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Impacts and uncertainties of climate change on stream flow of the Bilate River (Ethiopia), using a CMIP5 general circulation models ensemble

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The impact and uncertainty of climate change on stream flow of the Bilate River Watershed was assessed. Ensemble of 20 Coupled Model Intercomparison Project Phase 5 (CMIP5) general circulation models (GCMs) under two Representative Concentration Pathways and six GCM structures were selected to form 24 future climate scenarios for the watershed. Soil and Water Assessment Tool (SWAT) model was selected to simulate stream flow of the watershed. The respective statistical results of the coefficient of determination (R^2), Nash-Sutcliffe coefficient (NSE) and percent bias (PB) are 0.79, 0.78 and 0.56 for calibration period and 0.64, 0.60 and -21.7 for validation period which show that the model predicted the stream flow reasonably. The annual stream flow increased progressively throughout the century for all time periods. The increases under RCP 8.5 scenario are the larger compared to RCP 4.5 scenarios, approximately 42.42% during the 2080s period. The six GCMs selected to see the uncertainties related to GCMs suggest that the river flow will change by small amounts of -6.18 to 7.83% change compared with the baseline. The simulated runoff depended on the projected amount of rainfall embedded in the GCM structures selected to simulate the future climate and less dependent on the local temperature increment.

Key words: Climate change, Bilate River watershed, stream flow, soil and water assessment tool (SWAT), uncertainty.

INTRODUCTION

Based on the fact that a wide variety of natural resources, ecosystems and populations being affected by current and future climate variability and change, the potential consequences of climate change have received

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considerable attention internationally (Ryu et al., 2011). The third assessment report of the Intergovernmental Panel on Climate Change (IPCC, 2001) revealed the general impacts of climate change on water resources indicating an intensification of the global hydrological cycle and affecting both ground and surface water supply for domestic and industrial uses.

Understanding and quantifying the responses of hydrological processes to an increased atmospheric CO_2 concentration and climate change is critical for developing appropriate mitigation and adaptation strategies for sustainable water resources management within agricultural systems (Ficklin et al., 2009). Many studies have been done to investigate long-term hydrologic variability associated with climate change. Hydrologic models combined with climate scenarios generated from general circulation models (GCMs) are used to produce potential scenarios of climate change effects on water resources (Ficklin et al., 2009) and assessment of the sensitivity of a model to climate change provide insights to the sensitivity of the hydrological systems to changes in climate (Arnell and Liv, 2001; Ficklin et al., 2009).

Simulation models such as the Soil-Water Assessment Tool (SWAT) are frequently used to project the responses of watershed processes to climate change and provide a link between climate changes and water yields through simulation of hydrologic processes within watersheds (Butcher et al., 2014). Hydrologic models also allow various simulations to be performed based on user needs (Ficklin et al., 2009).

GCMs projected precipitation and temperature data are often used as input to a calibrated hydrological model to simulate the future hydrological cycle (Dessu and Melese, 2013). GCMs are commonly utilized for local-scale forecasts under global warming scenarios (Ryu et al., 2011). CMIP5 includes comprehensive GCMs including finer spatial resolution, associated with more complex orography of the region and different greenhouse gases emission scenarios (Taylor et al., 2012). The statistical downscaling approach such as delta approach is often applied in hydrological impacts studies due to its simplicity, flexibility and low computation cost (Wilby et al., 2002). Thus the objective of this study is to evaluate the response of the stream flow of the Bilate watershed to climate change using the SWAT model.

MATERIALS AND METHODS

Study area and data used

The absolute location of BRW, south-north extends from 6° 36'N 38°00'E at Lake Abaya Wolaita Zone SNNPR to 8°05'N 38°12'E at Gurage and Silte Zones border, SNNPR. On the other hand its west-east extension is from 7°18'N 46'E at Kambata Zone to 7°12'N38°22'E Sidama Zone. The watershed covers an area of about 5625 km square in the southern Ethiopian Rift Valley and partly in the Western Ethiopian Highlands.

The digital elevation model (DEM), daily precipitation and daily temperature, soil characteristics, land use and the river flow data are known to be the main data needed for the simulation of SWAT model. Digital Elevation Model (DEM) with 30 m resolution is acquired from the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER). The DEM shown in Figure 1 is used for derivation of spatial parameters for hydrological model. The topography of the BRW varies from lowlands of altitude 1,146 m above sea level (m.a.s.l.) near Lake Abaya to highlands with peak elevation of 3,393 m.a.s.l. towards the northern realm of the watershed. Stream (channel slope, length and width) and catchment characteristics (slope gradient, slope length, stream network) were derived from the DEM by using the Arc SWAT automatic watershed delineation tool.

There are more than 18 weather observation stations in and around the Bilate River watershed; but there are many missing values. The historical weather data for the period of 1980 -2013 for these stations were obtained from Ethiopian National Meteorological Agency (NMA) and further analyzed for simulation purpose.

The soil data used in this research was obtained from Food and Agriculture Organization of the United Nations data base (FAO, 2003). According to the FAO soil map, the soil depths in the study area is between 1.00 and 2.00 m and the dominant soil types are Eutric Nitosols, Plinthic Ferralsols, Eutric Cambisols, Ochric Andosols and Haplic Xerosols. The land use date with 500 × 500 m spatial resolutions were obtained from Ministry of Agriculture (MoA) which is derived from FAO 98 land use classification for Ethiopia and further reclassification was performed in the model used for simulation of hydrological processes. The land cover in the BRW is predominated by different types agricultural land (87%), grass and rangeland only 0.8% and the remaining mixed land cover including plantation forest, shrub land and wetland accounts about 12.2%. These days, the forests are transformed to croplands and/or grazing areas.

The river flow data from the gauging stations near Alaba Kulito, which has, relatively, long record of time series of daily flow data for the period of 1990-1996 was considered for calibration and daily flow data for the period of 1997-2002 used for validation purpose. The gauging station near Bilate Tena has very intermittent data only used for description of the characteristics of the flow but cannot be used for calibration and validation purpose.

Soil-water assessment tool (SWAT)

Several watershed simulation models have been developed so far, but it is not easy to choose the most suitable model for a particular watershed to address a particular problem. Even though there are no clear rules for making a choice from the existing watershed models, some guidelines can be considered (Fiseha, 2013). An extensive review on published literature related to calibration, validation, and application of watershed models in similar scenario is needed to get watershed model which is commonly used, accepted, and recommended in published literature; and all depending on the objective of the study at hand (Moriasi et al., 2007).

For this particular study, SWAT model was selected to simulate stream flow of the Bilate River watershed based on the following criteria's as suggested by (Fiseha, 2013):\

(i) Considering the availability of input data

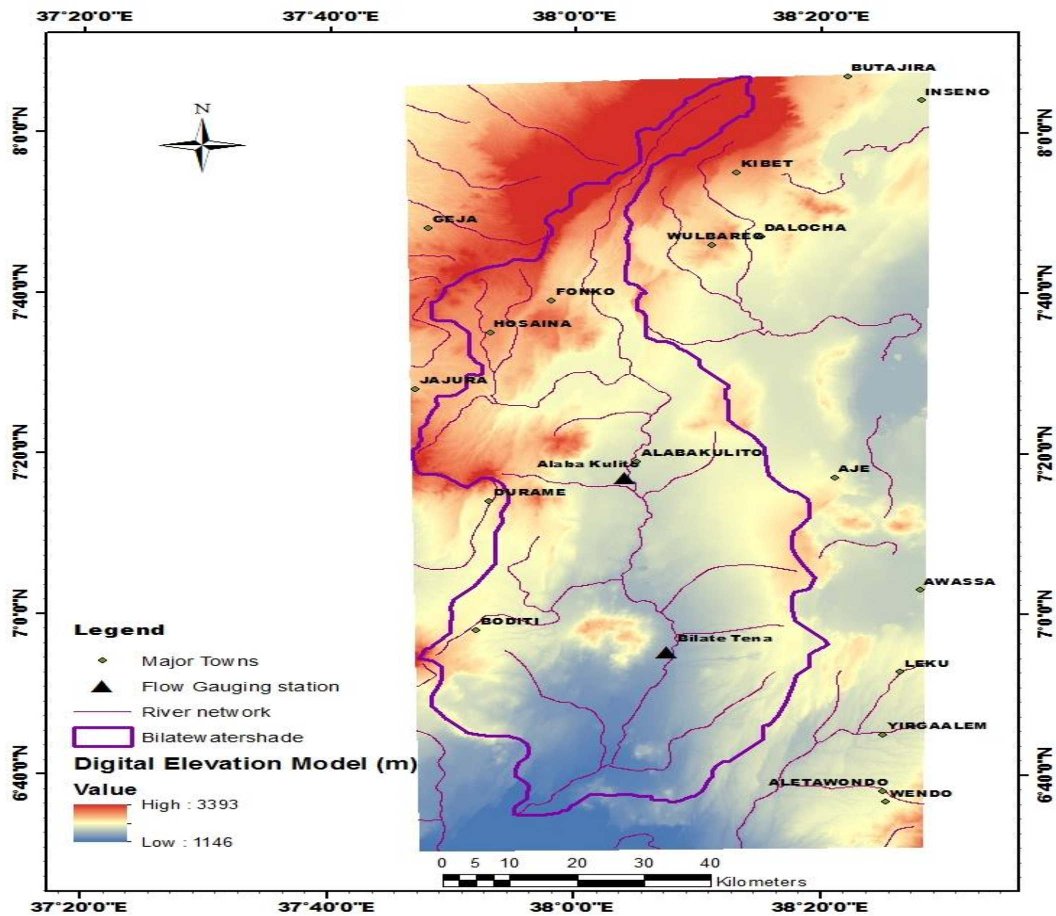

Figure 1. Digital elevation model (DEM) map of BRW.

(ii) Considering the nature and type of hydrologic process needs to be simulated

(iii) Considering the availability of the watershed simulation model itself

(iv) Considering the nature of data handling mechanisms (storage, retrieval and manipulation with use of Geographical Information Systems (GIS)).

The SWAT model is a watershed scale model created to run with readily available input data so that general initialization of the modeling system does not require complex data gathering or calibration. It was originally intended to model long-term runoff and nutrient losses from rural watersheds, particularly those dominated by agriculture (Arnold et al., 1998; Arnold and Fohrer, 2005; Easton et al., 2008; Pervez and Henebry, 2015). SWAT is a semi-distributed, continuous time model that operates on a daily time series (Narsimlu et al., 2015). The capabilities of SWAT in simulating various hydrological processes in different part of the world is discussed in scientific literatures (Gassman et al., 2007, 2014; Krysanova and White; 2015) and up to date publications were also available in the SWAT literature database at https://www.card.iastate.edu/swat_articles/.

The performance of SWAT in other parts of Ethiopia is also considered as criteria for selection of the model (Setegn et al., 2009; Easton et al., 2010; Betrie et al., 2011; White et al., 2011) and in other east African countries also satisfactory performance and applicability of SWAT was reported (Jayakrishnan et al., 2005; Mulungu and Munishi, 2007; Mango et al., 2011; Dessu and Melesse, 2012).

In SWAT, the simulation of the hydrology of a watershed is performed in two phases, the first is the land phase of the hydrological cycle while the second is routing phase of the hydrologic cycle. The land phase controls the amount of water, sediment, nutrient and pesticide loadings to the main channel in each sub basin and simulates the canopy storage, infiltration, redistribution, evapotranspiration, lateral subsurface flow, surface runoff, ponds, tributary channels and return flow. The routing phase can be defined as the movement of water, sediments, nutrients and organic chemicals through the channel network of the watershed to the outlet (Neitsch et al., 2005; Setegn, 2010).

The hydrological components of SWAT model are governed by the water balance equation which is depicted as follows (Equation 1) (Neitsch et al., 2005; Narsimlu et al., 2015):

$$SW_t = SW_0 + \sum_{i=1}^{t}\left(R_{day} - Q_{surf} - E_a - W_{seep} - Q_{gw}\right) \tag{1}$$

where SW_t is the final soil water content (mm); SW_0 is the initial soil water content on day i (mm); R_{day} is the amount of precipitation on day i (mm); Q_{surf} is the amount of surface runoff on day i (mm); Ea is the amount of evapotranspiration (ET) on day i (mm); W_{seep} is the amount of water entering the vadose zone from the soil profile on day i (mm); and Q_{gw} is the amount of return flow on day i (mm).

Model setup, calibration, validation and sensitivity analysis

The model setup is performed by the following four major steps: (i) watershed delineation and derivation of sub-basin characteristics, (ii) hydrological response unit definition, (iii) model run and parameter sensitivity analysis, and (iv) calibration and validation of the model (Fiseha, 2013). The input data like soil maps, land use and hydro-meteorological data for the basins were prepared and during the watershed delineation, the spatial datasets that include DEM, land use and soil maps were projected to the same coordinate system of zone 37 in Universal Transverse Mercator (UTM 37N) and the delineator in the ArcSWAT follows the steepest slope paths to define the stream networks.

The HRU definition was performed based on the soil, land cover and slope. In addition to the soil and land use data described earlier, five classes of slope were considered and they are 0-5%, 5-10%, 10-15%, 15-20% and ≥20%. The threshold values for multiple HRU definition were 10% for land use, 20% for soil and 5% for slope of ever sub basin area. Overall, there were 285 HRUs defined in the watershed within 31 sub basins. The model was then run by using weather data inputs from 7 stations for precipitation and 3 stations for temperature. The simulation was run first for the calibration period of 1987 to 1996 using the first three years as a warm up period. After the results of the first simulation were found, the sensitivity analysis and calibration of the parameters was based on the parasol calibration algorithm. Manually tuning the sensitive parameters finally resulted in ranked outputs that show how the catchment behaves under the given conditions.

The top ten most sensitive parameters were considered for further use in the model calibration and validation processes. The SWAT model performance was evaluated using statistical analyses to compare reliability and quality of simulated discharge against the observed data. The statistical approaches used in this study are the coefficient of determination (R^2), Nash-Sutcliffe coefficient (NSE) and percent bias (PB) (Nash and Sutcliffe, 1970; Gupta et al., 1999; Leong et al., 2014).

$$R^2 = \left(\frac{\sum_{i=0}^{n}(O-\bar{O})(P-\bar{P})}{\left[\sum_{i=0}^{n}(O-\bar{O})^2 \sum_{i=0}^{n}(O-\bar{P})^2\right]^{0.5}}\right)^2 \quad (1)$$

$$NSE = 1 - \frac{\sum_{i=1}^{n}(O-P)^2}{\sum_{i=1}^{n}(O-\bar{O})^2} \quad (2)$$

$$PB = \frac{\sum|O-P|}{\sum O}(100) \quad (3)$$

where O and P are observed and simulated stream flow, respectively and n is the number of measured stream flow. Both the R^2 and NSE ranges from 0 to 1 with higher value indicating good agreement between the model and the observation. The PB measures the tendency of the simulated flows to be larger or smaller than their observed counterparts; the optimal value is 0.0, positive values indicate a tendency to overestimation, and negative values indicate a tendency to underestimation. SWAT modeling performance is categorized as satisfactory if NSE > 0.5 and PB < ±25. Alaba station monthly stream flow from 1990 to 1996 and 1997 to 2002 were used for stream flow calibration and validation, respectively (Nash and Sutcliffe, 1970; Gupta et al., 1999).

The sensitivity analysis was made using a built-in SWAT sensitivity analysis tool that uses the Latin Hypercube One-factor-At-a-Time (LH-OAT) global sensitivity analysis procedure (Van Griensven et al., 2006). The sensitivity of all parameters was analyzed using average observed flow at Alaba Kulito gauging station and the optimization procedure was then set to minimize the sum of squared error objective function.

Climate change scenarios and climate projection models

During the IPCC Fifth Assessment Report, the Representative Concentration Pathways (RCPs), was used for the new climate model simulations carried out under the framework of the Coupled Model Intercomparison Project Phase 5 (CMIP5) of the World Climate Research Programme (IPCC, 2013). In this study, climate change scenarios were generated for two Representative Concentration Pathways (RCPs): RCP 4.5 and RCP 8.5 using 20 GCMs from CMIP5 bias-corrected under three time slices, near-term (2010-2039), mid-century (2040-2069) and end-century (2071-2099).

Data of the twenty GCMs (Table 1) from the Coupled Model Intercomparison Project Phase 5 (CMIP5) were provided by the AgMIP climate team from the NASA Goddard's online File Depot. Based on their underlying assumption and complexity, these GCMs can project a wide range of future climatic conditions (Sah and Zeleke, 2015). So far different studies have used outputs from a single GSM for impact studies (Smith et al., 2009) or out puts from several GSM individually (Setegn et al., 2010) but multi model ensemble simulations are known to provide more reliable information than that of a single model output (IPCC, 2007). In this study, ensemble mean outputs of the twenty GCMs (ensemble_20) were used.

The capacity of climate models in CMIP5 to represent a certain aspect of present climate has been studied by Ramirez-Villegas et al. (2013) for East Africa region. So, using ensemble mean outputs of these GCMs will help us to find the combination of GCMs that underestimate, overestimate and accurately capture annual data (Dessu and Melese, 2013).

In addition to the ensemble mean outputs of the twenty GCMs (Table 1) the climate uncertainty assessment used in this study includes 25 climate scenarios (Table 2) developed for climate impact and uncertainty analysis based on the modified QUEST-GSI methodology (Todd et al., 2011; Leong et al., 2014). According to Leong et al. (2014) some of the points considered while modifying the QUEST-GSI methodology are (1) the HadCM3 GCM is replaced by CMIP5 GCM ensemble of 20 GCMs (under RCP 4.5 and 8.5), (2) prescribed increases in global mean temperature (1-6°C) using ensemble_20, (3) six GCM structures from different countries and institutions (ACCESS1.0, BCC-CSM1.1, CanESM2, CCSM4, MIROC-ESM, NorESM1-M) under RCP 4.5, (4) prescribed warming of 2°C using ACCESS1.0, BCC-CSM1.1, CanESM2, CCSM4, MIROC-ESM and NorESM1-M.

The resolution of GCMs varies from 96 × 96 km^2 to 320 ×160 km^2 which is coarse and need to be downscaled before applying them to assess the impact of climate change on regional scale. Statistical downscaling involves developing a relationship between the large and local scales using historical data and then applying this relationship to adjust independent large-scale data down to the local scale (Kirchmeier et al., 2014). Statistical downscaling methods are typically as effective as and less expensive than dynamical downscaling and especially useful for temporal downscaling (Brown et al., 2008). In this study, the Delta method analysis protocol of the Agricultural Intercomparison and

Table 1. List of the global climate models in CMIP5 used in the study.

Model name	Modeling Center (or Group)
ACCESS1.0	Commonwealth Scientific and Industrial Research Organization (CSIRO) and Bureau of Meteorology (BOM), Australia
BCC-CSM1.1	Beijing Climate Center, China Meteorological Administration
BNU-ESM	College of Global Change and Earth System Science, Beijing Normal University
CanESM2	Canadian Centre for Climate Modelling and Analysis
CCSM4	National Center for Atmospheric Research
CESM1(BGC)	Community Earth System Model Contributors
CSIRO-Mk3.6.0	Commonwealth Scientific and Industrial Research Organization in collaboration with Queensland Climate Change Centre of Excellence
GFDL-ESM2G GFDL-ESM2M	NOAA Geophysical Fluid Dynamics Laboratory
HadGEM2-CC HadGEM2-ES	Met Office Hadley Centre
INM-CM4	Institute for Numerical Mathematics
IPSL-CM5A-LR IPSL-CM5A-MR	Institut Pierre-Simon Laplace
MIROC-ESM	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies
MIROC5	Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology
MPI-ESM-MR MPI-ESM-LR	Max-Planck-Institut für Meteorologie (Max Planck Institute for Meteorology)
MRI-CGCM3	Meteorological Research Institute
NorESM1-M	Norwegian Climate Centre

Improvement Project (AgMIP) was used to project the future climate state in the farm lands of Bilate watershed (Rosenzweig et al., 2013). The downscaled GCM simulations provided meteorological data, for input to the hydrologic model, on a daily time step.

RESULTS AND DISCUSSION

Results of sensitivity analysis, calibration and validation. Ranges of values used during the sensitivity analysis and the calibrated parameter value are shown in Table 3. The results showed that the most sensitive parameters are those representing the surface runoff, evaporation, soil water, groundwater and channel flow. The parameters governing the hydrological processes in the watershed in the order of their sensitivity rank are SCS runoff curve number for moisture condition II (CN2), soil evaporation compensation factor (ESCO), available soil water capacity (Sol_Awc), threshold water level in the shallow aquifer for return flow to occur (Gwqmn), effective hydraulic conductivity in main channel alluvium (Ch_K2), base flow recession constant (Alpha_Bf), Manning's roughness coefficient for main channel (Ch_N2), surface

Table 2. Climate scenarios for SWAT input (Ensemble_20 is the average of twenty GCMs).

ID	Model	Scenario	Period	Detail
1	Ensemble_20	4.5	2010-2039	
2	Ensemble_20	4.5	2040-2069	
3	Ensemble_20	4.5	2071-2099	Hydrological impact assessment
4	Ensemble_20	8.5	2010-2039	
5	Ensemble_20	8.5	2040-2069	
6	Ensemble_20	8.5	2071-2099	
7	Ensemble_20	4.5/+1°C	2010-2039	
8	Ensemble_20	4.5/+2°C	2010-2039	
9	Ensemble_20	4.5/+3°C	2010-2039	Prescribed temperature increase
10	Ensemble_20	4.5/+4°C	2010-2039	
11	Ensemble_20	4.5/+5°C	2010-2039	
12	Ensemble_20	4.5/+6°C	2010-2039	
13	ACCESS1.0	4.5	2010-2039	
14	BCC-CSM1.1	4.5	2010-2039	
15	CanESM2	4.5	2010-2039	GCM structure
16	CCSM4	4.5	2010-2039	
17	MIROC-ESM	4.5	2010-2039	
18	NorESM1-M	4.5	2010-2039	
19	ACCESS1.0	4.5/+2°C	2010-2039	
20	BCC-CSM1.1	4.5/+2°C	2010-2039	
21	CanESM2	4.5/+2°C	2010-2039	2°C increase in average global temperature
22	CCSM4	4.5/+2°C	2010-2039	
23	MIROC-ESM	4.5/+2°C	2010-2039	
24	NorESM1-M	4.5/+2°C	2010-2039	
25	Observed dataset	Baseline	1980-2009	Control run

runoff lag coefficient (Surlag), groundwater delay time (Gw_Delay) and aquifer percolation coefficient (Rchrg_Dp).

Calibration of the parameters was immediately followed after the sensitivity analysis. Stream flow at the Alaba Kulito gauging station was calibrated by auto-calibration and manual procedures for the period of 1990-1996. The model efficiency measures for initial monthly default simulation are, the coefficient of determination (R^2), Nash-Sutcliffe coefficient (NSE) and percent bias (PB) were 0.78, 0.45 and 42.39, respectively which show low performance of the model by the default parameter values. Thus, model parameter adjustments were undertaken for a realistic hydrologic simulation and the key hydrologic parameters shown in Table 3 were adjusted until the simulated flow was nearly equal to the observed flow during calibration processes. The statistical results show that the model predicted the stream flow at the Alaba Kulito gauging station reasonably because the coefficient of determination (R2), Nash-Sutcliffe coefficient (NSE) and percent bias (PB) are 0.79, 0.78 and 0.56, respectively.

Figure 2 shows hydrograph comparisons for the Bilate River watershed at the Alaba Kulito gauging station during simulation periods (1 January 1990 to 31 December 1996) to measure how the calibrated model predicts stream flows against the observed flows. Overall, the calibrated flows match observed flows well, but the magnitude of peaks during the summer (June-August) is somewhat different from the observed flow in particular years, such as July 1993, 1995 and 1996 (Figure 2).

In the validation process, the model was operated with input parameters set during the calibration process without any changes. A separate 6-year (1997–2002) simulation was used and it was found that the model has strong predictive capability with the coefficient of determination (R2), Nash–Sutcliffe coefficient (NSE) and percent bias (PB) of 0.64, 0.60 and -21.7 respectively. Statistical model efficiency criteria fulfilled the requirement of R2 > 0.6 and NSE > 0.5 which is recommended by SWAT developer (Nash and Sutcliffe, 1970; Santhi et al., 2001) and the PB < ±25 suggested by (Gupta et al., 1999). The model validation results for monthly flow (Figure 3) indicated generally a good fit between measured and simulated output and this shows the

Table 3. Hydrologic parameters included in SWAT sensitivity analysis for the Bilate River watershed.

Parameter	Description	Model process	Rank	Variation range	Fitted value
CN2	SCS runoff curve number for moisture condition II	Runoff	1	**-25 - +25**	20[C]
ESCO	Soil evaporation compensation factor	Evaporation	2	0-1	1[a]
Sol_Awc	Available soil water capacity	Soil water	3	-25 - +25	15[C]
Gwqmn	Threshold water level in the shallow aquifer for return flow to occur (mm)	Groundwater	4	0-1000	258[a]
Ch_K2	Effective hydraulic conductivity in main channel alluvium (mm h^{-1})	Channel flow	5	0-150	31[a]
Alpha_Bf	Base flow recession constant (days)	Groundwater	6	0-1	0.09[a]
Ch_N2	Manning's roughness coefficient for main channel	Channel flow	7	0-1	0.43[a]
Surlag	Surface runoff lag coefficient	Runoff	8	0-12	9.64[a]
Gw_Delay	Groundwater delay time	Groundwater	9	0-10	6.45a
Rchrg_Dp	Aquifer percolation coefficient	Groundwater	10	0-1	0.49[b]

a=default values are replaced by this value (absolute change); b= default values are multiplied by one plus this value (relative change); c=default values are increased by this value (absolute change).

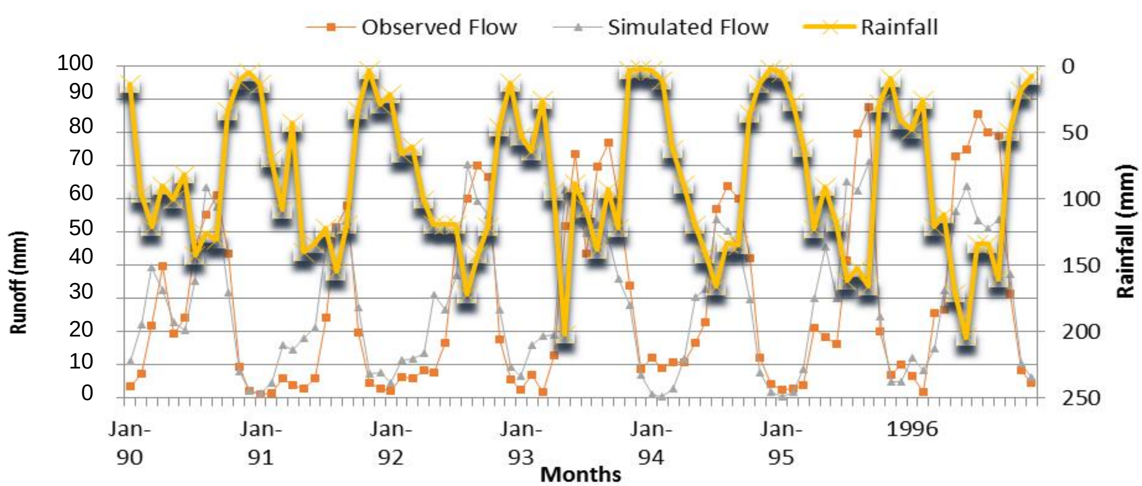

Figure 2. Manual calibration results for monthly flow at Alaba Kulito (1990 -1996).

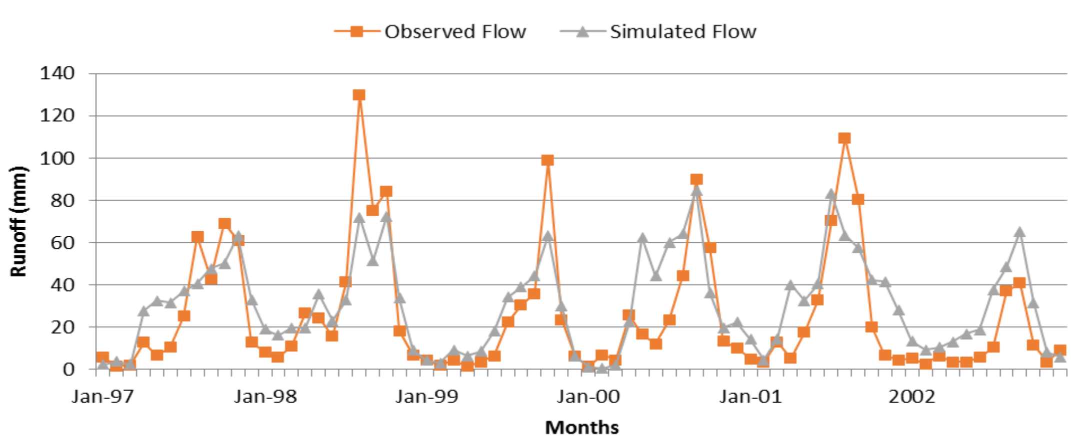

Figure 3. Simulated versus observed flow during validation period.

Table 4. Stream flow simulation changes against the base period simulation for different climate scenarios.

ID	Mean monthly stream flow (m^3/s /%)	Monthly Q95 (m^3/s /%)	Monthly Q5 (m^3/s /%)
1	31.66/10.9	7.86/1.66	61.09/-4
2	33.15/16.12	7.87/1.79	60.64/-4.71
3	35.25/23.48	9.19/18.88	61.81/-2.87
4	31.5/10.34	8.33/7.82	62.48/-1.83
5	34.38/20.43	8.54/10.48	63.84/0.31
6	40.66/42.42	10.49/35.7	76.79/20.67
7	30.73/7.65	7.31/-5.44	56.53/-11.18
8	31.53/10.45	8.07/4.37	59.72/-6.16
9	32.07/12.33	8.66/12.09	61.04/-4.09
10	32.53/13.95	8.79/13.72	61.92/-2.7
11	31.58/10.63	8.27/7.05	58.97/-7.34
12	31.75/11.2	8.52/10.23	59.2/-6.98
13	28.98/1.52	8.63/11.59	53.87/-15.35
14	30.78/7.83	6.65/-13.94	57.89/-9.04
15	29.86/4.59	6.22/-19.5	55.95/-12.08
16	29.5/3.34	7.8/0.9	53.82/-15
17	29.93/4.83	7.29/-5.73	53.9/-15.31
18	26.78/-6.18	5.77/-25.32	52.31/-17.81
19	28.62/0.25	8.17/5.66	51.6/-18.92
20	30.25/5.98	6.55/-15.22	56.06/-11.91
21	34.3/20.16	6.04/-21.87	65.33/2.65
22	29.06/1.81	7.72/-0.18	52.33/-17.77
23	28.78/0.81	7.06/-8.62	50.49/-20.66
24	26.46/-7.29	5.79/-25.14	50.65/-20.41
25	28.55	7.73	63.64

in the watershed to the best of their ability given available data and can be used to predict watershed response for various climate scenarios.

Climate change impact on stream flow

To evaluate the influences of climate change the monthly stream flow in the reach of sub basin 10 (Alaba Kulito station) during the period 2020, 2050 and 2080 are simulated by the calibrated SWAT model under different climate scenarios (RCP 4.5 and RCP 8.5). A baseline scenario, assumed to reflect current conditions, was executed prior to performing scenario simulations and the simulated baseline annual stream flow (ID 25) with the amount of 28.55 m^3s^{-1} is used as the reference frame to show the amount of change in the stream flow under different climate scenarios. Table 4 shows the results of the ensemble_20 annual stream flow changes as well as the results of the other developed climate scenarios for Alaba Kulito station. The annual stream flow increased progressively throughout the century for all time periods under both RCP scenarios. The increases under RCP 8.5 scenario are the larger compared to RCP 4.5 scenarios, approximately 42.42% during the 2080s period. The lowest stream flow change occurred under RCP 8.6 with an increase of 10.3% for the 2020s period. Under RCP 4.5 scenario, the annual stream flow is expected to increase by 10.9, 16.12 and 23.48% for the 2020s, 2050s and 2080s period, respectively.

The low flows (Q95) highly and progressively increased by 7.82, 10.48 and 35.7% for RCP 8.5 scenario for the 2020s, 2050s and 2080s, respectively. While the low flow under RCP 4.5 will increase very slightly (1.66 and 1.79%) for 2020s and 2050s but it will increase at 18.88% for 2080s. The high flows (Q5) slightly decreased for RCP 4.6 (-2.87 to -4%) and dramatically increased for RCP 8.5 (20.67%) for 2080s. Results for Bilate watershed pointed positive change of annual stream flow throughout the century by the ensemble of 20 GCMs which is driven by the projected increase in precipitation and shows that water resources of the Bilate River will be satisfactory until the end of the century.

Increases in stream flow are also projected for each

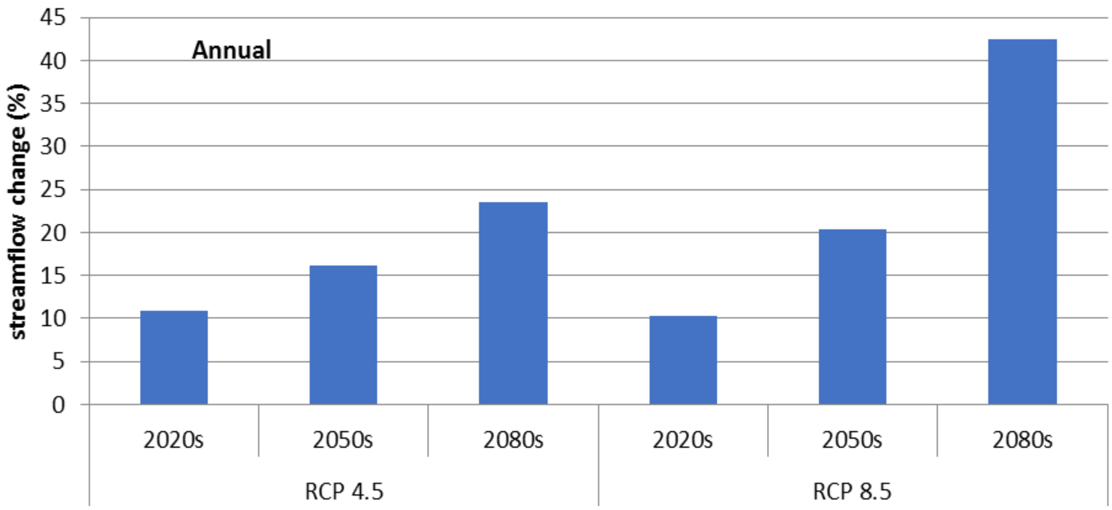

Figure 4. Annual stream flow changes at Alaba Kulito station of Ensemble_20 under RCP 4.5 and RCP 8.5 for the periods of 2020s, 2050s and 2080s.

month (Figure 5) with exceptions in the months of July and August where there will be a decrease of stream flow in the watershed. The largest projected monthly increases in stream flow will occur in December (5.67, 5.98, and 7.94 m^3/s for the RCP 4.5 and 6.06, 8.04 and 14.25 m^3/s for the RCP 8.5) in 2020s, 2050s and 2080s, respectively. While, the largest possible monthly decrease in stream flow will occur in the month of July (-10.21, -9.92, and -9.98 m^3/s for the RCP 4.5 and -11.25, -10.42 and -7.34 m^3/s for the RCP 8.5) in 2020s, 2050s and 2080s, respectively.

Climate impact uncertainty assessment

Figure 4 shows the projected changes in annual river discharge projected by the Ensemble of 20 CMIP 5 GCMs for three future time periods under two RCPs. An increase in annual river flow compared with the baseline is projected under all six scenarios. The magnitude of increase for annual river discharge ranges from 10.34 to 42.42%. The projected change in monthly discharge under all six scenarios mostly decreases in the rainy season and increases in the dry season (Figure 5).

For prescribed temperature increase of 1-6°C scenarios, mean annual river discharge does not show a linear decrease as it does in other watersheds in other studies (Leong et al., 2014; Khoi and Han, 2015) showing that the local temperature increments have less effect on the hydrology of Bilate River watershed similar to other river basin in East Africa region (Dessu and Melese, 2013). Figure 6a shows the changes in monthly discharge for all the six scenarios of prescribed temperature increase. The monthly river discharge in the wet season of the area (Jun- September) decreases from -2.23% in September for the 1°C scenario to -25.52% in July for the 3°C scenario and monthly discharge in the dry season (October-May) increases dramatically from 9.13% in October for the 1°C scenario to 77.23% in February for the 4°C scenario. Uncertainty in projected monthly stream flow for prescribed temperature scenarios varies from -24.97 to 64.24% for the 1°C scenario to the range of -22.71 to 65.35% for the 6°C scenario.

Five of the six GCMs (ACCESS1.0, BCC-CSM1.1, CanESM2, CCSM4, MIROC-ESM) under RCP 4.5 for 2020s show that annual stream flow will increase compared to the baseline, except for the NorESM1-M, which shows a change of -6.18% in annual stream flow. The six GCMs (ACCESS1.0, BCC-CSM1.1, CanESM2, CCSM4, MIROC-ESM, NorESM1-M) selected to see the uncertainties related to GCMs suggest that the river flow will change by small amounts of -6.18 to 7.83% change compared with the baseline. Projected changes in mean annual river discharge under the prescribed increase in mean temperature of 2°C shows similar trend of increase for five GCMs (ACCESS1.0, BCC-CSM1.1, CanESM2, CCSM4, MIROC-ESM) and a decrease of simulated stream flow for NorESM1-M. It was experiential that the simulated runoff in the Bilate River depended on the projected amount of rainfall and the GCM structure selected to simulate the future climate and less dependent on the local temperature increment.

Figure 6b and c shows that the projected increase and decrease of monthly stream flow changes for selected GCM structures and increase of 2°C on top of the downscaled temperature output of the selected GCM. The results show stream flow changes are evenly distributed throughout the year for both the causes.

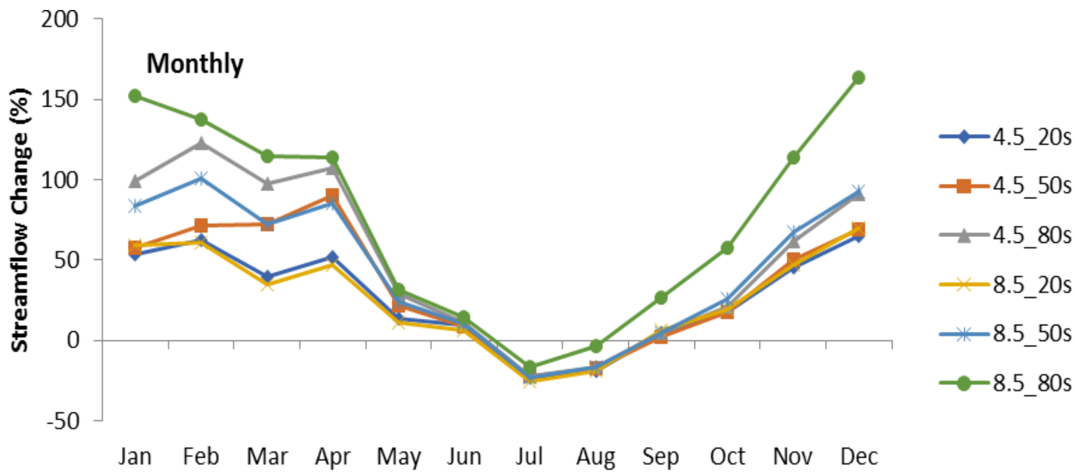

Figure 5. Monthly stream flow changes at Alaba Kulito station of Ensemble_20 under RCP 4.5 and RCP 8.5 for the periods of 2020s, 2050s and 2080s.

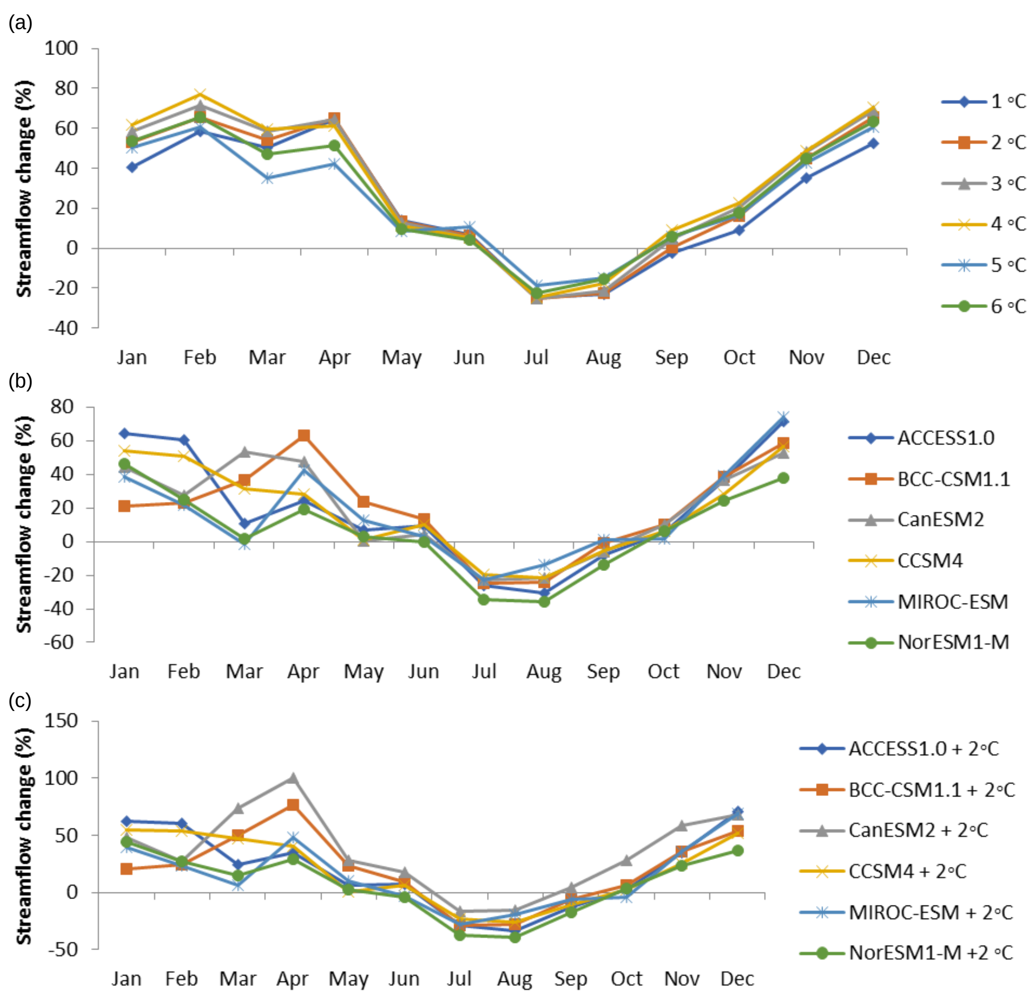

Figure 6. Changes of monthly discharge against the baseline at Alaba Kulito station for climate scenarios: (a) Prescribed temperature of 1-6°C, (b) GCM structure, and (c) 2°C increase in temperature.

Uncertainty in the Q5 ranges from -17.81 to -9.04% for GCM structures and from -20.66 to 2.65% for GCM plus 2 °C scenarios. These results showed that there will be decrease in the high flows in 2020s. Uncertainty in Q95 ranges from -25.32 to 11.59% for GCM structures. As shown in Figure 6b, ACCESS1.0 shows the largest variation (-30.39 to 71.6 7%) and CanESM2 shows the smallest variation (-23 to 52.8%) at monthly scale.

Conclusions

This study applied the SWAT model to assess the sensitivity of the Bilate River stream flow to individual and combined changes in temperature and rainfall with 25 different scenarios. The climate scenarios were generated from an ensemble of twenty GCMs from the Coupled Model Intercomparison Project Phase 5 (CMIP5) under RCP 4.5 and 8.5 scenarios for 2020s, 2050s and 2080s period. The results of calibration and validation of SWAT model showed that the model can be a reliable tool for hydrology cycle simulation in Bilate River watershed. Based on the different climatic scenarios, the simulation results indicated a range of possible hydrologic futures mostly an increase in annual river flow compared with the baseline is projected under all scenarios. The magnitude of increase for annual river discharge ranges from 10.34 to 42.42%.

The most up-to-date climate change impact and uncertainties on stream flow changes were assessed based on the modified QUEST-GSI methodology (Leong et al., 2014) with four major elements: (1) RCP emission scenarios, (2) prescribed increase of annual temperature of 1-6°C, (3) GCM structure, and (4) prescribed increase of temperature of 2°C. The analysis of the results of the simulations showed that uncertainties of the simulated runoff in the Bilate River depended on the projected amount of rainfall embedded in the GCM structures selected to simulate the future climate and less dependent on the local temperature increment. The ensemble of GCMs used in this study is only the simple mean of GCM structure outputs which could be improved by applying weights to GCMs based on their performance in projection of historical climate variables and also more climate scenarios should be developed in the future to better understand the range and quantify the impact of climate change on stream flow.

CONFLICT OF INTERESTS

The authors have not declared any conflict of interests.

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