Streamflow response under different climate change scenarios in data-scarce White Volta basin of West-Africa using a semi-distributed hydrologic model

S Abubakari\textsuperscript{1,2*}, X Dong\textsuperscript{1,2*}, J Liu\textsuperscript{1,2}, Y Li\textsuperscript{1,2}, T Peng\textsuperscript{1,2} and H Ma\textsuperscript{1,2}

1 College of Hydraulic and Environmental Engineering, China Three Gorges University, Yichang, Hubei, China
2 Collaborative Innovation Center for Territorial Sovereignty and Maritime Rights, Wuhan, 430072, China
E-mail: abubakarisulemanaa206@yahoo.com, xhdong@ctgu.edu.cn

Abstract. In this study, streamflow response in White Volta basin of West Africa was evaluated using ECHAM5 (MPEH5) GCM for two IPCC climate change scenarios (A1B and B1) and semi-distributed hydrologic model (SWAT) for three future time periods; 2020s, 2050s and 2080s using 1987-1996 as baseline. Both climate change scenarios project decrease in rainfall in 2020s but increases in 2050s and 2080s. Decrease in rainfall in 2020s was higher in B1 scenario compared to A1B; whereas for 2050s and 2080s, increases in rainfall were higher in A1B scenario than B1. Projected average changes indicate that overall the climate will be warmer and wetter in future. Projected annual streamflow volumes show disproportionate change (~220%) in response to slight changes in mean annual rainfall. Streamflow volume shows sharp changes for A1B scenario than B1 in 2020s whilst in 2050s and 2080s, the changes are moderate. Projected average annual streamflow changes are -3.1% in 2020s, 5.1% in 2050s and 13.3% in 2080s. Overall projected streamflow changes for both A1B and B1 scenarios were not so dramatic (less than ±20%). These call for adaptation strategies to reduce vulnerability and ensure water security within the basin.

1. Introduction
Although there are many discussions still ongoing, it is widely recognized that future impacts of climate change (CC) will be difficult to avoid. CC and its variability will significantly affect hydrologic cycles and this is likely to affect availability (both quantity and quality) and distribution of water resources in several regions around the world. According to Fifth Assessment Report (AR5) of Intergovernmental Panel on Climate Change (IPCC)[1], Africa's climate is already changing and the impacts are already being felt with further CC inevitable in the coming decades. The African continent will particularly be vulnerable due to the considerably limited adaptive capacity. Water plays important economic and social roles in sub-Saharan Africa. It is used for hydropower, agriculture, fishing, industry, livestock watering, transportation, urban development, emergency uses such as fire-fighting and recreation. These activities employ majority of people generating revenues which are fundamental to sustenance of economies of these countries. According to previous studies by Opoku-Ankomah[2]; van de Giesen et al.[3]; Jung and Kunstmann [4] and Sood et al.[5], there have been numerous changes in both spatial and temporal distribution of rainfall in Volta basin of West Africa. This has resulted in some sub-catchments having abundant freshwater leaving others with very limited water to satisfy increasing demands. Uncertainties arising out of CC and its...
variability will additionally exacerbate future water resources management, resulting in non-
attainment of Millennium Development Goals in areas such as health, eradicating poverty and hunger. This is going to pose challenges to growth and development of inhabitants in the basin.

There have been numerous studies utilizing climate models in quantifying effects of CC on hydrology and water resources management in White Volta River basin of West Africa. Obuobie [6] used climate series for 1991–2000 and 2030–2039 generated by stochastic downscaling model, Long Ashton Research Station Weather Generator (LARS-WG) and reflecting MM5-simulated monthly changes, future CC scenario IS92a and Soil and Water Assessment Tool (SWAT) to evaluate effects of CC on recharge of groundwater in White Volta River basin. Results of this study found increase in mean annual rainfall of about 6% in 40 years, resulting in increase of about 29% in groundwater recharge. Kankam-Yeboah et al. [7] used downscaled CC projections from ensemble of two Global Climate Models (ECHAM4 and CSIRO), A1F1 future CC scenario and SWAT model to estimate impacts of CC on streamflow in White Volta basin. Results of this study found that mean annual streamflow showed a decrease of 22% and 50% for 2006-2035 (2020s) and 2036-2075 (2050s) respectively relative to the baseline (1961-1990). Awotwi et al. [8] assessed impacts of CC on various water balance components of White Volta basin using downscaled CC projections from Regional Climate Model (REMO), A1B future CC scenario and SWAT model. Results of this study revealed that an increase of 8% and 1.7% of mean annual precipitation and temperature respectively in 2030-2043 leads to an increase of 26% in mean annual surface runoff relative to the baseline (1995-2008).

All these studies have focused on the response of streamflow to CC in White Volta River basin under a single future emission scenario. In this study, we attempt to investigate the projected changes in streamflow in White Volta River basin of West Africa under different CC emission scenarios. Results of this study will provide local policy makers with quantitative data for incorporation into CC adaptation strategies to reduce vulnerability and ensure water security within the basin.

2. Materials and Methods

2.1. Study Area

The White Volta River basin (Figure 1) is a major sub-basin of the Volta River basin of West Africa. It is located between latitude 8°N and 15°N, and longitude 1°E and 4°W. It is a transboundary river basin with a drainage area of about 106,300 km² and shared mainly by Burkina Faso and Ghana. The topography is predominantly flat with more than half of the basin lying in the elevation range of 200-300m with mean elevation of about 270m. The basin has two major climate zones: semi-arid climate in the north and humid climate in the south. Mean annual rainfall in the semi-arid north is around 600 mm whiles that in the humid south is around 1200 mm [9]. In the semi-arid north, mean monthly temperature ranges from 36°C in March to 27°C in August whiles in the humid south, it ranges from 30°C in March to 24°C in August. The basin wide mean annual temperature and Evapotranspiration (ET) are 26°C and 1650 mm respectively [9]. The soils in the basin are Luvisols, regosols, lithosols, vertisols, planosols, cambisols, and gleysols. The basin is dominated by luvisols, regosols and lithosols which cover about 70% of the basin area. The Land use/cover is predominantly savannah, grassland, and agriculture with small patches of forest.
2.2. Soil and Water Assessment Tool (SWAT) Model Description

SWAT is a process-based, continuous-time, semi-distributed hydrological model. It was developed by United States Department of Agriculture (USDA) Agricultural research Service (ARS) to predict impact of land use practices on water, sediment and agricultural chemical yields in large and complex watersheds with diverse weather, varying soils, land use and management and topographic conditions over long periods [10]. It uses GIS interface and operates on daily time step; however, daily outputs can be aggregated into monthly and annually outputs. It is a very robust model and has been used for CC studies all around the world.

2.3. Model Input Data

Digital Elevation Model (DEM). The DEM used for this study has spatial resolution of 90 m and was obtained from Shuttle Radar Topographical Mission (SRTM) (http://srtm.csi.cgiar.org/).

Land use/Land cover data. The land-use map is a modified Food and Agricultural Organization (FAO) map with spatial resolution of 400 m.

Soil Data. It is a Food and Agricultural Organization (FAO) digitized soil map of the world and derived soil properties. It has spatial resolution of 10 km with almost 5000 distinguishable soil types and was downloaded from WaterBase (http://waterbase.org/download_data.html).

Climate Data. The climate data is Climate Forecast System Reanalysis (CFSR) and was obtained from National Centers for Environmental Prediction (NCEP) (http://cfs.ncep.noaa.gov/cfsr).

River Discharge Data. Monthly discharge data was obtained from Global Runoff Data Centre (GRDC), Koblenz, Germany.

2.4. SWAT Model Set Up

The SWAT model was set up for White Volta River basin through Arc SWAT 2009 interface following step by step procedure outlined in SWAT user guide. First each basin was divided into sub-
basins based on DEM and stream networks of the basin. The number of sub-basins obtained was determined by threshold input value. Sub-basin delineation was followed by automatic parameterization of streams and subdivision of sub-basins into HRUs. Since topography of the basin is predominantly flat, with about 96% of the land having slopes less than 5%; single slope class option was used. This study employed multiple HRUs option where land use class percentage over sub-basin area was set to 20%, soil class percentage over land use area was 10% and slope class percentage over soil area was 20%. Threshold drainage area was set to 5,502.92639 km² and this created 14 sub-basins and 67 HRUs. The model was set up and run using climate data from 1985–1996.

2.5. Sensitivity Analysis
Twenty-one SWAT input parameters (Table 1) relevant to the study area were subjected to sensitivity analysis. The main aim of this exercise was to determine input parameters that had greatest influence on model output.

| No. | Parameter  | Range  | Description                                      |
|-----|------------|--------|--------------------------------------------------|
| 1   | ALPHA_BF   | 0-1    | Baseflow Alpha Factor                            |
| 2   | BLAI       | 0-1    | Maximum Potential Leaf Area Index                |
| 3   | CANMX      | 0-10   | Maximum Canopy Storage                           |
| 4   | CH_EROD    | 0-1    | Channel Erodibility Factor                       |
| 5   | CH_K2      | 0-150  | Channel Effective Hydraulic Conductivity         |
| 6   | CH_N2      | 0-1    | Manning’s Value for Main Channel                 |
| 7   | CN2        | ±25    | Initial Curve Number II                          |
| 8   | EPCO       | 0-1    | Plant Uptake Compensation Factor                 |
| 9   | ESCO       | 0-1    | Soil Evaporative Compensation Factor             |
| 10  | GW_DELAY   | ±10    | Groundwater Delay                                |
| 11  | GW_REVAP   | ±0.036 | Groundwater Revap Coefficient                    |
| 12  | GWQMN      | ±1000  | Threshold Water Depth in the Shallow Aquifer for Return Flow |
| 13  | RCHRG_DP   | 0-1    | Deep Aquifer Percolation Factor                  |
| 14  | REVAPMN    | ±1000  | Threshold Depth of Water in the Shallow Aquifer for “revap” to occur |
| 15  | SLOPE      | ±25    | Average Slope Steepness                         |
| 16  | SLSUBBSN   | ±25    | Average Slope Length                            |
| 17  | SOL_ALB    | ±25    | Moist Soil Albedo                               |
| 18  | SOL_AWC    | ±25    | Soil Available Water Capacity                    |
| 19  | SOL_K      | ±25    | Saturated Hydraulic Conductivity                 |
| 20  | SOL_Z      | ±25    | Soil Depth                                      |
| 21  | SURLAG     | 0-10   | Surface Runoff Lag Time                         |

2.6. Calibration and Validation
Due to lack of adequate daily discharge data, calibration of SWAT model was carried out using monthly discharge data at Nawuni flow station (see Figure 1) which represents outlet of White Volta basin. The time period selected for calibration was January 1985 to December 1991, using the first two years (1985-1986) as warm-up period. Thus January, 1987-December, 1991 was used for calibration and January 1992 to December 1996 for validation.

Performance indicators such as Nash-Sutcliffe model efficiency coefficient (NSE), coefficient of determination (R²) and PBIAS were used for evaluation of model performance. Model performance was considered acceptable when R² > 0.60, NSE > 0.50 and PBIAS was within ±25%. For detailed explanation and formulas of NSE, R² and PBIAS, reference can be made from [11].

2.7. Climate Change (CC) Scenarios and Projections
The IPCC A1B (medium emission) and B1 (low emission) scenarios were used for CC projections. The rainfall and temperature projections were from outputs of ECHAM5 (MPEH5) developed by Max Planck Institute for Meteorology (Germany).
The GCM output was downscaled through the use of the stochastic downscaling model, Long Ashton Research Station Weather Generator (LARS-WG). The downscaling process by LARSWG involved calibration and validation of the model using 30 years (1979-2008) of observed historical daily data at each of the 12 climate stations in the basin through the Site Analysis and Q test functions (step 1). The baseline data (1987-1996) for each station was generated using the Generator function (Step 2). The baseline data (step 2) was then driven by monthly CC scenario information from outputs of the GCM data to produce daily climate scenarios which are representative of the 2020s (2011-2030) and the 2050s (2046-2065) and 2080s (2080-2099) using the Generator tool incorporated in the model (Step 3). The downscaled daily climate outputs (step 3) were then used as SWAT input for CC impact assessment at the basin scale. For detail description of downscaling by LARS-WG, references can be made from [12].

3. Results and Discussion

3.1. Sensitivity Analysis

The results of sensitivity analysis carried on twenty-one (21) SWAT input parameters are presented in Figure 2. The fourteen most sensitive parameters were selected for calibration process.

![Figure 2. Ranking of twenty-one (21) SWAT Parameters during Sensitivity Analysis]

3.2. Calibration and Validation

The simulated streamflow (Table 2) showed 9.10% and 8.60% reduction for both calibration and validation periods respectively, compared to average observed monthly streamflow.

| Period          | Average obs. flow (m$^3$/s) | Standard deviation (m$^3$/s) | Model performance |
|-----------------|-------------------------------|-----------------------------|-------------------|
|                 | Obs.                          | Sim.                        | NSE               | $R^2$ | PBIAS |
| calibration(1987-1991) | 314.6                        | 286.0                       | 0.74              | 0.76  | 11.0% |
| validation(1992-1996)    | 269.9                        | 247.0                       | 0.73              | 0.74  | 8.6%  |

A comparison of hydrographs (Figure 3) and model performance (Table 2) shows that objective functions $R^2$ and NSE were greater than 0.70 for both calibration and validation periods. PBIAS was
within ±25% i.e. 11.0% and 8.6% for calibration and validation periods respectively. These indicate good correlation between monthly observed and simulated streamflow; which is a clear indication that physical processes in the basin are well reproduced by the model.

![Image of discharge during calibration and validation](image-url)

**Figure 3.** Discharge during a) calibration and b) validation for Nawuni (outlet)

### 3.3. Calibration and Validation

The performance of LARS-WG in simulating the baseline climate (rainfall, minimum and maximum temperatures) (Figure 4) was assessed using the p value for statistical significance testing provided by the model. The average p values for simulating daily rainfall, minimum and maximum temperature were 0.989, 1.000 and 0.998, respectively. This shows satisfactory reproduction of baseline values indicating minimum model biases and errors.

![Image of comparison of observed and simulated mean monthly rainfall and temperature](image-url)

**Figure 4.** Comparison of observed and simulated mean monthly rainfall and temperature

### 3.4. Future Climate Change Projections

Projection of future changes in climate were determined from outputs of ECHAM5 GCM for two climate change scenarios, A1B and B1; for three future time periods, 2011-2030 representing the 2020s, 2046-2065 representing the 2050s and 2080-2099 representing the 2080s. The future changes in climate (Figure 5) represent the change in precipitation and temperature respectively in future compared to baseline period (1987-1996).
Figure 5. Annual a) temperature and b) rainfall change in 2020s, 2050s and 2080s.

Annual average temperature increase is 0.52°C in 2020s, 1.62°C in 2050s and 2.94°C in 2080s. Further analysis revealed that A1B scenario projected higher future temperatures than B1. The projected changes indicate that overall, temperature will become warmer in future with higher increases anticipated at the end of the century (2080s).

For rainfall, both climate change scenarios projected decrease in 2020s but increases in both 2050s and 2080s. The decrease in rainfall in 2020s was slightly higher in B1 scenario compared to A1B; whereas for 2050s and 2080s, the projected increase in rainfall was higher in A1B scenario than B1. Both scenarios projected more precipitation in 2080s than in 2020s and 2050s. The projected average changes are -1.21% in 2020s, 2.56% in 2050s and 5.73% in 2080s. Unlike temperature changes, precipitation changes show much uncertainty exhibiting both negative and positive trends.

3.5. Streamflow Response to Climate Change

Figure 6 shows the effect of possible future climate change on annual streamflow.

Projected annual streamflow volume trends are synonymous to that of annual precipitation changes. The projected streamflow changes are expected to range between -2.0% and -4.0% in 2020s, +2.0% and +9.0% in 2050s and +12.0% and +15.0% in 2080s. The projected average changes are -3.1% in 2020s, 5.1% in 2050s and 13.3% in 2080s. Streamflow volume shows sharp changes for A1B scenario than B1 in 2020s whilst in 2050s and 2080s, the change is moderate.

The results also reveals disproportionate change in annual streamflow volumes (~220%) in respond to changes in mean annual rainfall. This finding support Sood[5], Obuobie[6], Awotwi [8] assertions that
there is a much larger non-linear response of streamflow to smaller changes in rainfall. Overall the projected streamflow changes in future for both A1B and B1 scenarios were not so dramatic (less than ±20%).

4. Conclusion
For this study, streamflow response under different climate change (A1B and B1) scenarios in data scarce White Volta basin of West Africa was investigated using the semi-distributed hydrologic model SWAT. For rainfall, both climate change scenarios projected decrease in 2020s but increases in both 2050s and 2080s. The decrease in rainfall in 2020s was slightly higher in B1 scenario compared to A1B; whereas for 2050s and 2080s, the projected increase in rainfall was higher in A1B scenario than B1. Both scenarios projected more precipitation in 2080s than in 2020s and 2050s. Projected average changes indicate that overall, the climate will become warmer and wetter in future. Projected annual streamflow volume trends were synonymous to that of annual precipitation changes with decrease in 2020s and increases in both 2050s and 2080s. There is disproportionate change in annual streamflow volumes (~220%) in respond to changes in mean annual rainfall. Streamflow volume shows sharp changes for A1B scenario than B1 in 2020s whilst in 2050s and 2080s, the change is moderate. Projected average annual streamflow changes are -3.1% in 2020s, 5.1% in 2050s and 13.3% in 2080s. Overall projected streamflow changes in future for both A1B and B1 scenarios were not so dramatic (less than ±20%).

Though there are uncertainties concerning CC scenarios and global climate model predictions, these results nonetheless will provide local policy makers with quantitative data for incorporation into CC adaptation strategies so as to foster resilience reduce vulnerability and ensure water security within the basin.

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