commonwealth Scientific and Industrial Research Organization and Bureau of Meteorology, Australia
02	CanESM2	Canadian Centre for Climate Modelling and Analysis, Canada
03	CNRM-CM5	Centre Europeen de Recherche et Formation AvanceesenCalculScientifique, France
04	CSIRO-Mk3-6-0	Commonwealth Scientific and Industrial Research Organization Queensland Climate Change Centre of Excellence, Australia
05	GFDL-ESM2M	Geophysical Fluid Dynamics Laboratory, America
06	IPSL-CM5A-LR	Institute Pierre-Simon Laplace, France
07	MIROC5	Atmosphere and Ocean Research Institute, Japan
08	MPI-ESM-MR	Max Planck Institute for Meteorology, Germany
09	MRI-CGCM3	Max Planck Institute for Meteorology, Germany
10	NorESM1-M	Norway Consumer Council, Norway
11	BCC-CMS1-1	Beijing Climate Center, China
12	BNU-ESM 3	Institute of global change and Earth System Sciences, Beijing Normal University, China
13	CCSM4	National Center for Atmospheric Research, America
14	CESM1-BGC	National Center for Atmospheric Research, America
15	GFDL-ESM2G	Geophysical Fluid Dynamics Laboratory, America
16	INMCM4	Institute of Numerical Calculation, Russia
17	IPSL-CM5A-MR	Institut Pierre-Simon Laplace, France
18	MIROC-ESM	Atmosphere and Ocean Research Institute, Japan MIROC-ESM-
19	CHEM	Atmosphere and Ocean Research Institute, Japan
20	MPI-ESM-LR	Max Planck Institute for Meteorology, Germany
21	GFDL-CM3	Geophysical Fluid Dynamics Laboratory, America

Appendix Table 2. Performance metrics (RMSE, RSQ and NSE) analysis for two models.

RMSE mean monthly rainfall							
Month	Observed	CanESM2		RMSE*	CSIRO-Mk3-6-0		RMSE*
1	34.6	25.2	9.4	20.75	19.3	15.3	20.5
2	14.0	34.4	–20.4		29.9	–15.8	
3	74.5	67.5	7.0		80.7	–6.2	
4	124.0	96.5	27.4		91.3	32.6	
5	147.0	131.9	15.1		156.9	–9.9	
6	196.0	203.8	–7.9		175.3	20.6	
7	231.1	203.3	27.9		254.3	–23.2	
8	190.3	214.8	–24.5		215.1	–24.8	
9	163.6	196.2	–32.7		145.7	17.9	
10	89.6	106.3	–16.7		120.3	–30.7	
11	24.2	50.6	–26.4		20.9	3.3	
12	18.0	30.3	–12.3		40.9	–22.9	

RSQ mean monthly rainfall					
Month	Observed	CanESM2	RSQ*	CSIRO-Mk3-6-0	RSQ*
1	34.6	25.2	0.9	19.3	0.9
2	14.0	34.4		29.9	
3	74.5	67.5		80.7	
4	124.0	96.5		91.3	
5	147.0	131.9		156.9	
6	196.0	203.8		175.3	
7	231.1	203.3		254.3	
8	190.3	214.8		215.1	
9	163.6	196.2		145.7	
10	89.6	106.3		120.3	
11	24.2	50.6		20.9	
12	18.0	30.3		40.9	

NSE of climatological (long-term) men monthly rainfall							
	Observed	CanESM2		NSE*	CSIRO-Mk3-6-0		NSE*
1	34.6	25.2	88.9	0.948	19.3	233.7	0.949
2	14.0	34.4	416.5		29.9	250.6	
3	74.5	67.5	49.3		80.7	38.5	
4	124.0	96.5	753.1		91.3	1066.0	
5	147.0	131.9	228.1		156.9	97.2	
6	196.0	203.8	62.1		175.3	425.2	
7	231.1	203.3	775.8		254.3	536.3	
8	190.3	214.8	601.8		215.1	614.3	
9	163.6	196.2	1066.2		145.7	319.0	
10	89.6	106.3	278.5		120.3	941.0	
11	24.2	50.6	694.6		20.9	11.1	
12	18.0	30.3	151.4		40.9	524.8	

Note: **Calculated based on equation.*

Appendix Table 3. Climatological mean annual precipitation (1976-2005) for each model and observation data for each station.

Models	Meteorological stations							
	Sokoru	Atnago	Hosaina	Jimma	Nekemte	Shebe	Sodo	Woliso
CanESM2	1360.9	1386.6	1152.2	1466.7	1488.8	1546.2	1143.6	1348.3
CSIRO-Mk3-6-0	1350.6	1359.7	1119.8	1446.0	1516.9	1516.7	1054.3	1295.0
MIROC5	1300.7	1406.1	1151.1	1502.0	1487.0	1559.3	1209.7	1384.4
IPSL-CM5A-LR	1446.7	1385.0	1187.2	1521.0	1464.7	1600.8	1191.1	1284.3
GFDL-ESM2M	1213.6	1350.2	1174.2	1506.8	1461.6	1587.8	1167.6	1231.8
NorESM1-M	1345.9	1399.5	1215.9	1590.8	1521.9	1680.3	1180.3	1287.3
MPI-ESM-MR	1366.6	1335.4	1115.7	1478.0	1499.3	1567.0	1075.2	1285.8
MRI-CGCM3	1381.2	1388.5	1198.8	1513.8	1541.8	1593.0	1161.9	1335.4
ACCESS1-0	1392.0	1403.3	1132.3	1504.5	1523.4	1591.3	1130.0	1316.3
CNRM-CM5	1364.2	1367.6	1143.4	1455.8	1437.5	1511.6	1176.0	1308.9
Observed	1306.9	1722.1	1231.5	1481.9	1972.9	1527.5	1302.9	1236.5