


Local climate change projections and impact on the surface hydrology in the Veia catchment, West Africa

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ABSTRACT

Water security has been a major challenge in the semi-arid area of West Africa including Northern Ghana, where climate change is projected to increase if appropriate measures are not taken. This study assessed rainfall and temperature projections and its impact on the water resources in the Veia catchment using an ensemble mean of four bias-corrected Regional Climate Models and Statistical Downscaling Model-Decision Centric (SDSM-DC) simulations. The ensemble mean of the bias-corrected climate simulations was used as input to an already calibrated and validated Soil and Water Assessment Tool (SWAT) model, to assess the impact of climate change on actual evapotranspiration (ET), surface runoff and water yield, relative to the baseline (1990–2017) period. The results showed that the mean annual temperature and actual ET would increase by 1.3 °C and 8.3%, respectively, for the period 2020–2049 under the medium CO₂ emission (RCP4.5) scenario, indicating a trend towards a drier climate. The surface runoff and water yield are projected to decrease by 42.7 and 38.7%, respectively. The projected decrease in water yield requires better planning and management of the water resources in the catchment.

Key words: climate change, regional climate models, SWAT model, Veia catchment, water balance components

HIGHLIGHTS

- Variations in the mean annual rainfall projection over the catchment were found, with 66 and 33% of the models indicating an increase and decrease, respectively, during the rainy season.
- The near future (2020–2049) climate under RCP4.5 scenario shows a warmer climate in the Veia catchment, with dry season temperature projections higher than the rainy season.
- Surface runoff and water yield are projected to decrease by 42.7 and 38.7%, respectively, in the future period 2020–2049. This would require water resource commission to plan and manage the water resources well at the catchment.

INTRODUCTION

Freshwater is an essential resource for human sustainability. This has made water-related ecosystem services provided by the environment valuable and important for humanity (Pert *et al.* 2010; Nedkov & Burkhard 2012). Though it is one of the world's most important natural resources, which is vital to both economic and social activities, it also constitutes less than 3% of the world's water resources. In the past decades, concerns about the management of this limited resource in river

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basins have increased due to changes in climatic conditions combined with anthropogenic influences (Zhang *et al.* 2008; Jones *et al.* 2015).

The changes in the global climate are believed to have significant impacts on local hydrological regimes (e.g. water yield) which support aquatic ecosystems, hydropower, and irrigation systems (Bessah *et al.* 2020). This has necessitated the frequent assessment of climate change impact on water resources using regional climate models (RCMs) across the world in the past years by many authors (e.g. Labat *et al.* 2004; Huntington 2006; IPCC 2007; Mongo *et al.* 2010). Given the frequent usage of RCMs for impact studies, significant efforts have been made in recent years towards improving RCMs' ability to reproduce the historical climate to help improve local-scale impact studies. However, the raw outputs from these climate models often provide biased representations in reproducing the current climate (Minville *et al.* 2009), therefore making them unsuitable for impact studies like hydrological modelling (Teutschbein & Seibert 2010; Olsson *et al.* 2017). Consequently, a common practice of resolving the scale mismatches between global/regional model output and local information is the application of downscaling methods. The application of bias-correction to climate model data often seems necessary to adjust RCMs precipitation and temperature outputs to better reflect the observed climate before being used for impact studies (Kleinn *et al.* 2005; Leander & Buishand 2007; Minville *et al.* 2009; Adeyeri *et al.* 2019).

In West Africa, most RCMs have been evaluated, some of which focused on the ability of the RCMs to reproduce the annual or seasonal climate (Paeth *et al.* 2011; Akinsanola *et al.* 2015; Okafor *et al.* 2019), and others on the accuracy of the RCMs data for impact studies (e.g. Déqué *et al.* 2016; Stanzel *et al.* 2018). Other studies have also addressed climate change and its impact on water resources using hydrological models (Jung 2006; Obuobie 2008; Kasei 2009; Awotwi *et al.* 2015). For example, Gyau-Boakye & Tumbulto (2006) reported that freshwater availability is likely to decrease up to about 35% on major tributaries of the Volta River in Ghana due to climate change. This decrease will worsen until 2050 due to increase in population, food, water, and energy demand by different sectors. In the White Volta basin, the use of RCMs for hydrological impact studies has been investigated in a few studies (Obuobie 2008; Kankam-Yeboah *et al.* 2013; Awotwi *et al.* 2015). For example, Obuobie (2008) reported that the White Volta basin groundwater resources are susceptible to climate change, which is evident in the reduction of the amount of groundwater recharge. Awotwi *et al.* (2015) also reported an increase in mean annual surface runoff, baseflow, and evapotranspiration (ET) by 26, 24, and 6%, respectively, from 2030 to 2043 due to the increase in precipitation (8%) and temperature of 1.7 °C. Kasei (2009) on the other hand projected a decrease in mean annual rainfall and a decrease in the surface runoff from the Volta Basin's water balance dynamics. These findings support the need for an improved modelling of the hydrological response of the Veia catchment (a sub-catchment of the White Volta basin) to climate change.

In order to design appropriate climate change adaptation strategies to support sustainable water resource development and management in any catchment, a detailed study of the distribution of the water balance components under future climate change scenario is necessary. In the Veia catchment, apart from broader-scale studies of climate change impact on water resources over the whole White Volta basin as indicated above, Limantol *et al.* (2016) showed that climate projections and their impacts on water availability within the Veia catchment have been sparsely studied. Therefore, this study used high-resolution models compared with the study by Awotwi *et al.* and Kasei in order to investigate the role of spatial resolution of models on hydrological component of a basin under climate change. This study aimed to investigate climate change projections for the Veia catchment and its effects on the surface hydrology using an already calibrated SWAT model driven by outputs from a combined RCMs ensemble and a Statistical Downscaling Model-Decision Centric (SDSM-DC) simulation under the Representative Concentration Pathway (RCP4.5) scenario.

STUDY AREA AND DATA

Study area

The Veia catchment is one of the sub-catchments of the White Volta Basin located between latitudes 10° 30'N–11° 08'N and longitudes 1° 15'W–0° 50'E with an area of 305 km² (Figure 1). The greater part of the catchment lies mainly in Ghana, with a small northern portion located in the south-central part of Burkina Faso. The climate of the catchment is influenced by the movement of the Inter-Tropical Discontinuity (ITD) over the West African region (Obuobie 2008). The catchment covers three agro-ecological zones: the Savanna and Guinea Savanna zones in Ghana and the north Sudanian Savanna zone in Burkina Faso. The catchment is characterized by a uni-modal rainfall regime from May to October with a mean annual rainfall of about 956 mm which normally peaks in August (Larbi *et al.* 2020). The mean temperature of the catchment is 28.9 °C while

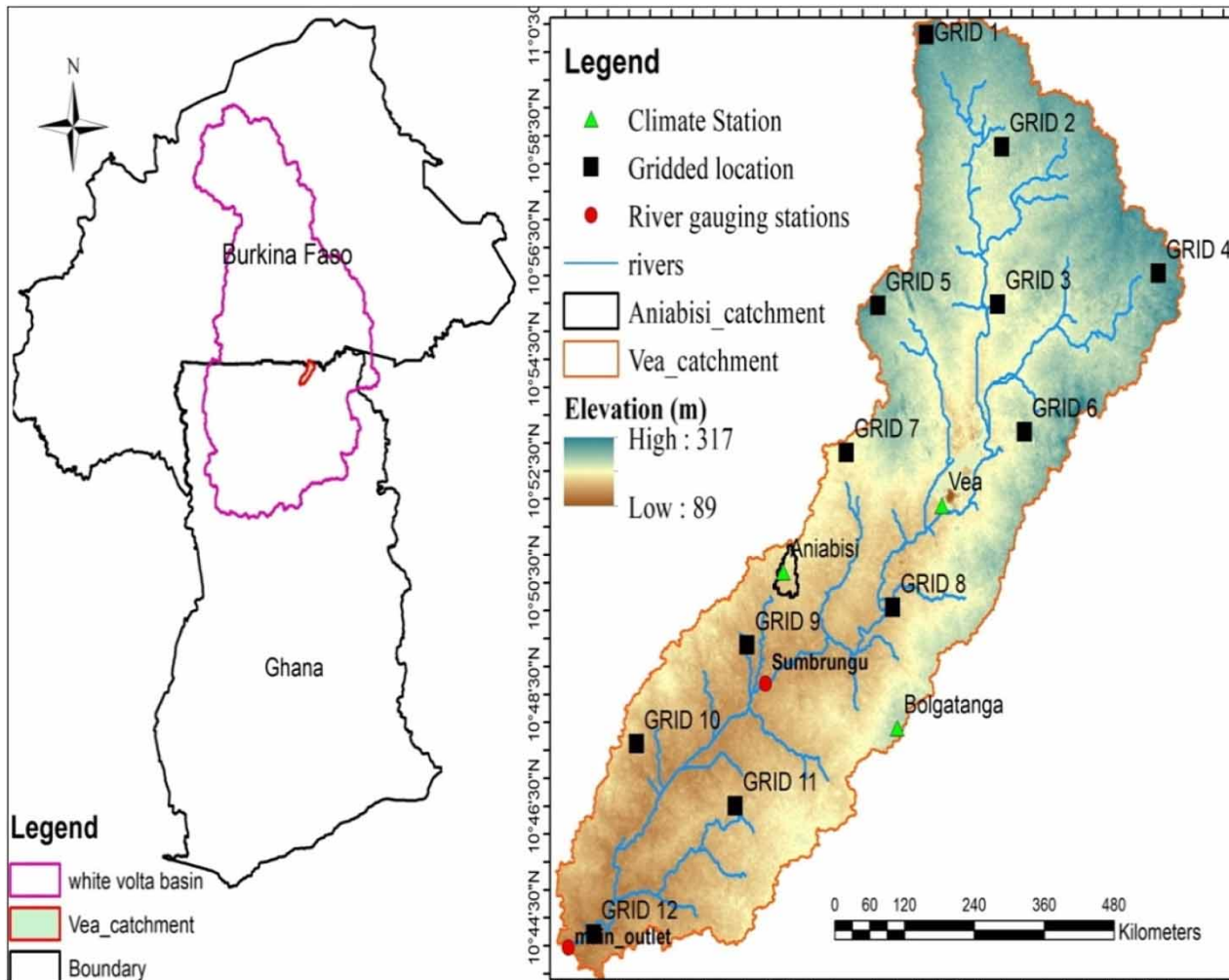


Figure 1 | Location of Vea catchment within the White Volta Basin, topography and climate location stations (gridded and stations) in the Vea catchment, after Larbi *et al.* (2018).

potential ET in the area exceeds monthly rainfall for the most of the year, except the three wettest months of July, August, and September (Larbi *et al.* 2020). The catchment is characterized by fairly low relief with elevation ranging between 89 and 317 m and is mainly dominated by cropland followed by grassland interspersed with shrubs and trees (Larbi *et al.* 2020). Rain-fed and irrigated agriculture, which is the main activity of the people in the catchment, is vulnerable to climate variability and change.

Datasets

Observation data

Historical daily rainfall, maximum and minimum temperature covering the period from 1981 to 2017 for the Vea, Aniabisi and Bolgatanga climate stations within the Vea catchment (Figure 1) were obtained from the Ghana Meteorological Agency. Due to the sparse distribution of *in situ* climate stations throughout the catchment, additional daily values of rainfall for 12 gridded locations were extracted from the Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) data to complement the *in situ* datasets. The CHIRPS incorporates 0.05° resolution satellite imagery with *in situ* station data to create gridded rainfall time series (Funk *et al.* 2015). These gridded locations (Figure 1) were selected to represent the three agro-ecological zones, namely the Savanna zone (GRID3, GRID 4, GRID 5, GRID 6, GRID 7, and GRID 8), Guinea Savanna zone (GRID 9, GRID 10, GRID 11, and GRD 12), and the north Sudanian Savanna zone (GRID 1 and GRID 2) in the study area. The performance of the CHIRPS data in reproducing the climatology of the Vea catchment has been evaluated in a previous study (Larbi *et al.* 2018).

Their study found a very high seasonal correlation coefficient ($r = 0.99$), Nash–Sutcliffe efficiency (0.98) and percentage bias (4.4 and -8.1%) between the stations and the CHIRPS data at the Veia catchment.

RCM datasets

RCM datasets (Table 1) from the CORDEX-Africa experiment and Weather Research and Forecasting Model (WRF) RCMs over West Africa (Heinzeller *et al.* 2017) were used for this study. The two CORDEX-Africa RCMs (REMO2009 and KNMI-RACMO22T) were downscaled dynamically from a common GCM. The 12 km spatial resolution Weather Research and Forecasting Models (WRF-HadGEM2 and WRF-GFDL) were dynamically downscaled from the General Fluid Dynamics Laboratory Earth System Model (GFDL-ESM2M) and the Hadley Global Environment Model (HadGEM2-ES) using the Weather Research and Forecasting RCM (Heinzeller *et al.* 2017). A detailed technical description and parameterization of the WRF models have been reported by Heinzeller *et al.* (2017). The RCM datasets used in this study at daily scale consist of rainfall, minimum and maximum temperature for the RCM historical (1981–2005) and RCP4.5 projected (2020–2049) periods. RCP4.5, which represents a moderate future emission scenario, is the only considered scenario because the projections for WRF-HadGEM2 and WRF-GFDL models are only available for the RCP4.5 emission scenario. These RCMs were chosen because (i) the two CORDEX-Africa RCMs at 50 km resolution are said to perform well over the study area (Kim *et al.* 2013; Akinsanola *et al.* 2015) and (ii) the WRF-RCM models are new and specifically tailored to West Africa with higher spatial resolution (12 km).

METHODOLOGY

Statistical Downscaling Model-Decision Centric data generation

The SDSM-DC is a hybrid statistical downscaling model that uses stochastic weather generator and multiple linear regression techniques to simulate local variables of regional circulation and atmospheric moisture predictors (Harpham & Wilby 2005). The SDSM-DC version 5.2 was used to generate daily rainfall and temperature datasets for the Veia catchment due to its very high spatial resolution (0.002 km). The datasets were generated through the following process: (1) data quality control; (2) predictor variable selection; (3) model calibration and validation; (4) local-scale weather generation; and (5) generation of future climate scenario. Large-scale atmospheric variables (predictor) acquired from the National Center for Environmental Prediction (NCEP) at 275 km spatial resolution for the Veia catchment were used together with the observed daily rainfall and temperature data for the SDSM-DC model downscaling. This was achieved by screening further the predictors to identify empirical relationships between the predictors and the predictands, in order to select the best predictors for temperature (Table 2) and rainfall (Table 3) required for the calibration of the SDSM-DC model.

The rainfall and temperature time series were considered as conditional and unconditional variables, respectively, based on their normal distribution. Correlation analysis was done at a 0.05 significance level based on the partial correlation value (Tables 2 and 3) and the p -value for the model calibration period of 1981–1995. Using the weather generator, the daily rainfall and temperature data were simulated for the period 1948–2010. After model validation and performance evaluation using an independent period (1996–2010), the calibrated SDSM-DC model was used to generate climate change scenario (RCP4.5) datasets for each station/gridded locations for the period 2020–2049. The input data for the RCP4.5 data generation were based on the projections from an ensemble mean of 41 GCMs of the 5th Coupled Model Intercomparison Project (CMIP5) of the World Climate Research Program (WCRP). The CMIP5 scenario run projected the mean daily rainfall and

Table 1 | Description of the regional climate models used in this study

GCM	RCM	Institution	Resolution (km)
ICHEC-EC-EARTH	REMO2009	Max Planck Institute- Computational methods in systems and control theory (MPI-CSC), Germany	50
ICHEC-EC-EARTH	KNMI-RACMO22T	Koninklijk Nederlands Meteorologisch Instituut (KNMI)	50
HadGEM2-ES	WRF- HadGEM2	WASCAL/KIT/IMK-IFU	12
GFDL-ESM2M	WRF-GFDL	WASCAL/KIT IMK-IFU	12

Table 2 | Partial correlation of predictors selected for the climate stations for the statistical downscaling of temperature variable

Predictors	Vea station		Bolgatanga station	
	T_{max}	T_{min}	T_{max}	T_{min}
Mean temperature at 2 m (temp)	0.34	0.63	0.23	0.45
Direct shortwave radiation (dswr)	0.29	0.18	0.19	0.18
Zonal velocity component at 850 hPa (p8_u)	-0.11			
Mean sea level pressure (mslp)	-0.43	-0.22	-0.18	-0.23
Potential temperature (pottmp)	0.55	0.56	0.36	0.28
Geopotential height at 850 hPa (p850)	-0.13			
Surface lifted index (lftx)		-0.23		-0.17
Relative humidity at 500 hPa height (r500)		-0.12		
Precipitable water (Pr_wtr)		0.4		

Table 3 | Partial correlations of predictors selected for the climate stations for rainfall variable

Predictors	Stations		Gridded locations			
	Vea	Bolgatanga	GRID 1	GRID 6	GRID 9	GRID 12
Surface lifted index	-0.49	-0.52	-0.52	-0.51	-0.50	-
Mean sea level pressure	-0.48	-0.47	-0.51	-0.52	-0.49	-0.63
850 hPa geopotential height	-0.32	-0.33	-0.34	-0.36	-0.34	-0.39
Potential temperature	0.50	0.50	0.53	0.54	0.50	0.69
Relative humidity at 500 hPa height	-	-	-	-	-	-0.31
Near surface-specific humidity	0.63	0.66	0.67	0.67	0.67	-
Mean temperature at 2 m	0.54	0.54	0.57	0.58	0.54	0.70

temperature to be 2.57 mm and 29.4 °C, respectively, for the Vea catchment between 2020 and 2049. The 2020–2049 RCP4.5 data were generated using the mean addition/change factor (Table 4) based on the evaluation of mean annual rainfall, minimum and maximum temperature changes for the historical (1981–2010) and future (2020–2049) periods.

RCMs performance evaluation, bias-corrections and change analysis

The performance of the raw RCMs and the SDSM-DC simulation in reproducing the long-term mean monthly rainfall and temperature patterns of the Vea catchment for the baseline period (1981–2005) was assessed using Taylor's diagram (Taylor 2001). The performance evaluation of the models was conducted at the catchment scale by comparing the arithmetic mean of the observation and each model simulated data. The biases in the models were computed using the mean bias (MB) and percentage bias (PBIAS) methods. The Taylor's diagram provides a statistical summary form of how well simulations match observations in

Table 4 | Mean addition/change factors for SDSM-DC simulation under the RCP4.5 scenario for the period 2020–2049 relative to the baseline period

Variables	Factor	
	Vea station	Bolgatanga station
Rainfall (mm/day)	-0.03	-0.13
Minimum temperature (°C)	0.41	0.51
Maximum temperature (°C)	0.87	0.67
Mean temperature (°C)	0.64	0.58

terms of their correlation (r), root-mean-square difference (RMSE), and standard deviation. Other statistics such as Nash–Sutcliffe Efficiency (NSE) were also computed and evaluated for all the climate models.

The biases in the RCMs at point scale were corrected using the Climate Model data for hydrologic modelling (CMhyd) tool (Rathjens *et al.* 2016). The variance scaling bias-correction method was used to correct both the mean and variance of the temperature time series (Chen *et al.* 2011). In this method, the mean of the simulated RCM is adjusted by the linear scaling method. Afterwards, the corrected mean temperature for the current and future scenario run is shifted monthly to a zero mean. The standard deviations of the shifted time series are then matched based on the ratio of observed and RCM control runs standard deviations. Finally, the standard deviation-corrected time series are shifted back using the corrected mean to obtain the final bias-corrected time series. The local intensity scaling (LOCI) method of precipitation bias-correction corrects MB in addition to wet-day frequencies and intensities (Schmidli *et al.* 2006). The method effectively improves the RCMs data which is known to consist of too many drizzle days. The biases in precipitation are corrected by first of all defining an RCM-specific threshold, such that the number of days greater than 0 mm of rainfall in the observed data becomes the same as that of the RCM data which are greater than the defined threshold. Based on the long-term monthly mean wet-day intensities, a linear/intensity scaling factor is estimated which is used to correct the RCM-simulated precipitation.

The bias-corrected rainfall- and temperature-simulated data (RCMs and SDSM-DC) were used to assess the projected changes in rainfall and temperature at the Veia catchment under the RCP4.5 scenario. The change analysis was conducted for the period 2020–2049 relative to the 1981–2010 period.

Quantification of climate change on water balance components using the SWAT model

The Soil and Water Assessment Tool (SWAT) model is a semi-distributed and continuous-time model developed at the United States Department of Agricultural Research Service (Arnold *et al.* 1998). As a physically based model, the SWAT analyses the catchment by dividing it into sub-catchments based upon drainage areas of the attributes which are further subdivided into homogeneous units called Hydrologic Response Units (HRUs) that consist of uniform land use, soil, relief, and management practices (Neitsch *et al.* 2005). Both physically and conceptual models exist. Examples of lumped conceptual models include the Hydrological Model focusing on Sub-flows' variation (HMSV) (Onyutha 2019) and Australian Water Balance Model (AWBM) (Boughton 2004). Examples of process-based or distributed models include the SWAT (Arnold *et al.* 1998) and MIKE Système Hydrologique Européen (SHE) (Abbott *et al.* 1986). In this study, the SWAT was adopted because of its capability as demonstrated in a previous study (Larbi *et al.* 2020) to adequately simulate results in both space and time over the study area.

The SWAT model was set up for the Veia catchment by delineating the catchment into 52 sub-catchments with an estimated total surface area of about 305.6 km², and 331 HRUs, using a 30 m digital elevation model, 10 km soil map, and 30 m classified 2016 land-use/land-cover map (Larbi *et al.* 2020). Detail characteristics of the different input data used for the SWAT model setup can be found in Larbi *et al.* (2020). The model was run using the observed daily climate (station and CHIRPS gridded) data for the period of 1990–2017 using the first 3 years (1990–1992) as a model warm-up period. The surface runoff was estimated using the Soil Conservation Service (SCS) curve number equation which is a function of land use, soil permeability, and antecedent soil water conditions (Neitsch *et al.* 2005). The Hargreaves method, which requires only minimum and maximum temperatures as input data, was used for the ET estimation. A detailed description of the model setup, sensitivity analysis, calibration, and validation is presented by Larbi *et al.* (2020).

The SWAT model sensitivity analysis was performed via the interface of SWAT-CUP using the Sequential Uncertainty Fitting version 2 (SUFI-2) procedure by testing a total of 13 parameters (Larbi *et al.* 2020) based on previous studies (e.g. Obuobie 2008) and SWAT documentation recommendations (Neitsch *et al.* 2011). The average slope steepness (HRU_SLP), SCS runoff curve number (CN2), baseflow alpha factor (ALPHA_BF), soil evaporation compensation factor (ESCO), and the threshold water depth in the shallow aquifer for return flow to occur (GWQMN) emerged as the most sensitive parameters for the Veia catchment.

The SWAT model was calibrated manually and automatically at the Sumbrugu gauge station, with an accuracy of R^2 and NSE for the calibration period (2014–2015) as 0.75 and 0.69, respectively, and for the validation period (2013) as 0.71 and 0.62, respectively (Larbi *et al.* 2020). The performance of the SWAT model was evaluated using the Nash–Sutcliffe model efficiency (Nash & Sutcliffe 1970; Equation (1)), coefficient of determination (R^2 ; Equation (2)), and PBIAS (Equation (3)).

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

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

$$\text{PBIAS} = \frac{\sum_{i=1}^n (O_i - P_i)}{\sum_{i=1}^n (O_i - \bar{O})} \times 100 \quad (3)$$

In these equations, O_i is the measured discharge data and P_i is the simulated discharge data, whereas \bar{O} and \bar{P}_i are the mean of the measured and simulated data, respectively.

It is worth mentioning that this study used the already calibrated and validated SWAT model for the Veia catchment by Larbi *et al.* (2020). The impact of climate change on water balance components (surface runoff, actual ET, and water yield) for the period 2020–2049 under the RCP4.5 scenario was assessed by driving the already calibrated SWAT model with the outputs from the ensemble of four RCMs and an SDSM-DC simulation combined.

RESULTS AND DISCUSSION

Performance evaluation of RCMs and the SDSM-DC simulations

A comparison between the observation, the raw CORDEX-Africa RCMs (REMO2009 and RACMO220T), and the WRF (WRF-GFDL and WRF-HadGEM) rainfall simulations for the period 1981–2005 (Figure 2) showed that the 12 km WRF RCMs simulated well the annual cycle of the mean monthly rainfall for the Veia catchment compared with the 50 km CORDEX-Africa RCMs (Table 5). The computed biases showed that the peak of the rainy season month of August was simulated reasonably well by RACMO22T with a PBIAS of -6% , followed by WRF-HadGEM and WRF-GFDL of -9.4 and -9.7% , respectively, but overestimated by REMO2009 with PBIAS of 12.7% . The end of the rainy season month of October was also overestimated by the RCMs, especially REMO2009 and RACMO22T.

The evaluation statistics presented in Table 5 and Figure 3 indicated that all the RCMs and the SDSM-DC model including the ensemble mean captured the mean monthly rainfall distribution well with correlation (r) above 0.95, RMSE below 0.5, and NSE above 7.0. For temperature, all the RCMs underestimated the mean monthly temperature (Figure 2(b)), except for REMO2009 that showed overestimation in June, July, August, and September. The mean temperature was simulated reasonably well by the SDSM-DC with high r , NSE, and PBIAS values compared with the CORDEX-Africa and WRF RCMs (Table 5 and Figure 3(b)).

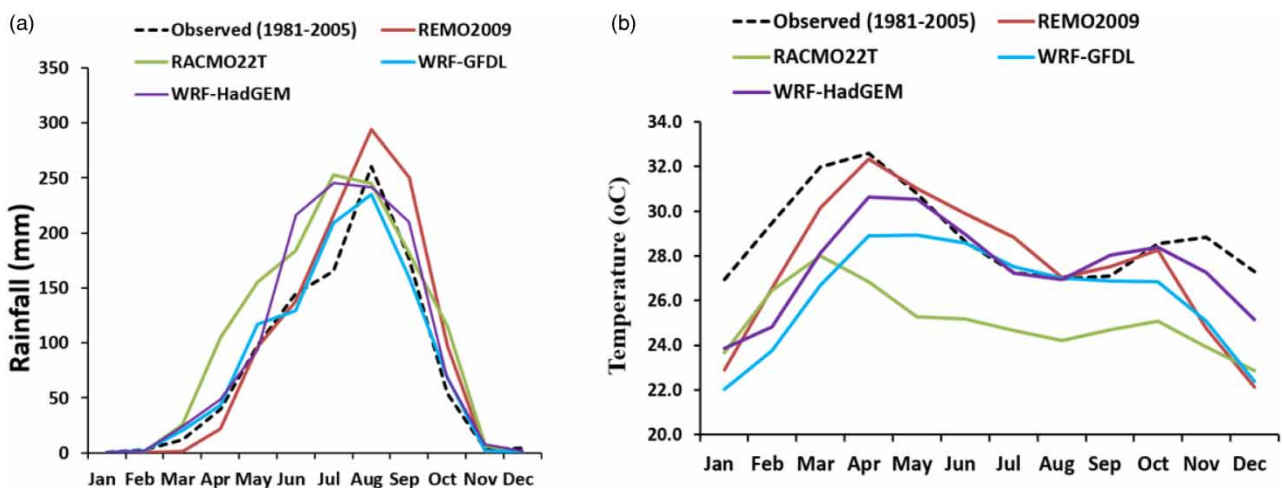


Figure 2 | Biases in raw RCMs simulated mean (a) monthly rainfall and (b) temperature for the Veia catchment for the period 1981–2005.

Table 5 | Statistical analysis of the raw RCMs and SDSM-DC performance in simulating the mean monthly rainfall and temperature of the Veia catchment for the period 1981–2005

Models	Rainfall			Temperature		
	PBIAS	MB	NSE	PBIAS	MB	NSE
RACMO22T	16.3	13.0	0.86	-12.0	-3.4	-4.5
REMO2009	32.5	26.0	0.71	-3.0	-0.8	-1.3
WRF-G	3.2	2.5	0.95	-7.9	-2.2	-3.0
WRF-H	21	16.7	0.84	-3.5	-0.9	-0.4
SDSM-DC	5.5	4.4	0.95	-0.4	-0.1	0.99
Ensemble mean	15.7	12.5	0.93	-5.3	-1.5	-0.5

Note: MB indicates mean bias; NSE indicates Nash-Sutcliffe efficiency.

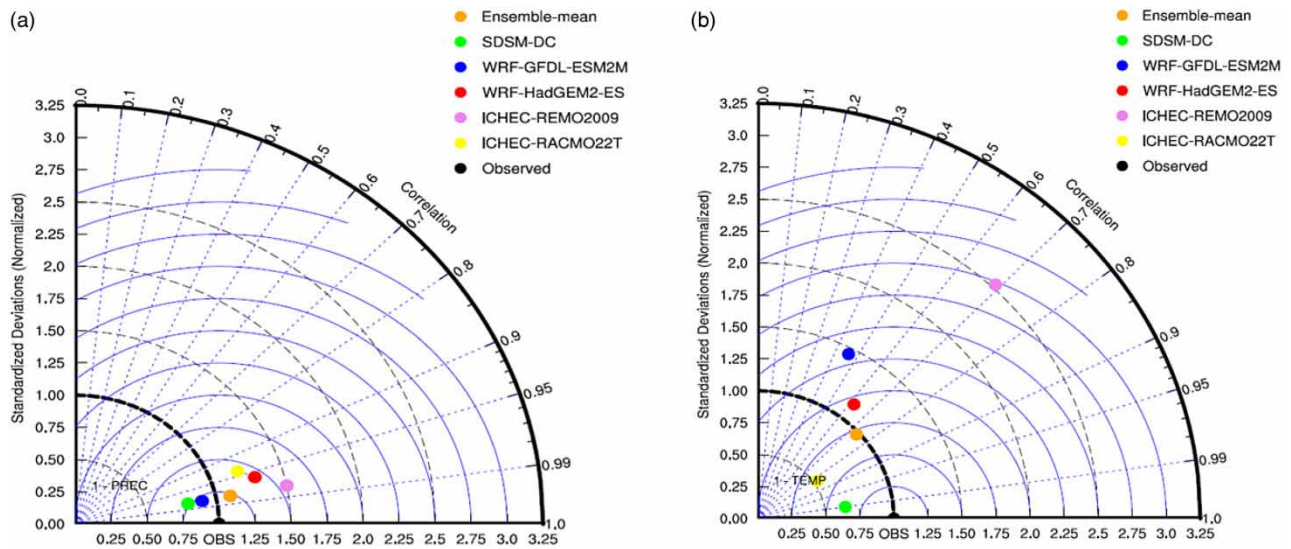


Figure 3 | Evaluation statistics of simulated and observed mean monthly (a) rainfall and (b) temperature for the Veia catchment using Taylor’s diagram.

Climate change projections and impact on water balance components

Rainfall and temperature projections under the RCP4.5 scenario

The results of annual rainfall projections at the Veia catchment under the RCP4.5 scenario are shown in Table 6. The 12 km RCMs projected an increase in the mean annual rainfall, while RACMO22T and SDSM-DC show a decrease in rainfall. The REMO2009 projected no change in rainfall. Overall, the ensemble mean of the models showed an increase in the mean

Table 6 | Mean annual rainfall and temperature projections by the various RCMs for the period 2020–2049 relative to the 1981–2010 period

Variables	Baseline (1981–2010)	RCP4.5 (2020–2049)					Ensemble mean
		REMO2009	RACMO22T	WRF- HadGEM	WRF-GFDL	SDSM-DC	
T_{max} (°C)	34.6	36.3 (1.7)	35.6 (1.0)	36.3 (1.6)	35.9 (1.3)	35.5 (0.8)	35.9 (1.3)
T_{min} (°C)	22.6	24.0 (1.5)	24.1 (1.6)	24.1 (1.5)	24.0 (1.4)	23.5 (1.0)	24.0 (1.4)
T_{mean} (°C)	28.6	30.2 (1.6)	29.9 (1.3)	30.2 (1.6)	29.9 (1.3)	29.5 (0.9)	29.9 (1.3)
Rainfall (mm)	941.5	941.2 (0.0%)	907.9 (- 3.5%)	1,082.9 (15.0%)	992.2 (5.4%)	826.2 (- 12.3%)	981.1 (4.2%)

Note: The projected changes in rainfall and temperature values are in the bracket.

annual rainfall (4.2% for 2020–2049) (Table 6). For temperature, all the models projected an increase for the period 2020–2049, with magnitudes higher in the minimum temperature compared with the maximum temperature in most models (Table 6). The ensemble mean showed an increasing trend of 0.02 °C/year, with the mean annual temperature projected to increase by 1.3 °C in 2020–2049. The projected increase in temperature by the ensemble mean is highest in the dry season (1.2 °C) and smallest in the rainy season (0.9 °C) at the Veia catchment.

The spatial patterns of the observed, future, and projected changes in mean annual temperature and rainfall are shown in Figure 4. The temperature ranges from 28.3 to 28.8 °C and decreases from the southern to the northern part of the catchment (Figure 4(a)). A similar pattern is also projected in the near future. However, the temperature change in the range of 1.1–1.5 °C would be higher in the northern part of the catchment compared with the southern part (Figure 4(c)). In the case of rainfall, the southern and the north-eastern part of the catchment receives higher rainfall compared with the central and the north-western part of the catchment (Figure 4(d)). A decrease in annual rainfall (21 mm) is projected at the central part of the catchment, while an increase (up to 65 mm) is projected at the north-eastern and southern part of the catchment (Figure 4(f)).

Climate change impact on the water balance components

The results for climate change impact under the RCP4.5 scenario for the mean monthly and annual actual ET, surface runoff, and water yield using the calibrated SWAT model are shown in Figure 5 and Table 7. The projected 1.3 °C increase in mean annual temperature in the future (2020–2049) resulted in an increase in actual ET of 9.0% relative to the SWAT simulated period (1990–2017) (Table 7). The evaporative fraction (ET/rainfall) increased from 74.3% in the current climate to 80% in the future, indicating a trend towards a drier climate despite a positive rainfall scenario. Water yield and surface runoff decreased by 38.7 and 42.7%, respectively. This can be attributed to the increase in the temperature and the subsequent increase in ET, which is an indication of the sensitivity of water yield and surface runoff to climate change.

At the monthly scale, there are observable changes in the water balance components between the baseline and the future period (Figure 5). While the mean monthly rainfall shows relatively no changes (Figure 5(a)), the ET in 2020–2049 would increase for all the rainy season months, with a projected increase of 11.8% during the three wettest months of July,

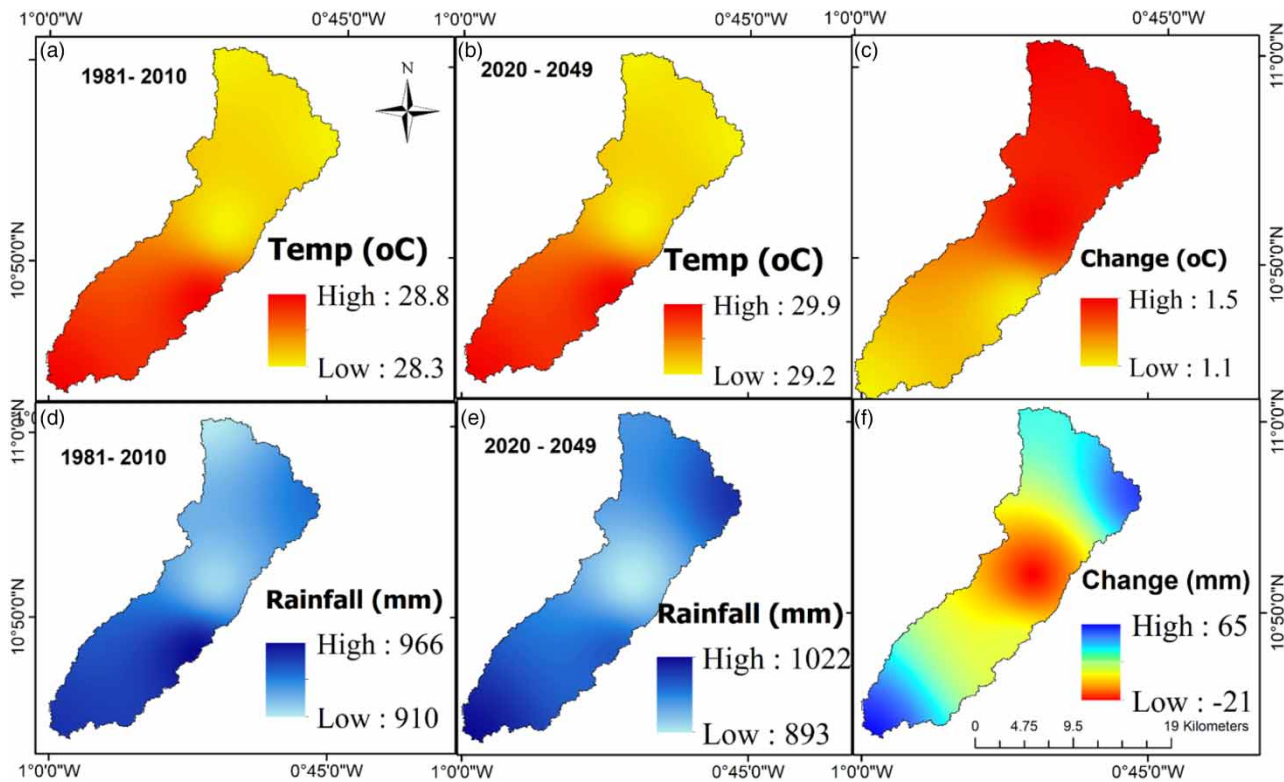


Figure 4 | Spatial distribution of the mean annual temperature and rainfall of the Veia catchment: (a, d) 1981–2010, (b, e) 2020–2049 (future), and (c, f) projected changes.

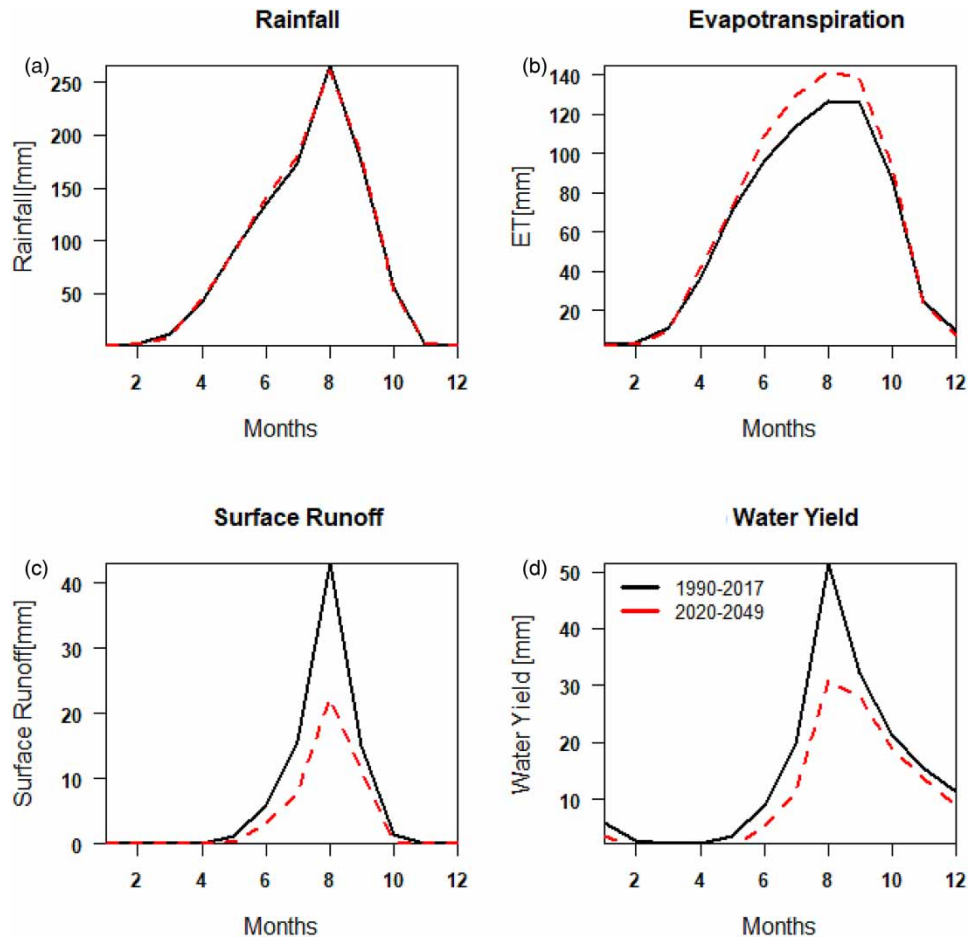


Figure 5 | Simulated mean monthly water balance components (rainfall, ET, surface runoff, and water yield) using the SWAT for 1990–2017 and future (2020–2049) RCP4.5 climate change scenario.

Table 7 | The simulated mean annual water balance components in 2020–2049 under the RCP4.5 scenario with reference to the baseline (1990–2017) period

Simulation period	Water balance components (mm)			
	Rainfall	ET	Surface runoff	Water yield
1990–2017	954.5	709.5 (74.3)	82.5 (8.6)	128.4 (13.5)
2020–2049	966.6	773.7 (80)	47.2 (4.7)	78.7 (8.1)
Changes (%)	1.3%	9.0	–42.8	–38.7

Note: Values in the bracket indicate the percentage of rainfall; ET means actual evapotranspiration.

August, and September (Figure 5(b)). This increase in ET translated to a decrease in surface runoff (42.8%) and water yield (38.7%) in the future over the same rainy season period (Figure 5(c) and 5(d)).

Spatial distribution of water balance components under the RCP4.5 scenario

The spatial distribution of the projected changes in the simulated water balance components is shown in Figure 6. The actual ET varies across the Vea catchment from 671.7 mm in the south to 1,102.5 mm in the north for the historical period (Figure 6(a)) and from 728 to 1,019 mm in the future period. Due to temperature increase and rainfall variation, ET is projected to increase in the catchment especially in the southern part where a higher temperature change is projected

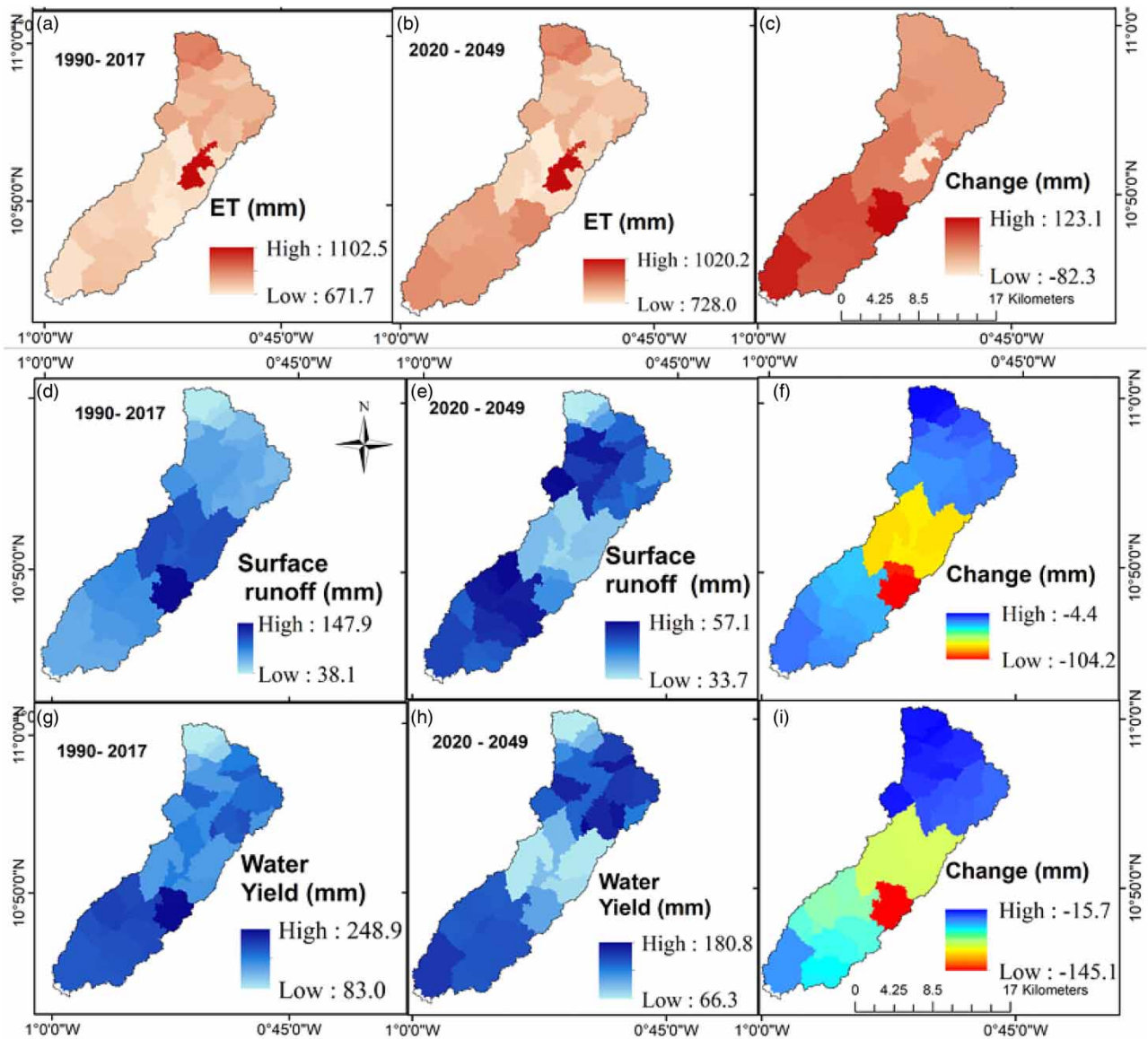


Figure 6 | Spatial distribution of the simulated parameters for the baseline (1990–2017) and the future (2020–2049) periods: (a–c) mean annual ET, (d–f) surface runoff, (g–i) water yield, and (c, f, i) projected changes.

(Figure 6(c)). Though there was a slight increase in mean annual rainfall over the two periods, surface runoff and water yield were projected to decrease in the Veia catchment (Figure 6(f) and 6(i)), and this can be attributed to the balance of water input and atmospheric demand. Both the water input (rainfall) and actual ET would increase within the period of 2020–2049.

DISCUSSION

In general, the baseline (1981–2005) evaluation of the mean monthly rainfall shows a good performance of the WRF 12 km climate simulations (WRF-GFDL and WRF-HadGEM) over the Veia catchment compared with the 50 km CORDEX RCMs. There was not much difference between the performance of the 12 and 50 km RCMs in simulating the mean monthly temperature of the catchment. This conforms to the study of Bessah *et al.* (2018) at the Pra river basin in Ghana that showed that the 12 km resolution WRF-GFDL and WRF-HadGEM models did not improve the simulation of the mean temperature. In most cases, the ensemble mean agrees more favourably with the observation, and this has long been recognized to hold for surface temperature and precipitation (Boer & Lambert 2001). The bias-corrected RCMs at the Veia catchment, especially at

the mean monthly scale, show an improvement compared with the raw RCM simulations, which support the results of [Teutschbein & Seibert \(2012\)](#). The results obtained for the mean annual temperature projections in the Veia catchment were found to be in line with studies such as [Kankam-Yeboah *et al.* \(2013\)](#) and [Awotwi *et al.* \(2015\)](#). For example, using ensemble (ECHAM4/CSIRO), [Kankam-Yeboah *et al.* \(2013\)](#) projected a decrease in mean annual rainfall of 19.6% and an increase in temperature of 1.9 °C in the White Volta basin for the 2050s (2036–2035) relative to the 1961–1990 period. [Awotwi *et al.* \(2015\)](#) made a similar observation by projecting an increase in the mean annual rainfall and temperature of 8% and 1.7 °C by the future 2030–2043 using REMO RCM. Similarly, [Obuobie \(2008\)](#) reported an increase in mean annual rainfall by 6% in the White Volta basin in the future 2020–2039 relative to the baseline (1991–2000) period. Also, the ensemble mean of the CIMP5 temperature projection for the Veia catchment showed an increase of 0.9 and 1.1 °C in the minimum and maximum temperatures, respectively, which is within the temperature projections from the ensemble RCMs used in this study.

In the case of streamflow and ET projections, the results obtained for this study are in line with what were found in other river basins in West Africa. For example, [Kankam-Yeboah *et al.* \(2013\)](#) reported a decrease in streamflow of 21.6 and 50.1% for the 2020 and 2050 s, respectively, at the White Volta basin due to temperature increase. Additionally, [Awotwi *et al.* \(2015\)](#) also discovered that an increase in temperature of 1.7 °C caused an increase in actual ET of 6% in the White Volta basin where this study is located. Similarly, [Bossia *et al.* \(2014\)](#), in the Ouéme river Basin of Benin, found a significant decrease in water yield up to 20% during the simulated period (2000–2029) for IPCC SRES A1B and B1 scenarios, although it has been shown that the implementation of different models in the same watershed may lead to different outcomes (e.g. [Parajuli *et al.* 2009](#)). And these differences in model results may be attributed to many factors including but not limited to the physics and structure of the models. Model calibration and validation is therefore always necessary to ensure that there are limited discrepancies in the results when different hydrological models are applied in the same watershed. Beside the SWAT model, the performance of different hydrological models has been compared ([Parajuli *et al.* 2009](#); [Badou 2016](#)). For example, [Badou \(2016\)](#) evaluated the performance of four different hydrological models (HBV-light, UHP-HRU, SWAT and WaSiM) in the Niger River basin in West Africa and found that none of the hydrological models clearly outperformed the others in the simulation of streamflow in all the basins. This suggests that there may not be too much difference in the results obtained with the use of SWAT for the Veia catchment when a different model is used for the same watershed, provided the model is well calibrated.

The Veia catchment is classified as a semi-arid area with high temperature and evaporative demand. Hence, the available rainfall does not fully satisfy the atmospheric demand. The slight increase in rainfall was accompanied by an increase in actual ET due to an increase in mean annual temperature which further raised the atmospheric water demand. The increase in ET in the future 2020–2049 can be attributed to the decrease in surface runoff and water yield at the catchment. Thus, an increase in the actual ET can result in a decrease in the runoff efficiency as more of the precipitation is used for ET ([Rasmussen *et al.* 2014](#)). The highest ET recorded in August can be attributed to the highest rainfall that month, and more transpiration by crops as a result of vegetation growth and development, while the lower ET recorded in November (end of the rainy season) is due to the end of the growing season of crops. In the catchment, the calculated ET–rainfall ratio of 74.3% is an indication that water loss in this area is dominated by ET processes. In fact, there are many other factors which may also impact on any river hydrology system besides climate change. For example, industrial construction, human activities, and land-use/-cover change are some of the drivers which are known to affect the local water balance components ([Holländer *et al.* 2014](#)). A study conducted by [Yira *et al.* \(2016\)](#) found that a decrease in ET (–5%) was due to land-use change in the catchment. In a similar study, [Wagner *et al.* \(2009\)](#) also found that the conversion of forest and savanna to cropland causes changes in surface soil layer and vegetation canopy which affects river hydrology.

Several sources of uncertainty could affect the results of this study. Some of these include: uncertainty associated with the climate modelling, hydrological modelling, and input data quality. In order to minimize some of these uncertainties associated (e.g. climate modelling uncertainty), an ensemble mean of different RCMs was applied in this study. This multi-climate modelling approach has also been employed by other studies such as [Koubodana *et al.*, \(2020\)](#) and [Cornelissen *et al.* \(2013\)](#), in order to reduce uncertainties in modelling. Other limitations include the use of a single hydrological model. The ensemble of hydrological models is more robust and usually compensates for the effects of model uncertainties, because the mean result is a more reliable estimation of future hydrology characteristics ([Nicolle *et al.* 2014](#)). All these limitations need to be considered in further studies in order to minimize uncertainties for the formulation of better policy strategies measured at the local scale. As a possible way forward, an uncertainty analysis with a focus on the overall predictive uncertainty (i.e. lumping

all the sources of uncertainty) is necessary. This is because analysis of these predictive uncertainties helps in capturing the overall range of expected uncertainty propagated through the modelling (Badou *et al.* 2018). Furthermore, it is important to understand the long-term persistence behaviour of hydrometeorological series, otherwise known as the Hurst–Kolmogorov Dynamics (HKD) (Dimitriadis *et al.* 2021). The importance of this behaviour in the hydrometeorological process is that it increases the statistical bias from all the estimation metrics from time series that are being affected by the autocorrelation structure such as marginal moments (mean, variance etc.) and trends (Dimitriadis & Koutsoyiannis 2018). However, the effect of the HKD was not examined in this study. Trend analysis from the output from this study should use the modified Mann–Kendal method (Adeyeri *et al.* 2017; Tyralis *et al.* 2018) that does not assume Gaussianity but also takes the long-term persistence into account.

CONCLUSION

This study evaluated the capability of multi-scale RCMs and SDSM-DC simulation in reproducing the climatology of the Vea catchment. The ensemble mean of climate model simulation and an already calibrated SWAT model were used to assess climate change impact on ET, surface runoff, and water yield for the period 2020–2049. The study revealed that due to high variability of rainfall over the Vea catchment, climate models with high spatial resolution such as WRF models for rainfall and SDSM-DC simulations for temperatures are recommended for impact studies over the study region. The results from the ensemble mean indicate that the catchment may become warmer especially in the dry season. The situation becomes critical due to the projected increase in the mean annual temperature by 1.3 °C under the RCP4.5 scenario, indicating a trend towards a drier climate despite a positive rainfall scenario. The results of the SWAT model indicate that climate change would affect the hydrology of the Vea catchment even under a moderate greenhouse gas emission scenario (RCP4.5). The increase in temperature translated into a decrease in the mean annual water yield and surface runoff of 38.7 and 42.8%, respectively, which is an indication of the vulnerability of the future water availability of the catchment to climate change. Based on the findings from this study, it is recommended that appropriate adaptation strategies such as rainwater harvesting, weather and climate information services, and the development of early warning systems can be adopted by water managers and policymakers to reduce the future impact of climate change at the Vea catchment. The results also highlight the need to strengthen the Vea irrigation project within the catchment and to enhance water production for future use due to the projected decrease in rainfall over the Vea dam station.

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DECLARATIONS OF INTEREST

None declared.

DATA AVAILABILITY STATEMENT

Data cannot be made publicly available; readers should contact the corresponding author for details.

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