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Impact of climate change on Lake Chamo Water Balance, Ethiopia

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One of the most significant potential concerns of climate change is to understand changes in hydrological components and subsequent change in lakes water balance. In view of this study, the water balance components such as surface water inflow from gauged and ungauged sub-watersheds, precipitation and evaporation pattern of the natural reservoir and their associated impacts vis-à-vis altering the water balance of terminal Lake Chamo has a major concern in the present study. The raw A1B scenario outputs are characterized by significant biases and hence subjected to bias correction before applying in the hydrological modeling. The bias correction for A1B scenario for precipitation, maximum and minimum temperature was done by using linear scaling approach. This analysis is based on projection of two different scenarios of future time horizons: 2030s (2031-2040) and 2090s (2091-2100). A hydrological model, Hydrological Byråns Vattenbalansavdelning (HBV), was used to simulate the current and future inflow to the lake. The performance of the model was assessed through calibration and validation process and resulted in R^2 from 0.64 to 0.81 during calibration and from 0.63 to 0.77 during validation and the relative volume error RV_E is from -1.77 to 4.42% at the three stations. Mean annual inflow to Lake Chamo from gauged and un-gauged catchment is 257 $mmyr^{-1}$. The estimated runoff for the period 2030s and 2090s is 215 and 147$mmyr^{-1}$ respectively. The result shows that the mean annual inflow is decreased by 16.3 and 42.8% in 2030s and 2090s, respectively from the base time period. The result revealed the maximum and minimum temperatures increase for the two scenarios in future time horizons. However, precipitation decreased in all future time horizons. The A1B scenario reveals the decreasing pattern of lake water storage due to decrease of inflows components such over lake precipitation and surface water inflow in all the future time horizons. In this scenario, the over-lake evaporation is increased by 0.73 and 2.6% at 2030s and 2090s.

Key words: Water balance, Lake Chamo, RCM, A1B, climate variability, HBV model.

INTRODUCTION

The impact of climate change on water resources is becoming a hotspot across the globe over the last couple of decades. Climate change wil likely alter the hydrological cycle in many ways and it may cause substantial impacts on water resource availability and changes in water quality.

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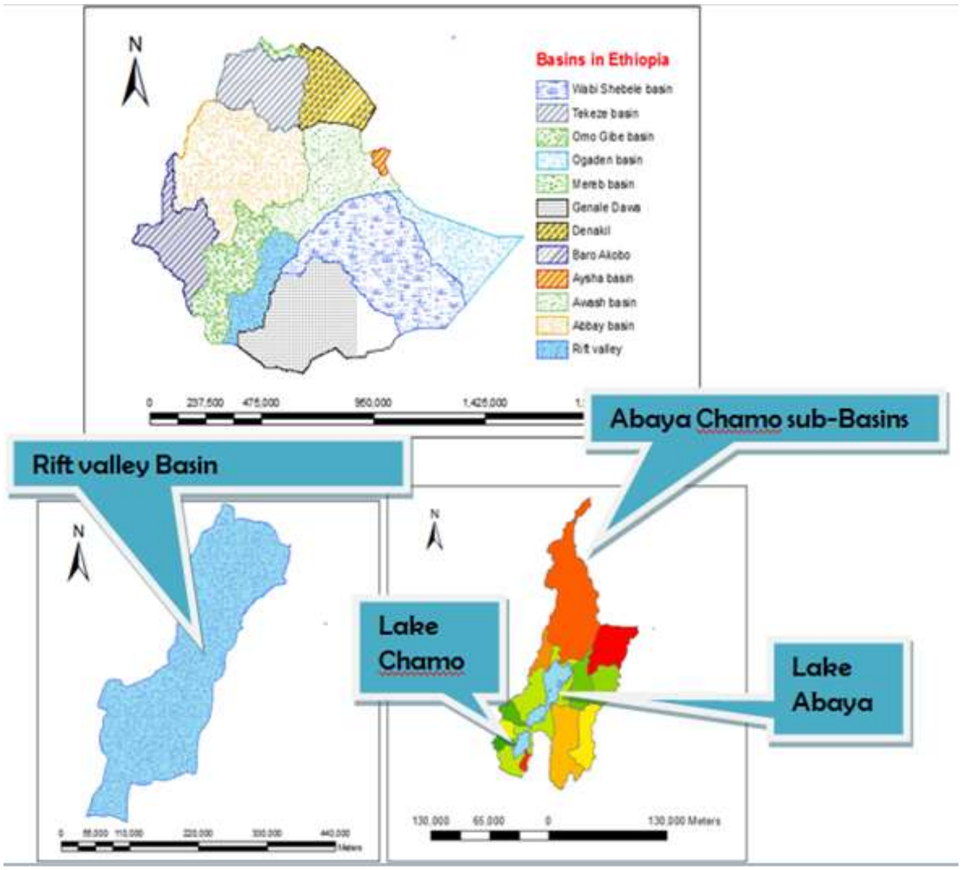

Figure 1. Map of the study area.

Lake is a large, inland body of standing water that occupies a depression in the land surface. Lakes and lake shores are attractive places to live and for recreation. Clean, sparking water, abundant wildlife, beautiful scenery, aquatic recreation and fresh breezes all come to our mind when we think of going to the lake. Despite the great value, lakes are delicate and ephemeral.

The main objective of this study was to identify and investigate the possible future climate change effects on Lake Chamo water balance. The results will be used to forecast lake water balance fluctuation and to suggest mitigation measures to alleviate the ensuing problems.

Study area

The southern part of Ethiopian Rift valley system is characterized by two adjoining lakes, Lake Abaya and Lake Chamo, separated by a small naturally created ridge called "God's Bridge" from the Abaya-Chamo Sub basin. Geographic Abaya Chamo sub-basin extends from 4°37'13" to 6°59'52" N latitude and 36°14'47" to 40°05'47" E longitude.

Lake Chamo is located in Southern Nations, Nationalities and People's Republic (SNNPR). It is part of the main Ethiopian rift system, situated to the south of Lake Abaya and the town of Arba Minch with mean elevation of with 1108 m (Figure 1).

WATER BALANCE TERMS FROM OBSERVED DATA

In this study, the Lake Chamo water balance (Equation 1) is solved for the period 1995 – 2004. Observation time series are available for rainfall (five stations), evaporation (two stations) and runoff from gauged catchments (one catchment). For both rainfall and evaporation area, averaged estimates are made by simple interpolation while, after screening, runoff time series are directly used.

$$\frac{\Delta S}{\Delta t} = P + Q_{gauged} + Q_{ungauged} - E - Q_{out}$$

Where: $\frac{\Delta S}{\Delta t}$: Is the change in storage over time [Mm^3 /day]; $\mathbf{P}$: the lake's areal rainfall of past records and RCM scenario outputs [Mm^3 /day]; $\mathbf{E}$: the open water evaporation of past records and RCM scenario outputs [Mm^3 /day]; $\mathbf{Q_{gauged}}$: the gauged catchments inflow estimated by HBV based on past records and RCM scenario outputs [Mm^3 /day]; $\mathbf{Q_{ungauged}}$: the ungauged catchments inflow estimated by HBV based on past records and RCM scenario outputs [Mm^3 /day]; $\mathbf{Q_{out}}$: the outflow from lake [Mm^3/day].

Meteorological balance terms

Daily lake rainfall has been estimated through inverse distance squared interpolation, inverse distance linear interpolation and through Thiessen polygons. Data for the period 1991– 2000 from Arba Minch, Mirab Abaya, Chencha, Gerese and gato station are used for the interpolation.

To estimate lake evaporation, the Penman-combination equation (Maidment, 1993) is selected, which has wide application as a standard method in hydrologic engineering. In this equation, the energy balance is combined with a water vapour transfer method and results in an equation to compute the evaporation from open water surface using standard climatological records of daily sunshine hours, temperature, humidity and wind speed. The Penman-combination equation for open water evaporation is:

$$\mathbf{ET_0} = \frac{0.408\Delta(R_n - G) + \gamma\frac{900}{T+273}U_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34U_2)}$$

Where: ETo- Reference evapotranspiration [mm day^{-1}]; R_n- net radiation at the crop surface [MJ m^{-2} day^{-1}]; G- soil heat flux density [MJ m^{-2} day^{-1}]; T- mean daily air temperature at 2 m height [°C]; U_2- wind speed at 2 m height [m s^{-1}]; e_s- saturation vapour pressure [kPa]; e_a- actual vapour pressure [kPa]; Δ- slope vapour pressure curve [kPa $°C^{-1}$]; γ - psychrometric constant [kPa $°C^{-1}$].

RUNOFF FROM UNGAUGED CATCHMENTS

Runoff from ungauged catchments is estimated by three procedures that are of different complexity. The first procedure applies a regionalization procedure where a regional model (Merz and Bloschl, 2004: Booij et al., 2007) is established between catchment characteristics and model parameters that in turn are used for ungauged catchment modeling. A second procedure simply transfers model parameters from neighboring or nearby catchments to ungauged catchments to allow for runoff simulation. In the third procedure, parameter sets of gauged catchments are transferred to ungauged catchments by simple comparison of catchment size. In all three procedures, the HBV-IHMS model (Integrated Hydrological Modeling System) (IHMS, 2006) is selected for simulation of catchment runoff. Effectiveness of the HBV model approach in regionalization studies is reported by Seibert (1999), Booij (2005) and Booij et al. (2007). Our study is different from these works in the sense that we simply applied regionalization procedures to seek closure of Lake Tana water balance while much work in regionalization and ungauged catchment hydrology focus on assessing predictive capability of runoff models as advocated by the International Association of Hydrologic Sciences (IAHS) in their 10-year Prediction in Ungauged Basins (PUB) project (Sivapalan et al., 2003). Such approaches also aim at assessing effectiveness of preference and non preference based multi-objective calibration (Wagener and Wheater, 2004) and also aims at testing specific catchment characteristics in establishing a regional model. Also, most studies use a large number of catchments (Booij et al., 2007) from which a large number is assumed to be ungauged to serve calibration and validation purposes while we only use five gauged catchments and a selection of catchments characteristics that are available from simple soil, land use and geologic maps or that can be extracted from a satellite-based SRTM DEM of 90 m resolution.

HBV-IHMS

The Hydrological Byråns Vattenbalansavdelning (HBV) model is a conceptual rainfall-runoff model for continuous simulation of catchment runoff. The model consists of subroutines for precipitation and snow accumulation, soil moisture accounting, actual evaporation and uses simple transformation functions and routing procedures. Soil moisture accounting is governed by two simple relations that are parameterized by FC which is the maximum soil moisture storage (mm) in the model, LP which is a limit for potential evapotranspiration and parameter which controls the contribution of soil moisture storage (SM) to the response function $\Delta Q/_{\Delta P}$.

$$\frac{\Delta Q}{\Delta P} = \left[\frac{SM}{FC}\right]^{Beta}$$

Q denotes discharge and P denotes precipitation while $\Delta Q/_{\Delta P}$ is to be interpreted as a runoff coefficient. Actual evapotranspiration, Ea, which is controlled by a soil moisture routine is linearly related to the potential evapotranspiration, Ep, and is:

$$\mathbf{EA} = \mathbf{Ep}\left[\frac{SM}{LP * FC}, 1\right]$$

In HBV-IHMS, the runoff routine comprises two reservoirs that distribute generated runoff over time to obtain the quick and slow parts of a catchment runoff hydrograph. Runoff generated from the upper reservoir represents quick runoff discharges while runoff from the lower reservoir represents groundwater discharges.

$$\mathbf{Q_o} = \mathbf{K} * \mathbf{UZ}^{(1+Alfa)}$$

$$\mathbf{Q_1} = \mathbf{K4} * \mathbf{LZ}$$

Where: $\mathbf{Q_o}$: Direct runoff from upper reservoir (mm), **K**: recession coefficient upper reservoir, **UZ**: upper reservoir storage (mm), $\mathbf{Q_1}$: lower reservoir outflow (mm), **LZ**: lower reservoir storage (mm) and **K4**: recession coefficient lower reservoir storage.

Model performance

The performance of the model must be evaluated for the extent of its accuracy. Hence, for this study, the model performance in simulating observed discharge was evaluated during calibration and validation by; inspecting simulated and observed runoff graphs visually, by calculating Nash and Sutcliffe efficiency criteria R^2 (commonly used in hydrological modeling) and by calculating the Relative Volume Error (RV_E).

The Nash and Sutcliffe coefficient (R^2) is a measure of efficiency that relates the goodness-of-fit of the model to the variance of measured data. R^2 can range from - ∞ to 1 and an efficiency of 1 indicates a perfect match between observed and simulated discharges. R^2 value between 0.9 and 1 indicate that the model

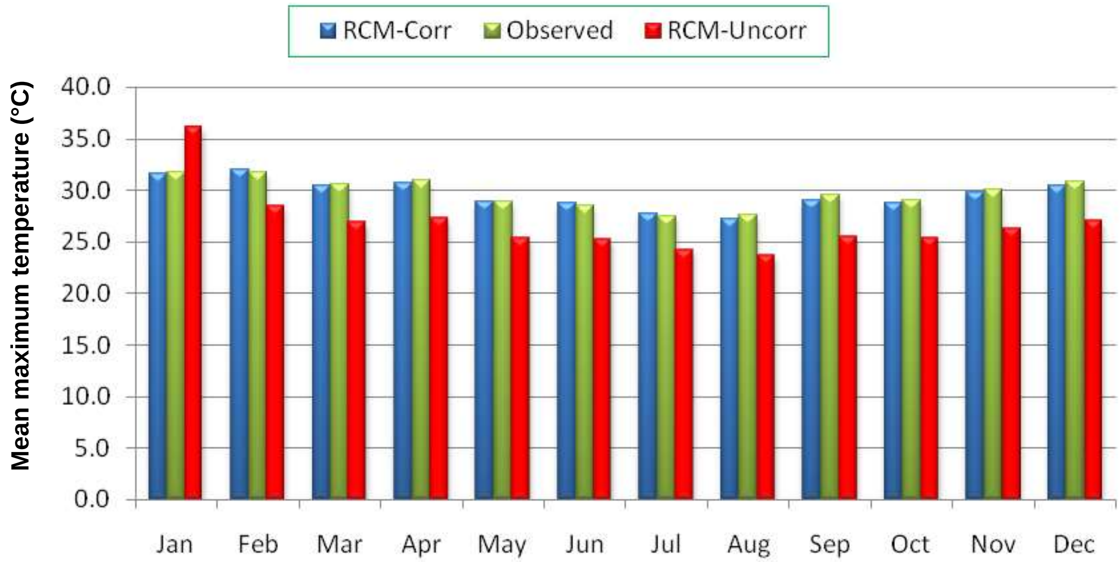

Figure 2. Comparison of mean monthly maximum temperature at Arba Minch Station.

performs very well while values between 0.6 and 0.8 indicate the model performs well (Rientjes et al., 2011). The largest disadvantage of this efficiency criterion is that larger value in a time series are strongly overestimated where as lower values are of minor importance. For the quantification of runoff prediction, this leads to an overestimation of model performance during peak flows and underestimation during low flow conditions:

$$\mathbf{R^2 = 1 - \frac{\sum_{i=1}^{n}\left(Q_{sim\,(i)} - Q_{obs\,(i)}\right)^2}{\sum_{i=1}^{n}\left(Q_{sim\,(i)} - \bar{Q}_{obs(i)}\right)^2}}$$

Where,

$\mathbf{Q_{obs}}$: Observed flow, $\mathbf{Q_{sim}}$: simulated flow and $\mathbf{\bar{Q}_{obs}}$: Average of observed flow.

The $\mathbf{RV_E}$ can vary between ∞ and - ∞ but it performs best when a value of 0 (zero) is generated. Since an accumulated difference between simulated, $\mathbf{Q_{sim(i)}}$ and $\mathbf{Q_{obs(i)}}$ is observed, discharge is zero. A relative volume error between +5% or -5% indicates that a model performs well while relative volume errors between +5 and +10 and -5 and -10% indicates a model with reasonable performance (Rientjes et al., 2011).

$$\mathbf{RV_E = \left[\frac{\sum_{i=1}^{n} Q_{obs\,(i)} - \sum_{i=1}^{n} Q_{sim\,(i)}}{\sum_{i=1}^{n} Q_{obs\,(i)}}\right] * 100\%}$$

RESULTS AND DISCUSSION

Maximum temperature

Observed, uncorrected RCM (RCM-uncorr) and bias corrected (RCM-corr) mean monthly maximum and minimum temperature magnitudes are presented for Arba Minch stations (Figures 2 and 4). RCM bias correction is done for A1B scenario minimum and maximum temperature, which shows significant difference from bias uncorrected mean monthly when compared with mean monthly-observed data. The deviation of maximum and minimum temperature between corrected and uncorrected RCM is 3.5 to 4.6°C and 0.1 to 1.6°C at Arba Minch station. This result indicates that using the RCM output without doing bias correction may lead to enormous uncertainty of hydrological analysis.

The maximum and minimum monthly absolute model error is found in the month of September and May, respectively. On average, the monthly absolute model error is found to be 0.1°C (Figure 3).

Minimum temperature

Bias corrected minimum temperature also shows a reasonably good agreement with the observed minimum temperature for all the months.

The maximum and minimum monthly absolute model error is found in the month of April and March, respectively. On average, the monthly absolute model error is found to be 0.2°C (Figure 5).

Precipitation

In comparison with the minimum and maximum temperature, the precipitation could not be able to replicate the historical (observed) data. This is due to

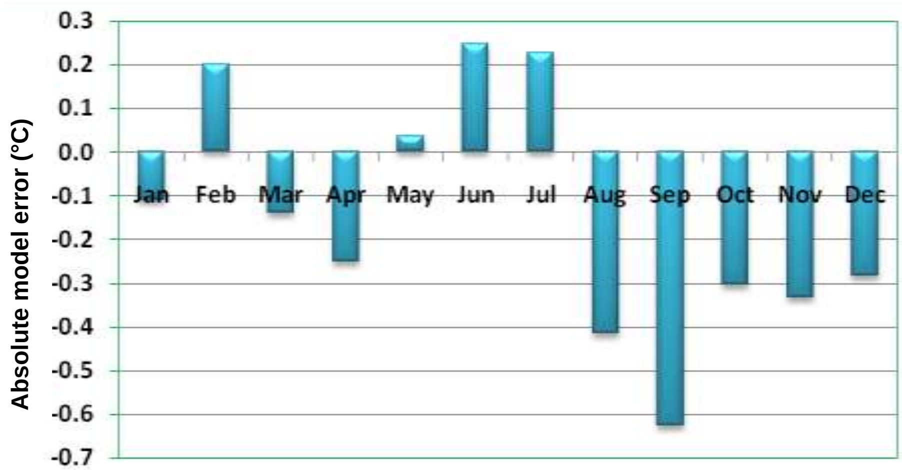

Figure 3. Absolute model error of maximum temperature (1991-2000).

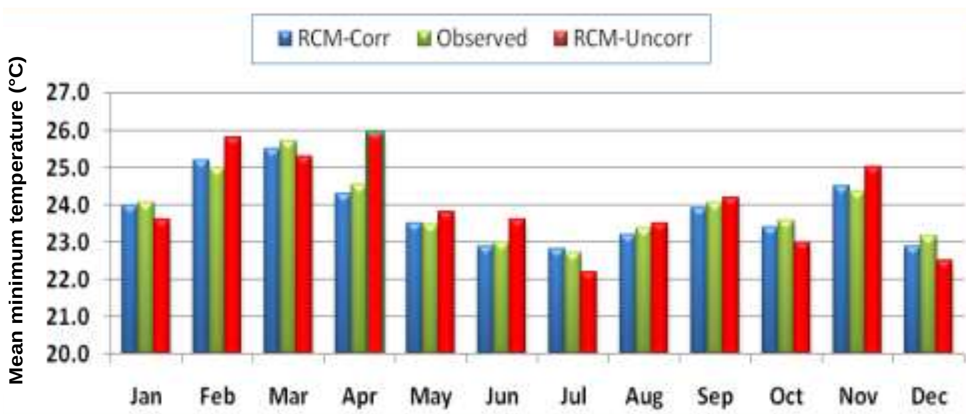

Figure 4. Comparison of mean monthly minimum temperature at Arba Minch station.

Figure 5. Absolute model error of minimum temperature (1991-2000).

complicated nature of precipitation processes and its distribution in space and time. Climate model simulation of precipitation has improved over time but is still problematic; also rainfall predictions have a larger degree of uncertainty than those for temperature. This is because rainfall is highly variable in space and so the

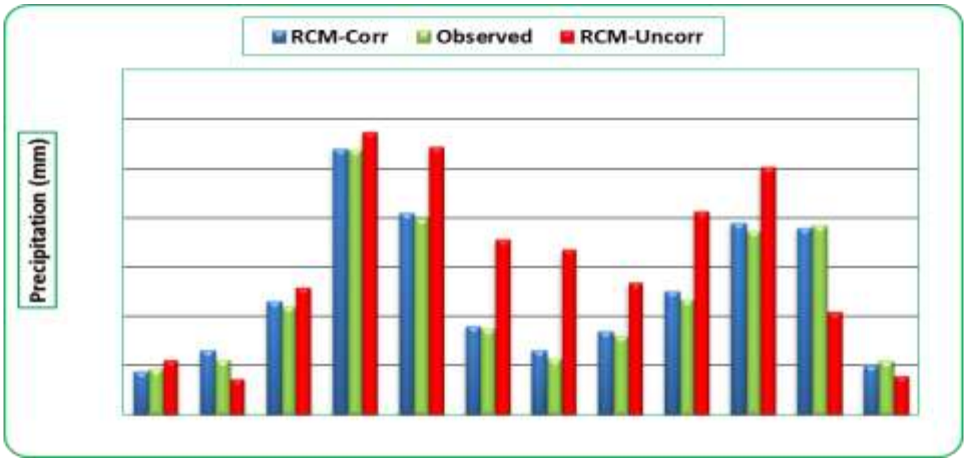

Figure 6. Mean monthly precipitation (1991-2000).

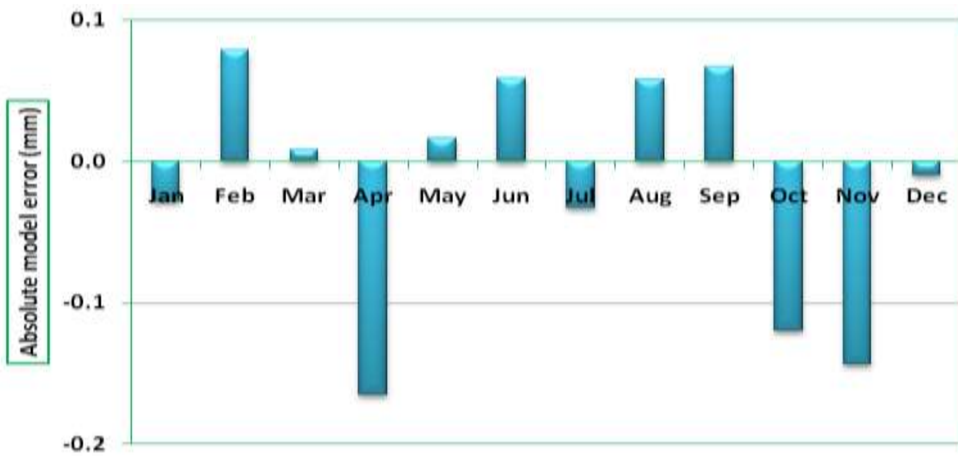

Figure 7. Absolute model error of precipitation (1991-2000).

relatively coarse spatial resolution of the current generation of climate models is not adequate to fully capture that change.

The bias corrected precipitation shows an average absolute model error of 0.1 mm (Figure 7).

Projected future climate change (scenario generation)

The term anomaly means a deviation of future climate condition from a baseline period (1991-2000) climate condition. In this study baseline period climatic condition is analyzed based on historical observations of the study area under consideration the anomaly of monthly precipitation is calculated as the difference from future monthly average precipitation to the baseline period monthly average precipitation values. Positive anomaly indicates increase from the baseline period value; a negative anomaly indicates decrease from the baseline period value. The temperature is also calculated in the same way precipitation is calculated.

RCM model scenarios (A1B) were also analyzed to generate temperature and precipitation scenarios of the two future time windows, namely 2031-2040(2030s) and 2091-2100(2090s).

Projected changes in monthly rainfall statistics

Projected changes in monthly rainfall statistics are vital means of evaluating the characteristics of rainfall at the study site. Figure 6 shows the general pattern of the change anomalies in April monthly mean precipitation for future period at Arba Minch station.

The RCM A1B scenario show an overall decreasing pattern in the month of January–April (0.2-1.8 mm) and October to December (0.4-2.4 mm) at 2030s and January to February (0.8-0.9 mm), April (0.9 mm) and October to December (0.6-3.0 mm) at 2090s. The consistent

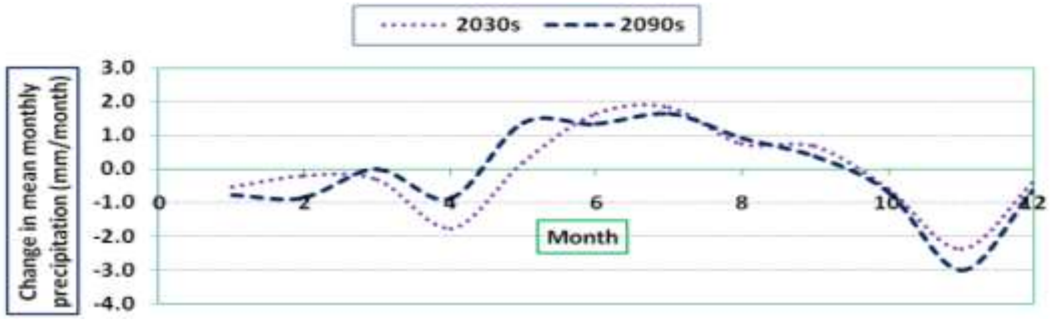

Figure 8. Change anomalies of mean precipitation for future windows at Arba Minch station.

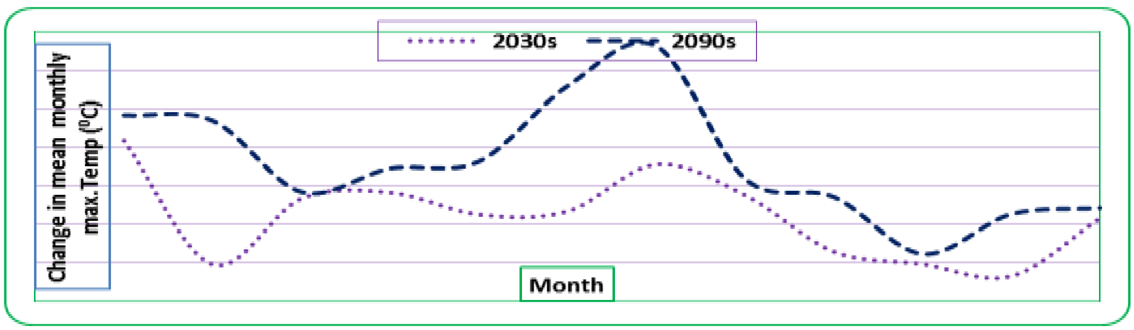

Figure 9. Change anomalies of monthly mean maximum temperature for future windows at Arba Minch station.

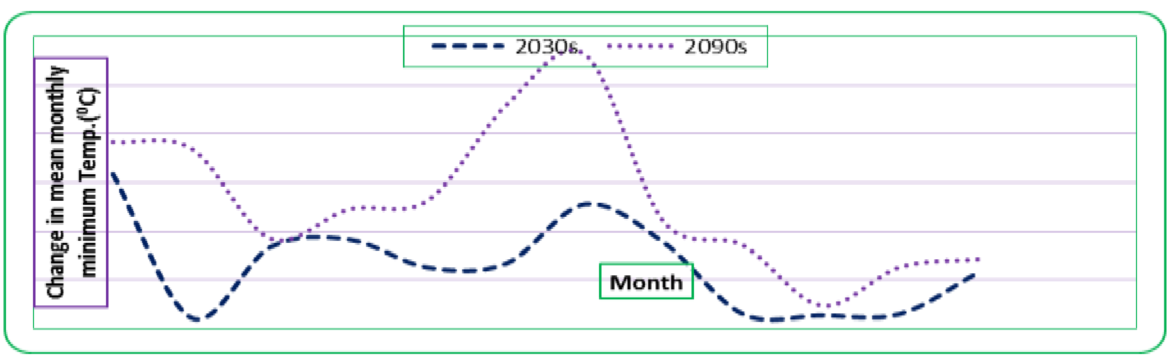

Figure 10. Change anomalies of monthly mean minimum temperature for future windows at Arba Minch station.

increasing pattern is revealed in the month of May to September (0.2-1.8 mm) at 2030s and 0.4-1.6 mm at 2090s. The month March at 2090s showed a similar pattern with the baseline period. The percentage change of future precipitation against observed baseline period is decreased by 3.9% at 2030s and 4.2% at 2090s (Figure 8).

Projected changes in monthly maximum temperature statistics

Figure 9 shows the change anomalies in mean monthly maximum temperature for future periods. The simulation indicates an overall decreasing pattern in the month November, February and October by 0.2°C and increasing pattern in the rest months from +0.1 to +1.6°C at 2030s. At 2090s, simulation indicates an overall increasing pattern of +0.1 to +2.8°C. The percentage change of maximum temperature against observed baseline period is increased by 2.04% at 2030s and 4.4% at 2090s.

Projected changes in monthly minimum temperature statistics

Figure 10 shows the change anomalies in mean monthly minimum temperature of for future periods. The future scenario simulation indicates an overall increasing pattern

Table 1. Optimum parameter during the calibration

S/N	Catchment	Parameter									
		Alfa	Beta	Fc (mm)	hq	K4	Khq	lp	Maxbas (day)	Perc (mm/day)	Rfcf
1	Kulfo	0.6	1	1500	21.42	0.008	0.06	1	1	3.5	1.54
2	Sile	4.8	0.5	1500	35	0.03	0.02	1	1	0.7	1.19
3	Sago	4.8	0.6	1500	32	0.02	0.02	1	1	0.6	1.18

of +0.1 to +1.6°C at 2030s and +0.2 to +2.8°C at 2090s. The percentage change of future temperature against observed baseline period is increased by 2.07% at 2030s and 5.5% at 2090s.

Evaluating the performance of RCM simulations against observed baseline period

Downscaling is conducted for precipitation, maximum and minimum temperature based on data of Arba Minch, Mirab Abaya, Gato and Konso stations for the period of 1991-2000. RCM (A1B scenario) model output performance is evaluated based on comparison of historic (observed) baseline period, 1991-2000. Daily mean downscaled RCM output and observed precipitation, maximum and minimum temperature is compared to check whether the historic (observed) condition can be replicated or not. Therefore, it is vital that model simulated precipitation and temperature data should have the same statistical properties as the observed meteorological time series data.

Hydrological model

Calibration and validation

The HBV-model is calibrated and validate for the observed period of ten years (1995-2004) and the best-fit parameters sets are selected. Calibration aimed at the water balance and over all shape agreement of the observed discharge using RV_E (relative volume error) and R^2 (Nash and Sutcliffe coefficient). In simulation of the runoff, the observed period is divided into three zones, namely; warm up period (1995), calibration period (1996-2001) and validation period (2002-2004).The calibration and validation is carried out for both daily and monthly time steps. It is observed that the model has a very good capability to simulate the observed flow for both low flow and high flow period.

Table 1 shows recommended values of selected parameters for Chamo sub-basin to be calibrated and the most optimum parameter set used in the calibration.

The observed and simulated runoff hydrograph using the above optimum parameter is shown in Figure 11. Visual inspection of the observed and simulated runoff shows good performance of the model.

Generally, the values of the performance criteria show that during the calibration period, overall performance of HBV model is somewhat better as compared to the validation period (Table 2).

Water balance

There are many processes that contribute to the Lake Chamo water balance. Inflow to the Lake Chamo is the sum of lake areal rainfall, runoff from gauged and un-gauged catchments. The outflow component of the Lake Chamo is open water evaporation. The groundwater flow component is assumed to be negligible and hence not included in the present analysis. Lake level is simulated by using area-volume and elevation-volume relationships.

After estimation of the lake water balance components, a spreadsheet water balance model is developed. The model is developed to calculate the inflow and outflow components separately in terms of volume. The initial volume and area of the lake is simply defined by fixing the initial value to an observed lake level. In the model, both evaporation and rainfall are defined as a function of the lake surface area (Table 3).

In general, result of A1B scenario indicates a decrease of inflows to the lake and over lake precipitation, but an increase of over lake evaporation for the future. The decrease of lake water balance for the future indicates the lake water drop off.

There are still many sources of uncertainty and errors in the water balance but quantifying and reducing the errors is far from trivial. Uncertainties associated with lake-groundwater interaction estimations of lake water balance components such as open water evaporation, lake areal rainfall, runoff from gauged and un-gauged catchments may affect the lake water balance modeling endeavor (Table 3).

Daily lake water level simulation

For lake level simulation all mass balance terms are solved on a daily step and results of lake level simulations are compared with the observed lake levels (Figure 12).

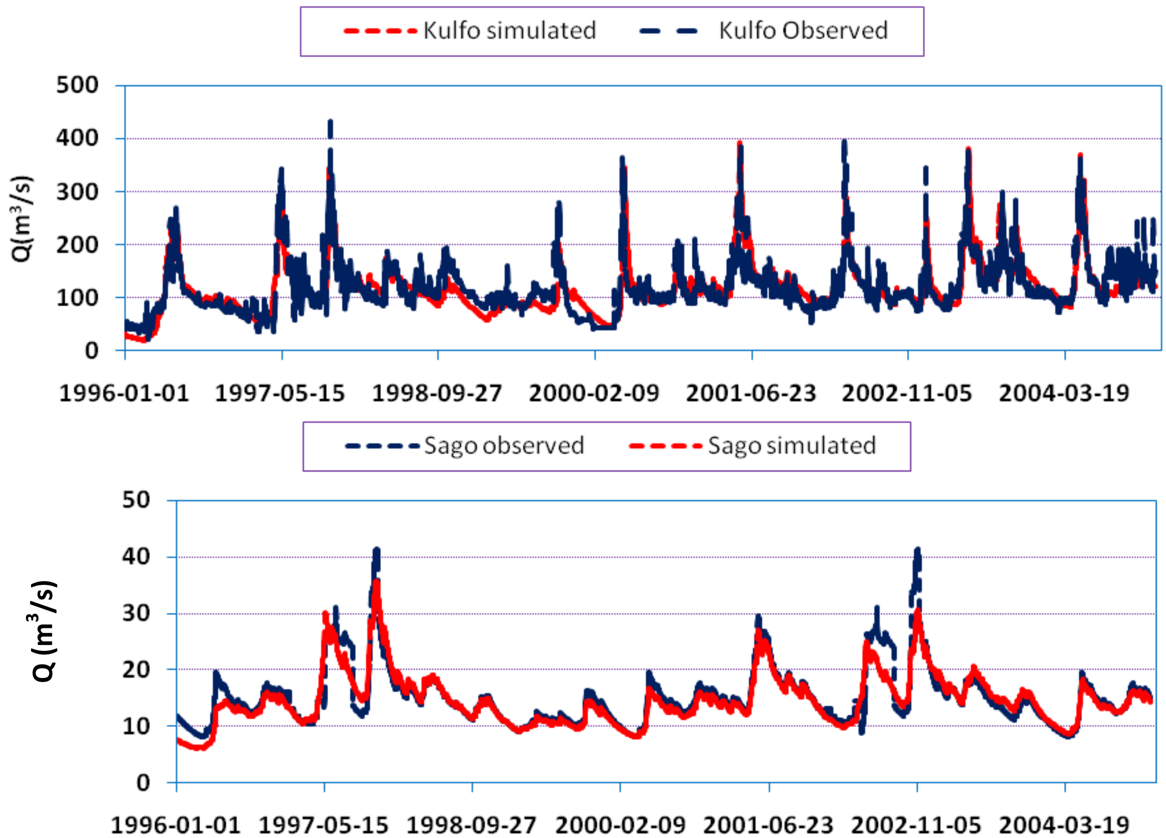

Figure 11. Observed and simulated graph of Kulfo and Sago catchment.

Table 2. Summarized objective function during calibration and validation.

Catchment name	Calibration		Validation	
	R^2	RV_E	R^2	RV_E
Kulfo	0.64	0.85	0.63	1.26
Sago	0.79	4.42	0.77	2.25
Sile	0.81	2.13	0.76	-1.77

Table 3. Lake Chamo water balance components.

Water balance components	Unit	1996-2004	2030s	2090s
Lake areal rainfall	$mmyr^{-1}$	897	869	808
	$MCMyr^{-1}$	295	286	265
Gauged river inflow	$mmyr^{-1}$	161	153	98
	$MCMyr^{-1}$	53	50	32
Un-gauged river inflow	$mmyr^{-1}$	96	62	49
	$MCMyr^{-1}$	32	20	16
Lake evaporation	$mmyr^{-1}$	1217	1226	1249
	$MCMyr^{-1}$	400	403	410
Lake outflow		0	0	0

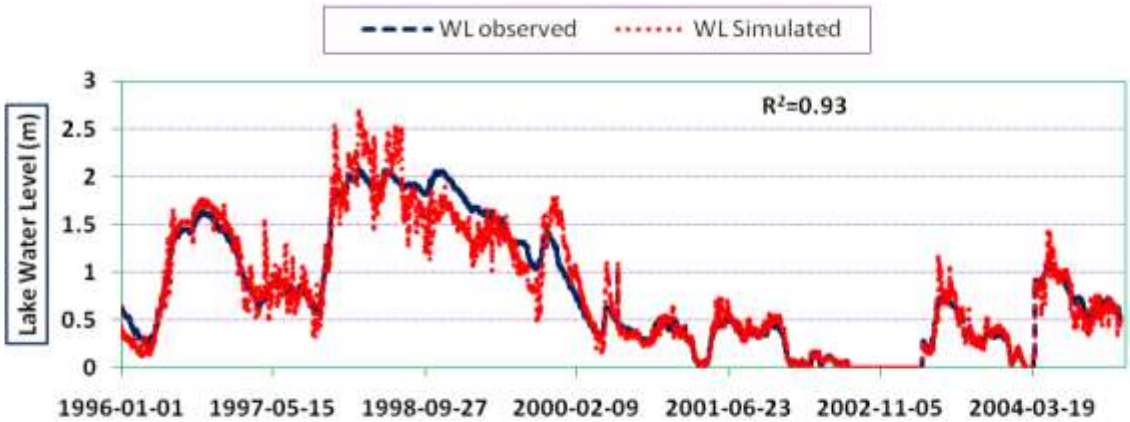

Figure 12. Observed and simulated graph of Lake Chamo water level.

Conclusion

In this study, daily water balance of Lake Chamo was simulated giving due emphasis for un-gauged river inflows. River flow from un-gauged catchment is estimated by transferring model parameters of gauged catchments by area ration approach. Based on the study conducted, the following conclusions were drawn.

1. The result of climate projection reveals that the RCM bias corrected by linear scaling approach has very good ability to replicate the historical maximum and minimum temperature and precipitation for the observed period.
2. The percentage change of maximum temperature scenario against observed baseline period is increased by 2.04% at 2030s and 4.4% at 2090s. The percentage change of minimum temperature scenario against observed baseline period is increased by 2.07% at 2030s and 5.5% at 2090s. This causes its own impact on the lake water balance by increasing the evaporation from the lake.
3. The result shows the mean annual precipitation is decreased by 3.1 and 10% in 2030s and 2090s, respectively from the base time period. This causes its own impact on the Lake water balance by changing the volume.
4. HBV-96 hydrological model is used for calibration and validation by using daily data of precipitation and potential evapo-transpiration. The result of hydrological model calibration and validation indicates that the HBV model simulates the runoff considerably good for the study area. The model performance criterion which is used to evaluate the model result indicates that the daily Nash and Sutcliffe efficiency criteria (R^2) was between 0.81 and 0.64 during calibration and 0.77 and 0.63 during validation period.
5. The simulated flow at 2030s and 2090s with scenario from RCM A1B shows reduction of runoff in the watersheds and it is directly related to the reduction in precipitation and rising in potential Evapo-transpiration. The mean annual inflow is decreased by 16.3 and 42.8% in 2030s and 2090s respectively from the base time period. 6.32.1% of inflow of Lake Chamo is from ungauged river and 67.9% is from gauged river.
7. Human activity and catchment mismanagement have accelerated lake water degradation.

CONFLICT OF INTERESTS

The authors have not declared any conflict of interests.

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