The impact of climate and land-use changes on the hydrological processes of Owabi catchment from SWAT analysis

Article *in* Journal of Hydrology: Regional Studies · September 2019

DOI: 10.1016/j.ejrh.2019.100620

6 authors, including:

Marian Osei
Kwame Nkrumah University Of Science and Technology
6 PUBLICATIONS 6 CITATIONS
SEE PROFILE

Leonard Amekudzi
Kwame Nkrumah University Of Science and Technology
78 PUBLICATIONS 402 CITATIONS
SEE PROFILE

David Dotse Wemegah
Kwame Nkrumah University Of Science and Technology
17 PUBLICATIONS 48 CITATIONS
SEE PROFILE

Kwasi Preko
Kwame Nkrumah University Of Science and Technology
26 PUBLICATIONS 173 CITATIONS
SEE PROFILE

Journal of Hydrology: Regional Studies 25 (2019) 100620

Contents lists available at ScienceDirect

Journal of Hydrology: Regional Studies

journal homepage: www.elsevier.com/locate/ejrh

The impact of climate and land-use changes on the hydrological processes of Owabi catchment from SWAT analysis

Marian Amoakowaah Osei*, Leonard Kofitse Amekudzi, David Dotse Wemegah, Kwasi Preko, Emmanuella Serwaa Gyawu, Kwasi Obiri-Danso

Kwame Nkrumah University of Science and Technology, PMB, Physics Department, Kumasi, Ghana

ARTICLE INFO

Keywords:
Hydro-climate
Stream-flow
Water resource management
Climate change
SWAT model

ABSTRACT

Study region: The 69 km^2 Owabi catchment in Ghana.
Study focus: The Soil-Water-Assessment-Tool (SWAT) was used to assess the hydro-climatic variability resulting from anthropogenic activities from 1986 to 2015. Specifically, the model simulated historic and projected stream-flow and water balance. Future stream-flow projections were modelled for three climate ensembles under three different representative concentration pathways (RCPs) for two land-use categories.
New hydrological insights for the region: Initial results revealed that forest and topography played major role in water loss, whereas evapotranspiration and surface runoff were the dominant modulating processes. Monthly calibration/validation of the model yielded acceptable results with NSE, R^2, PBIAS and RSR values of 0.66/0.67, 0.67/0.67, 8.2%/8.0% and 0.59/0.58 respectively. Uncertainty was fairly low and the model enveloped about 50% of the observed stream-flow. The RCP projections for all land use categories showed decreasing rainfall and streamflow trends. The model proved efficient in determining the catchment hydrology parameters and has potential to be used for further modelling of water quality and pollution to aid in effective water management.

1. Introduction

Rainfall plays a significant role in the hydrology cycle and is an essential resource for global socio-economic activities. Major stakeholders depend on various aspects of the cycle on different time scales. For instance, rain-fed agriculture which is dominant in Africa has been found to operate well if soil moisture is replenished at least every 15 days (Lofgren and Gronewold, 2014). Stream-flow which is also important for flood control, hydro-power, navigation and ecological factors has its high and low extremes being controlled by rainfall and groundwater base-flow respectively (Lofgren and Gronewold, 2014).

Water planners and managers rely on assumptions that past and future climatic trends will be the same and hence, water supply systems such as dams are built with these assumptions in mind (Mukheibir, 2007). However, current climate change and variability is offsetting precipitation globally, posing a dire threat to Water Resource Management (WRM). According to studies by Kankam-Yeboah et al. (2012) [and see references therein], without climate change considerations, Ghana is likely to be water deficient by 2025. This situation is projected to exacerbate with increased anthropogenic activities, which will negatively impact future water resources by restricting their use to meet growing demand (Kankam-Yeboah et al., 2012). The most anticipated anthropogenic

* Corresponding author.
E-mail address: marianosans92@gmail.com (M.A. Osei).

https://doi.org/10.1016/j.ejrh.2019.100620
Received 24 December 2018; Received in revised form 25 June 2019; Accepted 24 July 2019

activity which will affect water availability is land use and land cover changes. Studies in Ghana have shown that land degradation arising from improper agricultural practices and illegal mining have a high negative impact factor on river systems (Ayivor and Gordon, 2012). Urbanisation has also posed serious threat on agricultural land and water bodies resulting in 38% and 3% decline between 1985 and 2010 in Accra (Yeboah et al., 2017). Adjei et al. (2014) observed that changes in land use from 1986 to 2008 has gradually reduced the area of water coverage at the Lake Bosomtwe Basin at a pace of 0.03% per annum. This lake is amongst the few youngest and best preserved meteorite craters found globally (Adjei et al., 2014) [and references therein].

WRM problems are best tackled through the Integrated Water Resource Management (IWRM) approach by providing a stronger coordination between stakeholders in planning and managing of water resources in river basins (Zhang et al., 2014). Ghana's implementation of IWRM at the river basin level begun with the most 'water stressed' basins in the country (Water Resource Commission, 2012a). One of such basins is the Pra of which the Owabi catchment serves as a sub-tributary; a dam on this catchment provides 20% of total potable water to the Kumasi metropolis and its environs. However, increasing human activities including deforestation, sand-winning, illegal logging, indiscriminate dumping of waste has reduced the quality and quantity of water production at the dam. Consequently, this has imposed severe threat on water resource and ecosystem management. Various studies have been undertaken to quantify this damage on the Owabi catchment. For instance, Forkuo and Frimpong (2012) mapped the Owabi catchment using GIS and observed a 38.9% decrease in forest cover from 1986 to 2007 which is attributable to increase in human activities and population explosion within the catchment area. Agyen-Brefo (2012) explored the effects of encroachment on sustainable public land management at Owabi and found a resulting negative effect on land use planning and building regulations, high cost of water production and reduction of government revenue. In addition, water quality at the catchment using factor analysis has shown a degradation of the catchment water when compared to World Health Organisation standards for safe drinking water (Akoto and Abankwa, 2014). Although these studies are extremely useful for water management, their impacts on the hydrology is yet to be assessed. Hence the present study performed a hydro-climatic modelling to observe the impact of the landuse changes on the catchment. A well-documented and tested hydrological model which has been widely used for these assessments is the Soil-Water-Assessment-Tool (SWAT) (Arnold et al., 2012a,b; Shope et al., 2014).

The SWAT model incorporates a geographical information system (GIS) interface to give meaningful insights into the water balance, sediments and pollutant transfer in a drainage network (Uzeika et al., 2011). The SWAT model is prominent for its continuous long-term simulations of hydro-climatic variables (Sudjarit et al., 2015) as well as satisfying its developmental aim of testing and predicting water and sediment routing in ungauged basins (Gayathri et al., 2015). It is capable of evaluating the effects of best management practices on water resources in both large and small river basins (see Uzeika et al., 2011; Srinivasan et al., 2010; Shope et al., 2014; Me et al., 2015) and has returned favourable performance rate when calibrated.

For instance, Abraham et al. (2007) calibrated and validated the SWAT model for an Ethiopian catchment and found slight under- and over-estimation of peak flows for some years. Nonetheless, the overall performance of the model was good for catchment simulations. Govender and Everson (2005) used the manual calibration technique to model stream-flow for two catchments in South Africa where the increasing demand for timber has drastically changed land use/cover and hydrological processes. Although there was a good response between simulated and observed stream-flows, the model was unable to account for evapotranspiration losses. Schuol and Abbaspour (2006) deduced that the model has a huge potential for freshwater quantification after application to the Niger, Volta and Senegal river basins in West Africa. A study by Begou et al. (2016) on the Bani catchment revealed that calibration at the subbasin scale resulted in better performance than using global parameter set. The SWAT model has also been a promising tool in studying the effects of landuse and landcover evolution on hydrology. Ongoing studies such as Guzha et al. (2018) in East Africa and Demeke and Andualem (2018) and Welde and Gebremariam (2017) in Ethiopia observed increases in streamflow, surface runoff and peak flows when forest land is degraded. Puno et al. (2019) also observed that urbanisation has resulted in increases in evapotranspiration, baseflow and surface runoff. Meanwhile an increase in forest cover showed minimal decrease in surface runoff and baseflow. Some other studies include; Ghaffari et al. (2010), Pokhrel (2018), Nie et al. (2011) and Li et al. (2019).

Over Ghana, only a handful of studies have been undertaken using the SWAT model. Kankam-Yeboah et al. (2013) investigated the impact of climate change on stream-flow in two selected river basins (White Volta and Pra) in Ghana. After model calibration, their results revealed a decline between 22% and 50% of stream-flow in both the White Volta and Pra basins for the periods of 2006–2035 and 2036–2075. Sood et al. (2013) found a decrease of about 40% in river flows resulting from decreases in rainfall and increases in temperature. Bair (2014) applied the SWAT model in a cocoa growing region within the Pra basin to aid in future studies of land management practices. The results showed that the SWAT model was not yet accurate enough to be used in predicting changes in land management practices based on a negative Nash Sutcliffe Efficiency score of -0.43. The model was also found to be a promising tool when used as part of an integrated decision support system to monitor the effects of small-scale irrigation methods on agriculture and socio-economic activities (Worqlul et al., 2018). Based on SWAT model simulations, Akpoti et al. (2015) found that wet and dry season discharges have increased by 1% and 6% due to changes in landuse and land cover between 2000 and 2013 at the Black Volta river basin. At the White Volta Basin, Awotwi and Kumi (2015) observed changes in the water balance with a decrease in land cover correlating with decline in surface water and baseflow and increase in evapotranspiration rates.

The aim of this study is to model the impact of climate and land-use changes on the hydrological processes of Owabi catchment using SWAT. Specifically, the SWAT model was used to simulate stream-flow and establish the water balance and project stream-flow amounts under different climatic and land-use scenarios for the catchment. The study is the first of its kind to be performed on a smaller ungauged catchment in Ghana. The remaining part of the paper is structured as follows; the study site is described in Section 2, the methodology is given in Section 3, results and discussions in Section 4 and finally the conclusions in Section 5.

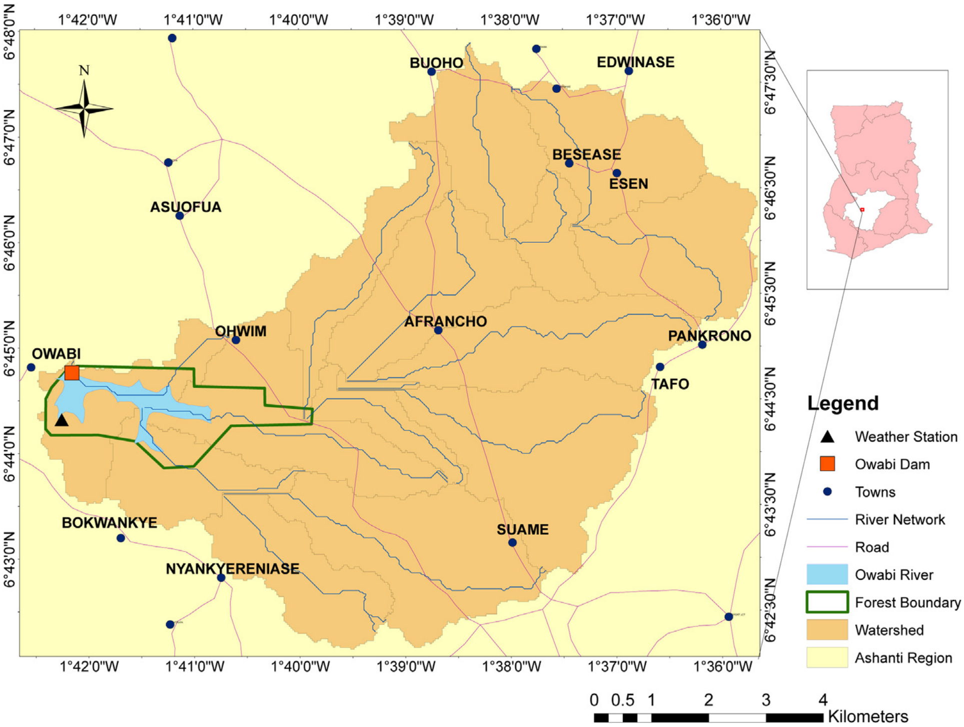

Fig. 1. The Owabi catchment comprising of the Owabi Dam and the Forest Reserve.

2. Study site description

The Owabi catchment (Fig. 1) has been designated since 1988 as the only inland Ramsar site in Ghana. It comprises of the forest reserve (sanctuary) and the Owabi waterworks and covers about 69 km^2 (Akoto and Abankwa, 2014) of land area. Its location is between latitudes 6.7292° N and 6.7519° N and longitudes 1.7139° W and 1.6704° W. Within the catchment is a 13 km^2 forest reserve enclosing a water reservoir (Forestry Commission, 2014).This forest reserve is one of the smallest conservation sites in Ghana and its protection responsibility lies solely with the Department of Game and Wildlife (Forkuo and Frimpong, 2012). Nonetheless, protection of the site has not deterred high human encroachment and other illegal activities. The hydrological unit is situated in the inner perimeter of the sanctuary (Fig. 1). The river was dammed in 1928 with the primary aim of supplying 20% of potable drinking water to the Kumasi metropolis.

The catchment rests in the forest belt of Ghana where rainfall is strongly modulated by the West African Monsoon (WAM) and convective activities resulting from movements of the Inter-tropical Discontinuity (ITD). The WAM is primarily driven by temperature and energy gradients between the Gulf of Guinea and the Sahara (Amekudzi et al., 2015). Movement of the ITD results in bimodal rainfall regimes in this region with the presence of the river and dense vegetation inducing a micro-climate which influences the rainfall patterns, temperature and humidity in the catchment. The mean rainfall is about 1450 mm per annum (Aryee et al., 2018) and average monthly temperatures between 24.6 and 27.8 °C. Geologically, the area falls within the Birimian meta-sediment of the Kumasi Basin which consists of phyllites, granodiorites, schists, greywackes, tuffs and the associated granitoid (Forkuo and Frimpong, 2012; Forestry Commission, 2014) and Orthic Acrisols as the dominant soil type.

3. Methodology

3.1. SWAT model description

SWAT is a river-basin scale semi-distributed and physically based model that operates on a daily timescale but also capable of simulating outputs on monthly and annual timescales. It was initially developed by the United States Department of Agriculture to model land management practices on sediment, water and agro-chemical yields in ungauged catchments. The model is highly rated for its computational efficiency and long term continuous simulations. The important inputs of the model include; rainfall and temperature, digital elevation model, soil and land use maps as well as output simulations of water balance, nutrient and sediment loadings (Arnold et al., 2012b).

The computational hydrology framework of the model is based on the land and water/routing sections of the hydrological cycle. The land division regulates the amount of water, nutrient, sediment and pest loadings into the main channel in every subbasin. The latter division defines the path of water and sediments through the basin channels to the outlet (Sudjarit et al., 2015). The initial step

Table 1
SWAT input database.

Data type	Description	Available sources	Spatial resolution
Digital elevation model (2000-02-01:2000-02-29)	SRTM 1-Arc-Second Global v3	www.earthexplorer.usgs.gov	30 m × 30 m
Land-use raster (annual 1992–2015)	ESA CCI LC v1.6.1	UCLouvain (2017)	300 m × 300 m
Soil map raster (2007-02-28)	Digital global soil map FAOv3.6	WaterBase (2016)	1:5,000,000 m
Historic meteorological data (1980–2015)	Daily rainfall and temperature	Ghana Meteorological Agency	Station point data
Climate projection data (2020–2050)	Daily rainfall and temperature	CCCMA (2016)	0.22° × 0.22°
Hydrological data (2001–2010)	Monthly stream-flow (unit in cumecs (cms))	Ghana Hydrological Service Department (Offinso gauging station on the Offin River)	Station point data

for catchment simulation is the catchment delineation where subbasins and hydrological response units (HRUs) are defined (Arnold et al., 2012a).

SWAT utilises Eq. (1) to simulate the hydrological cycle (Ghoraba, 2015). The hydrological cycle is climate dependent and supplies energy and moisture inputs such as daily rainfall, maximum and minimum air temperatures, wind speed, relative humidity and solar radiation. The data can be read directly from files by SWAT to produce simulated data at runtime.

$$\mathrm{SW}_t = \mathrm{SW}_o + \sum_{i=1}^{t} (R_{\mathrm{day}} - Q_{\mathrm{surf}} - E_a - w_{\mathrm{seep}} - Q_{\mathrm{gw}})_i \tag{1}$$

where t is time (days), SW_o and SW_t are the initial and final soil water content, R_{day}, Q_{surf}, E_a, w_{seep} and Q_{gw} are the quantities of rainfall, surface runoff, total evapotranspiration, amount of water entering the vadose zone from the soil profile and return flow respectively. All parameters have units in mm and i represents the parameter value for a day.

3.2. Data sources

3.2.1. GIS interface and spatial dataset

The open source QGIS version 2.6.1 and QSWAT version 1.4 (SWAT v2012), downloaded from http://swat.tamu.edu/software/, were employed for the study. Spatial input dataset were obtained from open source websites shown in Table 1. The catchment elevation (Fig. 2) was within 220 m and 394 m with mean of 265 m above mean sea level. All these data excluding hydro-meteorological parameters were in a raster format and geo-processed for model input as described in Dile et al. (2016).

After model run, a total area of 69 km^2 basin boundary was delineated, with 16 subbasins and 80 HRUs. Six dominant land-use categories and one soil type were observed within the Owabi catchment as shown in Fig. 2. The observed soil (Orthic Acrisols) are deeply weathered and consist of thin, dark greyish brown, humus-stained, sandy loam and silt loam topsoils with moderate fine granular structure (Adjei-Gyapong and Asiamah, 2002). It also has a high water holding capacity at the first horizon (top or surface soil)(FAO, 1977; WRB, 2014). However the density of the second horizon is high which limits internal drainage by obstructing the infiltration of water into much deeper layers (FAO, 1977; WRB, 2014).

3.2.2. Hydro-meteorological input

Daily rainfall and temperature (minimum and maximum) were obtained from Ghana Meteorological Agency (GMet) from 1980 to 2015 (Table 1). Missing rainfall and temperature gaps were filled using the arithmetic averaging method from the closest meteorological stations. These stations (see Fig. 3) included, Barekese 6.8481° N, 1.7198° W, Offinso 7.3049° N, 1.7928° W and Kumasi Airport 6.7125° N, 1.5911° W. Based on the climatic data available, the Hargreaves method was used for the estimation of evapotranspiration rates on the catchment.

The lack of stream-flow data was a major limitation of this paper for model calibration and validation. This limitation can be offset through the application of regionalisation or artificial neural networks for stream-flow determination (Hrachowitz et al., 2013). The regionalisation scheme uses multiple donor catchments to extract detailed information to increase the predictive performance of the hydrological model at the ungauged basin (Arsenault and Brissette, 2016). Stream-flow records were transferred from the Offinso gauging station whose main channel (the Offin River) drains into the Barekese Catchment. This station is the closest and located about 30 km away from the Owabi catchment. Similar attributes of the Barekese catchment with the Owabi catchment are a mean elevation of 277 m, Orthic Acrisol as soil type, semi-deciduous forests, Voltain, Birimian and Granite geology, bi-modal rainfall regime and rapid urbanisation in the last decade (Ghana Statistical Service, 2014). Annual rainfall at is about 1400 mm Domfeh et al. (2015) while based on studies such as Forkuo and Frimpong (2012) and Aryee et al. (2018), the annual mean rainfall for Owabi ranges between 1450 and 1488 mm. This imply a rainfall difference of about 50–90 mm at the two catchments. Based on their similarity index, the physical similarity regionalisation method as used in Oudin et al. (2008); Swain and Patra (2017); Arsenault and Brissette (2016) and references therein was used. The raw stream-flow data at Offinso is transferred to the Owabi catchment and used for model analysis. Prior to this, a drainage area ratio was implemented to downscale the discharge data to catchment size of Owabi. However, this method failed with extremely low and unrealistic discharge estimates for Owabi. Thorough review of the

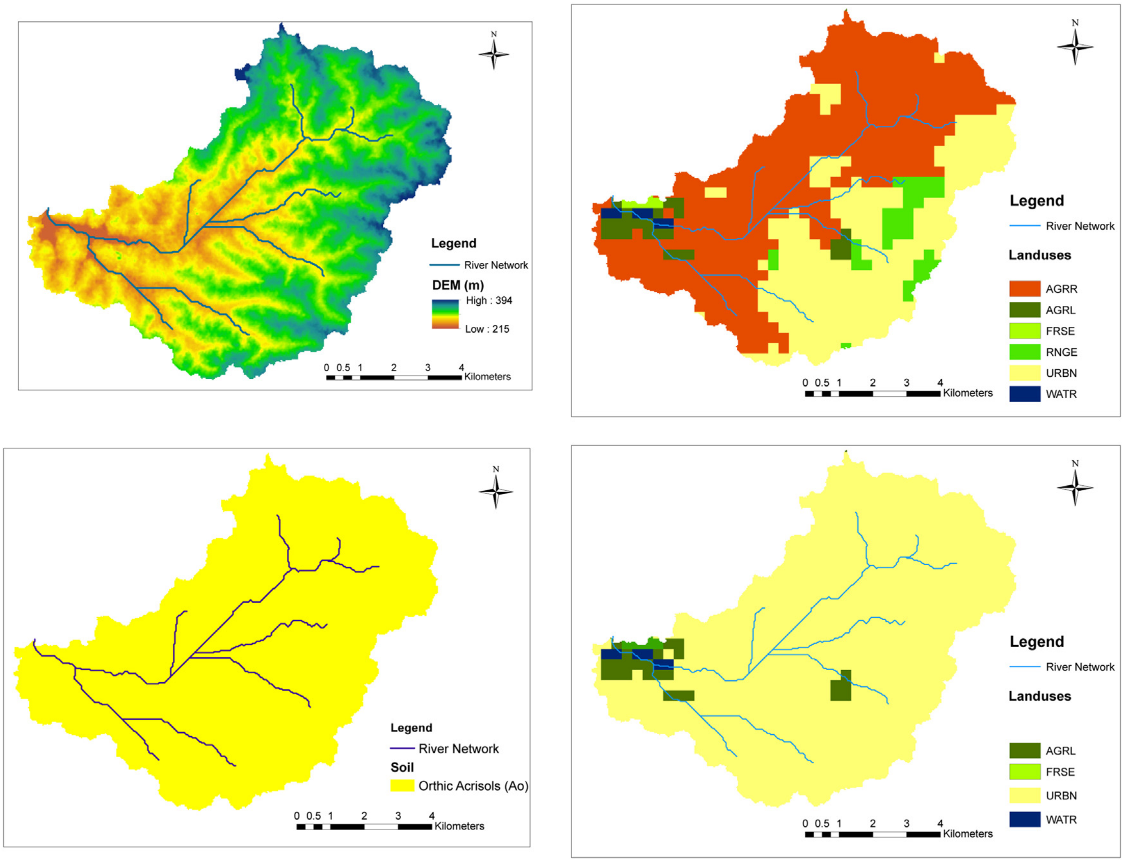

Fig. 2. DEM, land use category 1 [LU1], soil type and land use category 2 [LU2] (bottom right) for the catchment.

regionalisation methods can be found in Hrachowitz et al. (2013). The stream-flow data time-series was monthly and spanned the period of 2001–2010 as seen in Table 1.

3.2.3. Projection dataset (land-use)

A 30-year (2021–2050) stream-flow for the Owabi catchment was predicted under two land-uses and three climate change scenarios. For the landuse, AGRL comprises of a mosaic greater than 50% natural vegetation of trees, shrubs and herbaceous cover with cropland covering less than 50% while AGRR is rainfed cropland (UCL-Geomatics, 2017). The AGRL footprint at the Owabi catchment is observed as part of the 13 km^2 forest reserve (FRSE) which is under strict protection of the Ghana Forestry Commission. Forest guards are known to patrol the forest at least twice a day, with severe penalties awarded on any defaulters. The cropland component of AGRL are usually subsistence farming undertaken by residents who reside close to the forest boundaries and hence makes for the lower 50% in cropland. The total area of the landuse WATR is similar to the protected forest cover has remained intact over the years, probably due to the existence of the forest. Currently, these landuses (RNGE and AGRR) are under an ongoing severe threat of conversion to settlement due to rapid urbanisation and the proximity of the catchment area to the central business district of the Kumasi metropolis. Since forestry rules are unlikely to be relaxed for the benefits of residents, it is likely that current settlement areas can either remain the same, or grasslands (RNGE) and rain-fed croplands (AGRR) would be urbanised to support growing population. These assumptions formed the criteria for developing the two land-use scenarios. For land-use scenario 1 (LU1), an unchanging land-use category as observed in the baseline trend was considered. In land-use scenario 2 (LU2) (Fig. 2), the conversion of all land-uses except forest (FRSE), natural vegetation (AGRL) and water (WATR) categories into settlement/urbanisation areas was assumed.

3.2.4. Projection dataset (climatic)

Future daily rainfall and temperature (minimum and maximum) from the Fourth Generation Canadian Regional Climate Model (CanRCM4) were used as climate forcing for the SWAT model. These were projected under three Representative Concentration Pathways (RCP2.6, 4.5 and 8.5) and contained three different ensembles (r1i1p1, r2i1p1 and r3i1p1). The three ensembles differed only in their initial conditions (r1,r2,r3), but have the same initialisation methods (i1) and underlying perturbation physics (p1) (Taylor et al., 2010). The RCPs have been called according to the radiative forcing of greenhouse gases and other agents by the year of 2100 (Van Vuuren et al., 2011). The RCP2.6 suggests a low level forcing with emissions reaching a peak of 3.0 W/m^2, RCP4.5 is a

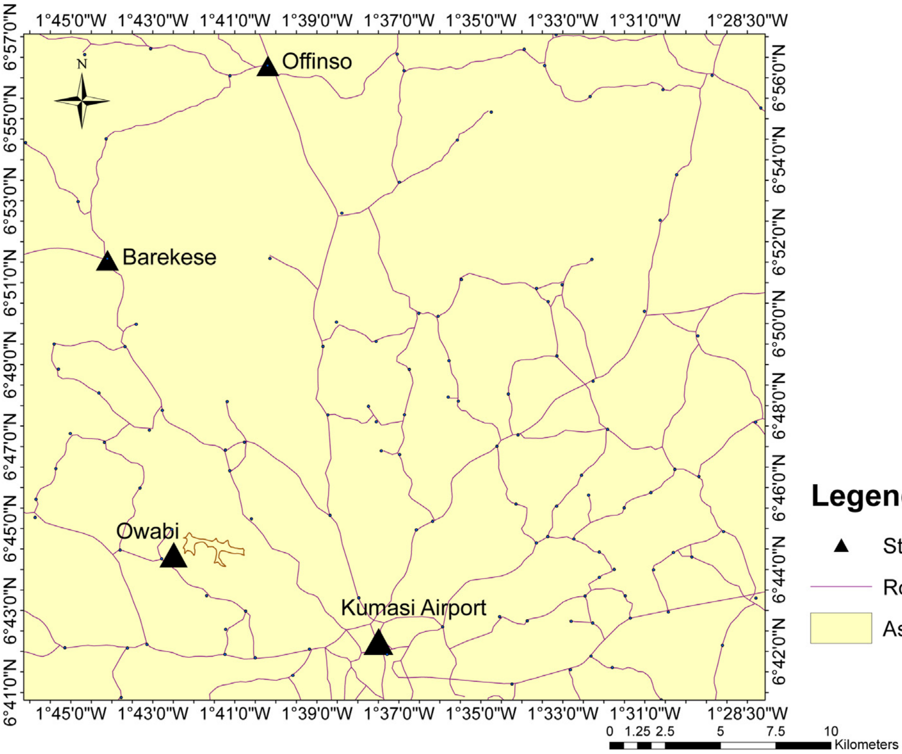

Fig. 3. Location of hydro-meteorological stations.

stable pathway which peaks at 4.5 W/m^2, whiles RCP8.5 is the worst scenario with rising radiative forcing of 8.5 W/m^2 (Van Vuuren et al., 2011).

The CmHyd software (Rathjens et al., 2016) was used for bias correction of the projection climate data and has about seven bias correction options available for precipitation and temperature. These comprised of; distribution mapping of precipitation and temperature, linear scaling, delta-change correction, precipitation local intensity scaling, power transformation of precipitation. All these options were used to correct for biases in the historic rainfall and temperature datasets which included the observed data and that of the RCM from 1980 to 2015. After correction, the best algorithm option was the distribution mapping and hence was chosen for the climate change analysis.

Due to the high variability of rainfall, the distribution mapping module assumes a Gamma distribution of the dataset with shape and scale parameters α and β respectively. The distribution profile is controlled by α, and for $\alpha < 1$, the distribution is exponentially shaped, $\alpha = 1$ gives a special exponential distribution case, whiles $\alpha > 1$ gives a skewed uni-modal distribution (Teutschbein and Seibert, 2012). Alternatively, β determines the dispersion of the Gamma distribution with smaller (larger) values leading to a compressed (stretched) distribution with lower (higher) probabilities of extreme events (Teutschbein and Seibert, 2012). For the temperature data, the module assumes a Gaussian distribution due to less variations especially in the tropics with location and scale parameters μ and σ. The location of the distribution is controlled by μ whiles σ determines the standard deviation with smaller (larger) indicating lower (higher) probabilities of extreme events (for further review, see Teutschbein and Seibert, 2012).

The bias corrected rainfall and temperature for the historical climate model spanning overlapping years of 1979–2005 revealed a satisfactory correlation with the measured datasets under all RCP ensembles. For instance, for the RCP2.6 ensemble r1i1p1, the observed historical rainfall was found to be exponentially skewed ($\alpha = 0.96$) whiles the bias corrected model historic was uni-modally skewed ($\alpha = 4.09$), with higher tendencies of extreme events especially in the wet seasons [$\beta = 9.89$ (observed historic) and $\beta = 2.62$ (model historic)]. Standard deviations for minimum and maximum temperatures were also quite low for extremities (observed historic: 1.40, 2.59 and corrected model historic: 1.58, 2.34).

3.3. Calibration, validation and uncertainty assessment

The auto-calibration tool, SWAT-CUP with the Sequential Uncertainty Fitting version 2 (SUFI-2) algorithm (Abbaspour, 2015) was used for calibration techniques. SUFI-2 is known to estimate both parameter and model uncertainties in hydrological models (Abbaspour, 2015). Table 2 shows the objective functions used in assessing the overall model performance as well as their required satisfactory thresholds as described in Moriasi et al. (2007) and Abbaspour (2015). The Global sensitivity test for sensitivity analysis was evaluated using the t-stat and the p-value whiles p and r factors were used for uncertainty analysis at a 95% prediction uncertainty (95PPU). The p-factor is the percentage of the measured data that is captured by the 95PPU and an ideal value of 1 indicates

Table 2
Statistical indices and their optimal thresholds for stream-flow according to Moriasi et al. (2007) and Abbaspour (2015).

Objective function	Threshold (for stream-flow)
p-factor	≥ 0.70
r-factor	Closer to 0
t-stat	Larger absolute value
p-value	≤ 0.05
NSE	≥ 0.50
R^2	≥ 0.50
PBIAS	± 25%
RSR	≤ 0.70

that all correct processes have been accurately captured by the model (Arnold et al., 2012b). However, for stream-flow, a p-factor > 0.70 is the better choice of model fit, although it is also acceptable for the model to cover more than half of the observed data (Abbaspour, 2015). The r-factor shows the calibration quality and an ideal value of 0 implies a direct fit of the simulated stream-flow with the observed (Arnold et al., 2012b). Other model performance indices used included, Nash-Sutcliffe Efficiency (NSE), Percentage Bias (PBIAS) and RMSE Standard Deviation Ratio (RSR) (Arnold et al., 2012b).

4. Results and discussions

4.1. Sensitivity analysis

For calibration analysis, 14 parameters (Arnold et al., 2012b) (see Table 3) that affect surface runoff and baseflow have been selected from literature. The selected parameters were also chosen to reflect as much as possible all hydrological processes that might be occurring within the Owabi catchment. The results of the global sensitivity analysis showed that three (3) of these parameters regulated the outlet stream-flow in the basin. These included surface (CN2, SURLAG) and groundwater (ALPHA_BF) processes. The curve number for average soil moisture (CN2) was the most sensitive among these three with other catchment studies reporting likewise [see Arnold et al. (2012b) and references therein].

4.2. Performance of SWAT (calibration/validation) using the physical similarity method

The performance of the physical similarity method was based on the statistical indices obtained during the model calibration and validation and this was hypothesised to have a direct relationship. Such that, a satisfactory model performance corresponded with a satisfactory performance of the physical similarity approach. The SWAT model was run for 36 years, with the first 6 years used as model initialisation (warm-up). The model was calibrated from 2001 to 2006 (6 years) and validated from 2007 to 2010 (4 years). The results of the calibrated and validated model is shown in Fig. 4.

For calibration/validation, there was consistency in the model's simulation of the seasonal stream-flow dynamics and concurrently followed the rainfall pattern. The SWAT model performance was satisfactory as evident in the NSE (0.66) and R^2 (0.67) considering that the observed data was obtained from a catchment which is about 12 times the size of the study area. The performance was enhanced especially during the dry seasons with occasionally slight overestimations in some few cases. The only sensitive groundwater parameter is the baseflow which serves as a secondary contributor of stream-flow in the form of lateral flow during the dry season to support water production by the Owabi water processing plant. It was also observed that for rainy months (see Fig. 4) in

Table 3
Parametric table (Arnold et al., 2012a).

Parameter	Full meaning
ESCO.hru	Soil evaporation compensation factor
SOL_AWC.sol	Available water capacity of the layer of soil
CH_N2.rte	Mannings ‘n’ coefficient
SURLAG.bsn	Surface runoff lag coefficient
GW_DELAY.gw	Groundwater delay-time
GWQMN.gw	Groundwater minimum threshold
OV_N.hru	Mannings ‘n’ value for overland flow
GW_REVAP.gw	Groundwater revap coefficient
RCHRG_DP.gw	Deep aquifer percolation fraction
SOL_BD.sol	Moist bulk density
CH_K2.rte	Effective hydraulic conductivity in the main alluvium channel
CN2.mgt	Curve number
SOL_K.sol	Saturated hydraulic conductivity
ALPHA_BF.gw	Baseflow alpha factor

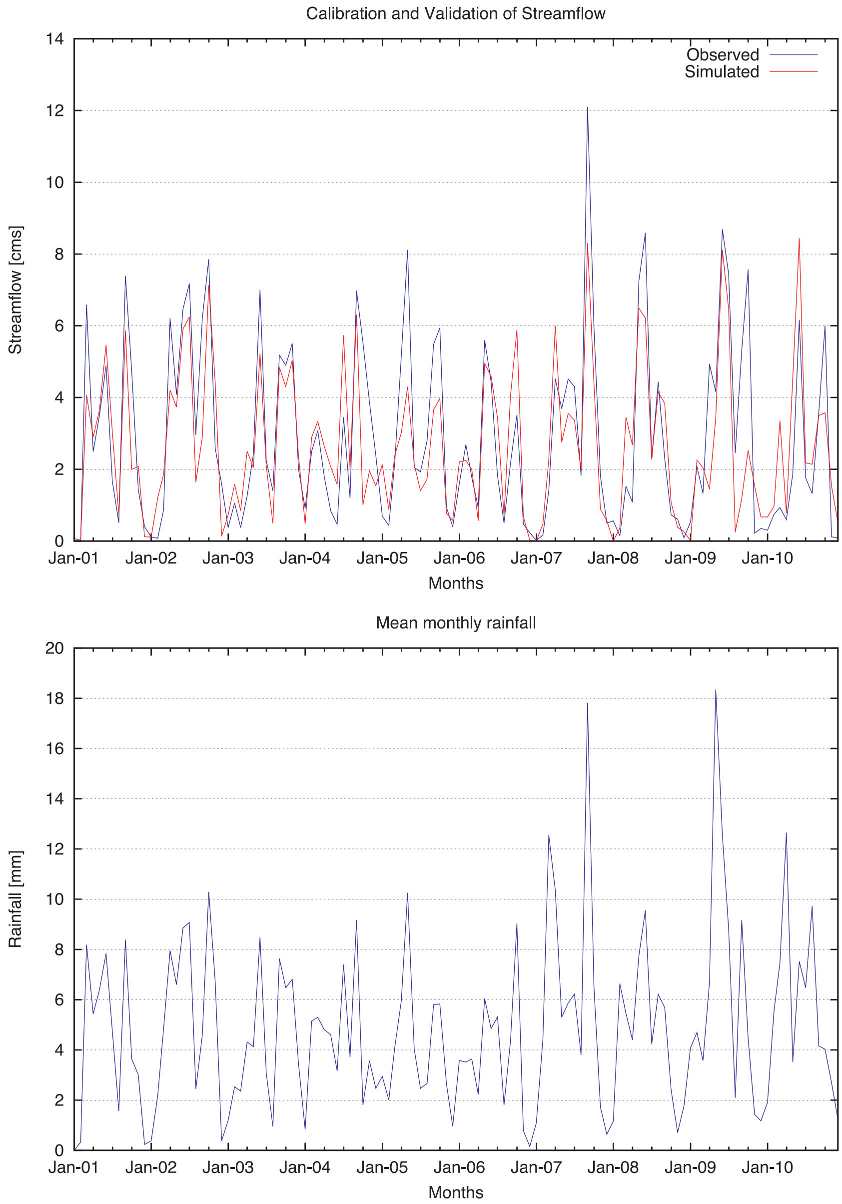

Fig. 4. Mean monthly simulated stream-flow (top) and observed rainfall (bottom) for calibration (2001–2006) and the validation period (2007–2010).

which the mean monthly rainfall amounts were lower (hence low stream-flow amounts), the model treated such periods as dry and always over-estimated the stream-flow amounts. This is observable in March to July 2004 and September to October 2006, where stream-flow observed for the rainy period were lower than other calibration years. The low rains experienced in the former months resulted in short intense rainfall in September to December 2004, which was poorly captured by the model. Overall, the prediction error for stream-flow calibration was within an acceptable range as reflected in the PBIAS (8.2%) and RSR (0.59).

The monthly validation (Fig. 4) also showed a good output between the simulated and the observed stream-flow datasets. The overall model performance conforms with a hydrological review undertaken by Gassman et al. (2007). The highest observed stream-flow peak during calibration was obtained in May 2005 (8.12 cms), however this was poorly simulated by the model (4.30 cms). Alternatively the highest best simulated peak stream-flow by the model was in October 2002 (7.12 cms). Likewise, for validation, the peak was seen in September 2007 for observed (12.11 cms) and June 2010 for simulated (8.44 cms). Table 4 shows a summary of the statistics obtained for model calibration and validation. Overall, the acceptable values obtained from the statistical metrics gives a first hand indication that the physical similarity method is an efficient means of generating stream-flow at the Owabi catchment.

Table 4
Model performance metrics.

Objective function	Calibration (2001–2006)	Validation (2007–2010)
p-factor	0.51	0.52
r-factor	0.55	0.45
NSE	0.66	0.67
R^2	0.67	0.67
PBIAS	8.2%	8.0%
RSR	0.59	0.58
Mean obs	2.90	2.90
Mean sim	2.66	2.66
Stddev obs	2.30	2.85
Stddev sim	1.83	2.27

4.3. Uncertainty analysis

The parameter uncertainty that results from non-uniqueness of effective model parameters, conceptual model and input uncertainties (Schuol and Abbaspour, 2006) were satisfactory as observed from 95PPU (Table 4). The model bracketed about 0.51/0.52 of the observed data at the expense of a quite low enveloping width of 0.55/0.45. The model uncertainties would be the inability to incorporate some important processes occurring within the catchment in the SWAT model setup. Most of these processes especially from human activities which are likely to go unnoticed are bound to occur upstream of the Owabi dam which is highly populated. However, although previous sand-winning activities on the catchment could affect the hydrology, its extent was not incorporated due to inadequate quantification data.

The inability of the model to capture the accepted 70% of observational data might be associated with uncertainties in the input dataset. Both rainfall, temperature and stream-flow data are influenced by systematic errors of measuring instruments. However, the spatial distribution of temperature is homogeneous within the tropics and specifically around the Owabi catchment and hence has minimal errors on model calibration. Rain gauges on the other hand, are known to have uncertainties with average systematic error magnitudes of about 5-6% and random error magnitude of about 5% (McMillan et al., 2012). It has been ascertained that the Owabi meteorological station has not been relocated since the beginning of the study period and therefore, any erroneous measurements may arise from faulty instruments or the inability of the rain gauges to measure intense short and long duration of storm events. Furthermore, the neighbouring station gauges used for gap in-filling are likely to propagate their individual errors also into the Owabi climatic dataset.

The stage-discharge measurement of stream-flow at the Offin River is also prone to errors during discharge computations in both instrumentation and quality control which results in potential outliers in dataset. Although the uncertainty is acceptable, the transfer of raw stream-flow data from the donor to receiver catchment could also force errors to be transferred directly into the calibration process, especially in inaccurate simulation of high peak flows.

4.4. Water balance

The most important components of the water balance of any hydrological basin are the rainfall, surface runoff, baseflow, lateral flow and evapotranspiration. However, unlike rainfall that is easily measured, the other variables need prediction for their quantification (Ghoraba, 2015). The best parameter values were used to rerun the calibrated model to obtain an estimate of the water balance for the catchment. The SWAT-Check tool (White et al., 2014) was also employed to obtain the percentage distribution of rainfall for the water balance components. The 30-year seasonal water balance is visualised in Fig. 5 which shows that the most dominant pathways for water loss on the catchment was observed to be actual evapotranspiration (AET) and surface runoff. Due to the quick response to rain and a hydrological soil group of type D within the entire basin, surface runoff (Hortonian) contributes to about 68% of total flow at the catchment with baseflow obtaining the remaining 32%. The total flow represents the total amount of water that is converted into stream-flow. Furthermore the evapotranspiration has the highest percentage of rain water loss at 55% while the stream-flow variance in rainfall was found to be 42%. Percolation and deep recharge had the least amounts of 16% and 1% respectively.

The 30-year potential evapotranspiration (PET) average as calculated from the Hargreaves method. The Owabi catchment is located within the equatorial region and hence much higher insolation and temperatures that favours the potential evapotranspiration (Sanderson et al., 2010).

The seasonal trend of PET (Fig. 5) observed higher tendencies before the onset of rains in March, but experiences reduction when penetrating into the major and minor wet seasons resulting from rigorous convective activities that occur due to the northward movement of the ITD in early March. During the wet season, PETs are constantly low from June to September with slight increases for the dry season. The former condition might arise from high humidity and thick monsoonal clouds that negatively affect PET rates by backscattering insolation to space. The dynamics of the PET can also be observed in Fig. 6 with respect to changing land-use. Prior to increasing settlement especially from 2001, PET is found to be higher than rainfall, which stems from the higher coverage of closed and open forest canopies at the catchment. Forkuo and Frimpong (2012) found that the forest cover at the Owabi catchment has

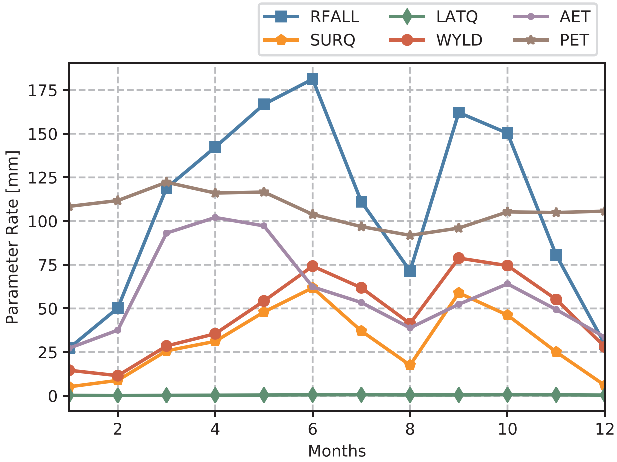

Fig. 5. A 30-year (1986–2015) mean monthly water balance (RFALL: rainfall, LATQ: lateral flow, AET: actual evapotranspiration, SURQ: surface runoff, WYLD: water yield, PET: potential evapotranspiration).

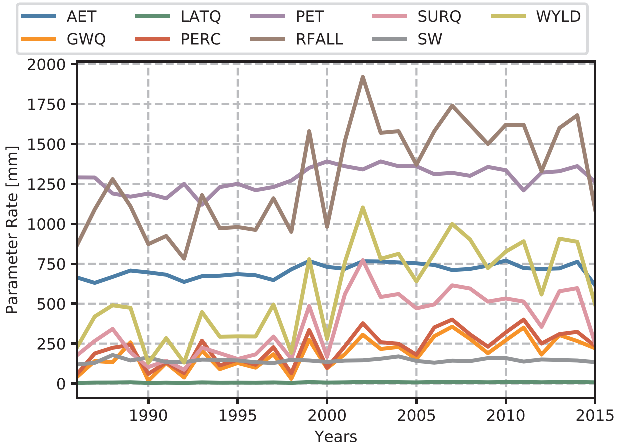

Fig. 6. Mean annual variability of water balance for the Owabi catchment (SURQ: surface runoff, SW: final soil moisture, AET: actual evapotranspiration, PET: potential evapotranspiration, LATQ: lateral flow, GWQ: groundwater flow, PERC: percolated flow).

witnessed a 38% decline since 1986 with closed and open forests decreasing and increasing at a rate of 3% and 5% respectively (Gyawu, 2017). The decreasing amount of forest cover imply a lower potential for evapo-transpiration rates.

The Owabi catchment falls under a wet climatic regime which is known to support higher evapotranspiration with the presence of dense forested vegetation (Sanderson et al., 2010; Kumagai et al., 2005; Bonal et al., 2016). These forests enhance evaporation by assisting in the aerodynamic transport of intercepted water into the atmosphere (Legesse et al., 2003). The AET rates (Fig. 5) were highest during the northern hemisphere summer monsoon especially July, also in response to convective activities. The contrary effect can be observed for the dry months, where high temperatures and quick evapotranspiration are likely to leave the surface soil depleted of moisture (Sharma, 1988). Any potential evaporation would occur from groundwater storage through the root-stem-leaf of trees and most plants especially grasslands and natural vegetation could reach their wilting point. Circumstances like these are likely to give rise to hydrological drought within the catchment. On the other hand, the roots of forested trees could reach more depths for soil water in order to maintain transpiration for the dry period and subsequently result in a higher net average annual evapotranspiration (Fig. 6). The eight month of August is termed the “little dry spell”; wind directions are still southwesterly, however, the ITD is displaced northward and this does not favour rains in the south of the country (Parker, 2017). The processes are observed to decline but with higher magnitude relative to the major dry season.

Water yield (SURQ + LATQ + GWQ − transmission loss − pond abstractions) is an essential component of the hydrological cycle and determines how much water leaves the outlet at a given time (Ghoraba, 2015). The rate of water yield was quite high on the catchment which favours the Owabi water treatment plant and other agricultural activities. Its seasonal fluctuation is controlled mainly by surface runoff and base-flow (Fig. 5). Subsurface contribution to the water yield is small with low lateral flow due to the high demand of evapotranspiration of the forested vegetation. For the annual variations (see Fig. 6), the parameters depicted trends as that of the rainfall, with the exception of lateral flow which remained fairly constant. The soil moisture exhibited less variability on the annual time-scale although the land is undergoing intensive land-use changes. However, the impact of increasing rainfall has

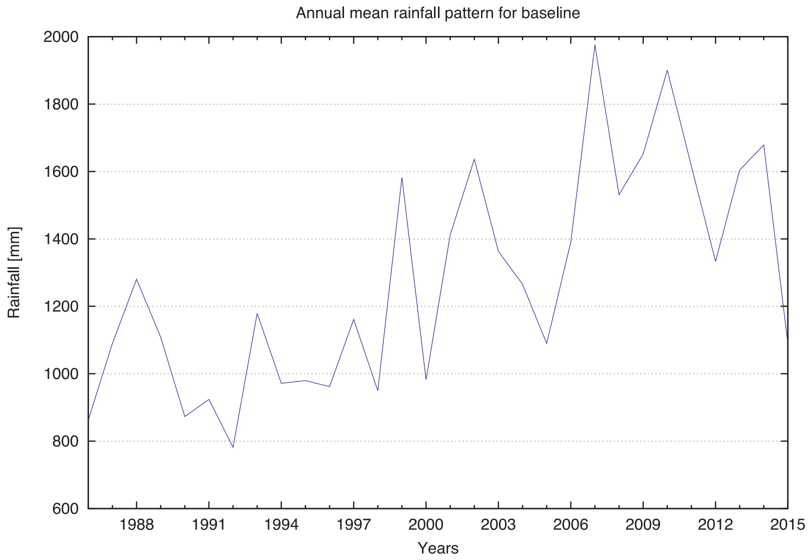

Fig. 7. Mean annual rainfall for baseline (1986–2015).

resulted in positive impacts on the percolation, groundwater, surface runoff and water yield. The positive feedback of the effects of the rains is more pronounced in the surface runoff. This is observable from 2001 to 2014, and can be implied as the breakpoint year in which anthropogenic invasion resulting from deforestation and destruction of natural vegetation covers to accommodate settlement from population explosion increased. On the other hand, if the natural vegetation cover still existed, this would have reduced the rate of surface runoff from increasing rains. The work of Forkuo and Frimpong (2012) and Gyawu (2017) showcases this drastic land cover evolution.

4.5. Hydro-climatic projection trends

Trends in mean ensemble projection rainfall (Fig. 8) shows a decrease as compared to the baseline rainfall (Fig. 7). The 30-year averages of each ensemble mean of rainfall (Table 5) showed percentage decrease of approximately 29%, 28% and 30% for RCP2.6, RCP4.5 and RCP8.5 as against the baseline average (1293.1 mm). Rain intensity and rainy days are expected to decrease as projected by the IPCC (Pachauri et al., 2014) for most regions in Africa. The RCP4.5 scenario with the ensemble r2i1p1 (not shown) is likely to produce most rains as compared to the other scenarios and ensembles. The years of extreme rainfall under RCP4.5 mean exhibited a near-decadal trend with increments observed from 2023, 2032 and 2043. The inter-annual variability in rainfall amounts is expected

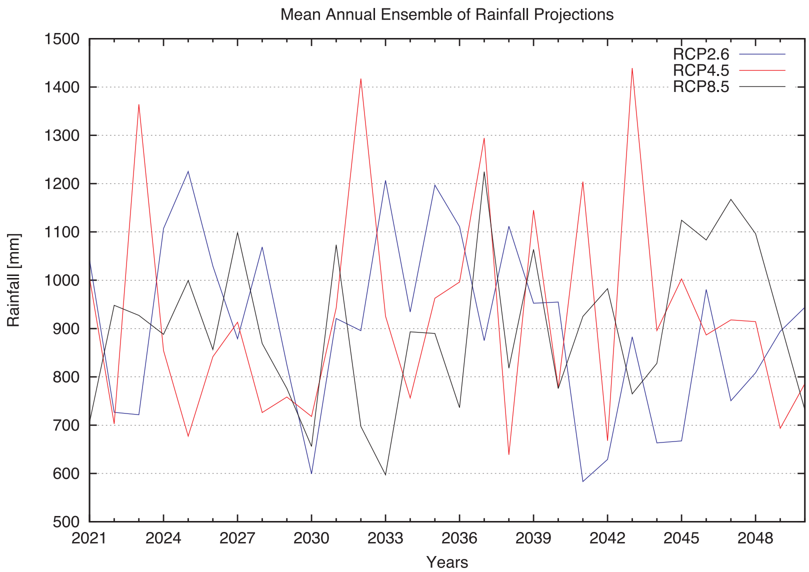

Fig. 8. Mean annual rainfall for ensemble mean projections (2021–2050).

Table 5
A 30-year average rainfall (mm)/stream-flow (cms). LU1 and LU2 correspond to streamflow amounts generated under land use scenarios 1 and 2.

Ensembles	RCP2.6 Rainfall/LU1/LU2	RCP4.5 Rainfall/LU1/LU2	RCP8.5 Rainfall/LU1/LU2
r1i1p1	758.40/1.00/1.06	969.16/1.45/1.51	754.52/1.04/1.10
r2i1p1	1011.65/1.52/1.58	947.82/1.44/1.50	987.31/1.49/1.56
r3i1p1	948.67/1.36/1.42	865.52/1.24/1.29	969.30/1.46/1.52
Mean	906.24/1.00/1.06	927.51/1.10/1.15	903.70/1.04/1.10

to peak in 2035 for RCP2.6 in ensemble r3i1p1, 2037 for RCP4.5 in ensemble r2i1p1 and 2027 for RCP8.5 in ensemble r3i1p1. With respect to the mean these peaks will be realised in 2025 (RCP2.6), 2046 (RCP4.5) and 2037 (RCP8.5). The erratic dynamics of the rainfall patterns for the catchment must be a first step warning signal to bring together water planning stakeholders for the implementation of appropriate measures to meet future water demands.

Fig. 9 shows the annual trends of future stream-flow generation at the Owabi catchment. From Table 5, it was observed that insignificant differences existed between stream-flow amounts for LU1 and LU2 scenarios and hence, most references would be in line with the former scenario. This negligible difference may arise from an already high CN2 at the catchment which ranges from medium to high with and undulating topography. Runoff coefficient is also high especially in urbanised areas due to the impervious pavement structures. These factors coupled with the soil type (orthic acrisols) results in high runoff hence the negligible differences in stream-flow amounts regardless of the landuse. It has been found that acrisols under a protective forest cover have a porous surface soils which improves the infiltration capacity of the soil (FAO, 1977; WRB, 2014) and this is a characteristic of the Owabi forest reserve. However at areas where the forest has been cleared, used for urbanisation or bare, the surface soil degrades and slakes to forms a hard surface crust which allows insufficient penetration of water leading to inevitable devastating surface erosion (FAO, 1977; WRB, 2014). The slightly negligible disparities in the stream-flow amounts for LU1 and LU2 also imply that the catchment would likely be more susceptible to changes in climate than land-use dynamics and this might result from the regulation of catchment water loss by the existing forest cover. The stream-flow amounts will decline directly with the rainfall except for years of extremities. The mean ensemble stream-flow peaks are expected to occur for the same years as the rainfall, however for RCP8.5 stream-flow has the highest peak is observed in 2047. Climate change will also result in decreases in water yield with its seasonal variations still controlled by surface runoff which ultimately influences stream-flow. According to the Water Resource Commission of Ghana (Water Resource Commission, 2012b), water demand within the Kumasi metropolis has an increasing trend of about 26 million cumecs in 2013 to about 47 million cumecs in 2025. These demands are likely to be met if there is proper harnessing of water storage and processing during years of extremities at the Owabi water processing plant. On the other hand, these adequate measures could also boost water availability for other socio-economic and agro-irrigational demands. However, a pit-fall during wet years would be the transport of sediments during surface runoff into the Owabi river. An increase in sediment load without adequate sedimentation measures is likely to decrease water quality which would make processing very expensive. Hence creating a deficit in water demands and supply. The overall deficit in future stream-flow amounts should be a wake-up call for the Ghana Water Company Limited and the Water Resources Commission to implement adequate adaptation and mitigation measures for the preservation of the Owabi river and the

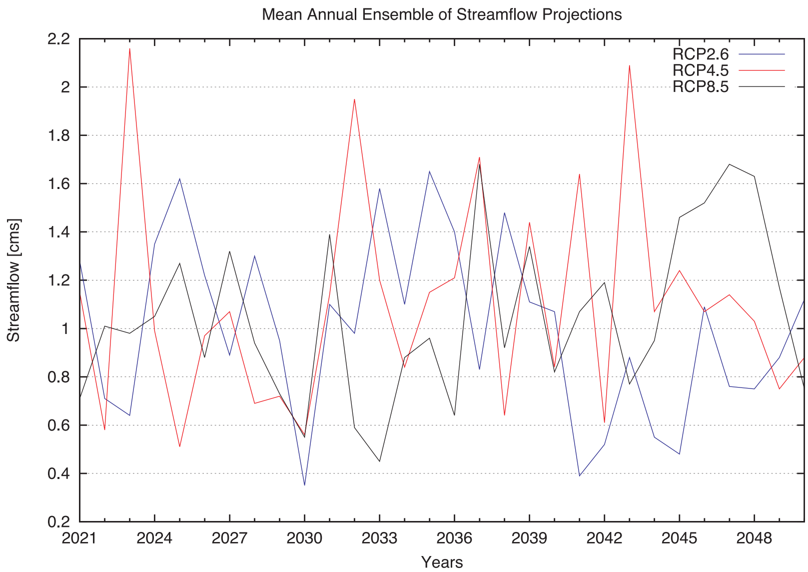

Fig. 9. Mean annual stream-flow for ensemble mean projections (2021–2050).

entire catchment.

5. Conclusions

Management of water resources at the Owabi catchment has become a challenge due to increasing human activities. This has posed a serious threat on the lifespan of the Owabi dam which supplies about 20% of potable water for the Kumasi metropolis. A hydro-climatic study was carried out using the SWAT model to assess the catchment hydrological response to the anthropogenic invasion. The model was specifically employed to simulate both historic and projected stream-flow as well as water balance whiles the SUFI-2 algorithm embedded in the SWAT-CUP software was used for model calibration and validation for the catchment.

QGISv2.6 interface was used to launch SWATv2012 for QSWAT v1.4. Initial results revealed the forest and topography played major role in water loss at the catchment as evapotranspiration and surface runoff were the most dominant modulating processes. The monthly sensitivity analyses showed three (3) parameters of which the curve number (CN2) ranked first as the most sensitive in controlling runoff amounts into the river. The uncertainty was observed to be quite low as the model enveloped about 50% of the observed stream-flow within a width of 0.45–0.55 which suggests a satisfactory model performance.

Future stream-flow predictions were modelled for three climate ensembles each for RCP2.6, RCP4.5 and RCP8.5 climatic scenarios and two land-use scenarios, LU1 and LU2. The downscaled rainfall trends showed decreases in rainfall totals between 2021 and 2050 for ensembles in the RCPs as compared to the base-line. The rainfall decreases will be translated directly into catchment stream-flow generation for LU1 and LU2. There is therefore the need to formulate and implement appropriate procedures for the protection of the water resources at the Owabi catchment. On the other hand, it would be a commendable effort to construct localised dams for present and future rain-water harvesting and storage to meet agro-irrigational and de-stress water demands at the Owabi dam.

The use of the SWAT model for hydrological assessment of the Owabi catchment has also been successful and further studies on the assessment of water quality and pollution is currently being undertaken to provide a holistic view of water resource management at the catchment. This would in the long-term aid effective decision making and boost water production for the Kumasi metropolis.

Author contributions

Marian Amoakowaah Osei: Data curation, investigation, methodology, software, validation, visualisation, writing and editing
Leonard Kofitse Amekudzi: Conceptualisation, supervision and editing
David Dotse Wemegah: Conceptualisation, field supervisor and editing
Kwasi Preko: Editing
Emmanuella Serwaa Gyawu: Editing
Kwasi Obiri-Danso: Funding acquisition

Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

We express our sincere gratitude to Building Stronger Universities Phase 2 (BSU II) and Kwame Nkrumah University of Science and Technology (KNUST) for funding of this study. Mrs. Jamilatou Begou for our training in the use of the SWAT model and Mr. Charles Yorke for making available the climate data from GMet.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.ejrh.2019.100620.

References

Abbaspour, K., 2015. SWAT-CUP. eawag.
Abraham, L.Z., Roehrig, J., Chekol, D.A., 2007. Calibration and validation of SW hydrologic model for Meki watershed, Ethiopia. Conference on International Agricultural Research for Development, University of Kassel-Witzenhausen and University of Gottingen.
Adjei, P.W., Buor, D., Addrah, P., 2014. Geo-spatial analysis of land use and land cover changes in the Lake Bosomtwe Basin of Ghana. Ghana J. Geogr. 6, 1–23.
Adjei-Gyapong, T., Asiamah, R., 2002. The interim Ghana soil classification system and its relation with the World Reference Base for Soil Resources. Quatoriziéme réunion du Sous-Comité ouest et centre africain de corrélation des sols 51–979.
Agyen-Brefo, R., 2012. The Effects of Encroachment on Sustainable Public Land Management: A Case Study of the Owabi Catchment Area in Kumasi (Master's thesis). Kwame Nkrumah University of Science and Technology.
Akoto, O., Abankwa, E., 2014. Evaluation of Owabi Reservoir (Ghana) water quality using factor analysis. Lakes Reserv. Res. Manag. 19, 174–182.
Akpoti, K., Antwi, E., Kabo-bah, A., 2015. Impacts of rainfall variability, land use and land cover change on stream flow of the Black Volta Basin, West Africa. Water Environ. J. 29, 259–267.
Amekudzi, L., Yamba, E., Preko, K., Asare, E., Aryee, J., Baidu, M., Codjoe, S., 2015. Variabilities in rainfall onset, cessation and length of rainy season for the various

agro-ecological zones of Ghana. Entropy 3, 416–434.
Arnold, J., Kiniry, J., Srinivasan, R., Williams, J., Haney, E., Neitsch, S., 2012a. Soil and Water Assessment Tool: Input/Output Documentation Version 2012. Texas Water Resources Institute.
Arnold, J., Moriasi, D., Gassman, P., Abbaspour, K., White, M., Srinivasan, R., Santhi, C., Harmel, R., van Griensven, A., van Liew, M., Kannan, N., Jha, M., 2012b. SWAT: model use, calibration and validation. Trans. ASABE 55, 1491–1508.
Arsenault, R., Brissette, F., 2016. Analysis of continuous streamflow regionalisation methods within a virtual setting. Hydrol. Sci. J. 61, 2680–2693.
Aryee, J., Amekudzi, L., Quansah, E., Klutse, N., Atiah, W., Yorke, C., 2018. Development of high spatial resolution rainfall data for Ghana. Int. J. Climatol. 38, 1201–1215.
Awotwi, A.F.Y., Kumi, M., 2015. Assessing the impact of land cover changes on water balance components of White Volta Basin in West Africa. Water Environ. J. 29, 259–267.
Ayivor, J., Gordon, C., 2012. Impact of land use on river systems in Ghana. West Afr. J. Appl. Ecol. 20, 83–95.
Bair, R.T., 2014. A SWAT Model for a Cocoa Growing Region in Ghana. Biological and Agricultural Engineering Undergraduate Honors Theses.
Begou, J., Jomaa, S., Benabdalla, S., Bazie, P., Afouda, A., Rode, M., 2016. Multi-site validation of the SW model on the Bani catchment: model performance and predictive uncertainty. Water 8, 1–23.
Bonal, D., Burban, B., Stahl, C., Wagner, F., Hérault, B., 2016. The response of tropical rainforests to drought lessons from recent research and future prospects. Ann. For. Sci. 73, 27–44.
CCCMA, 2016. http://www.cccma.ec.gc.ca/data/data/shtml. (Accessed 27 May 2016).
Demeke, G., Andualem, T., 2018. Application of remote sensing for evaluation of land use change responses on hydrology of Muga Watershed, Abbay River Basin, Ethiopia. J. Earth Sci. Clim. Change 9, 2.
Dile, Y., Srinivasan, R., George, C., 2016. QGIS Interface for SWAT (QSWAT), Version 1.3.
Domfeh, M., Anyemedu, F., Anornu, G., Adjei, K., Odai, S., 2015. Assessment of the water balance of the Barekese Reservoir in Kumasi, Ghana. J. Sci. Technol. 35, 34–51.
FAO, 1977. FAO-UNESCO Soil Map of the World, 1:5000000 vol. 6: Africa.
Forestry Commission, G., 2014. Owabi Wildlife Sanctuary/Ramsar Site: Management Plan.
Forkuo, E., Frimpong, A., 2012. Analysis of forest cover change detection. Int. J. Remote Sens. Appl. 2, 82–92.
Gassman, P., Reyes, M., Green, C., Arnold, J., 2007. The soil and water assessment tool: historical development, applications, and future research directions. Trans. ASABE 50, 1211–1250.
Gayathri, D., Ganasri, B., Dwarakish, G., 2015. A review on hydrological models. Aquat. Procedia 4, 1001–1007.
Ghaffari, G., Keesstra, S., Ghodousi, J., Ahmadi, H., 2010. SWAT-simulated hydrological impact of land-use change in the Zanjanrood Basin, Northwest Iran. Hydrol. Process. 24, 892–903.
Ghana Statistical Service, G., 2014. 2010 Population & Housing Census: District Analytical Report (Offinso Municipality).
Ghoraba, S., 2015. Hydrological modeling of the Simly Dam watershed (Pakistan) using GIS and SW model. Alex. Eng. J. 54, 583–594.
Govender, M., Everson, C., 2005. Modelling streamflow from two small South African experimental catchments using the SWAT model. Hydrol. Process. 19, 683–692.
Guzha, A., Rufino, M.C., Okoth, S., Jacobs, S., Nóbrega, R., 2018. Impacts of land use and land cover change on surface runoff, discharge and low flows: evidence from East Africa. J. Hydrol. Reg. Stud. 15, 49–67.
Gyawu, E.S., 2017. Assessment of the Hydrological Response of Owabi Catchment to Land Use/Land Cover Change (Master's thesis). Kwame Nkrumah University of Science and Technology.
Hrachowitz, M., Savenije, H., Blöschl, G., Mc Donnell, J., Sivapalan, M., Pomeroy, J., Arheimer, B., Blume, T., Clark, M., Ehret, U., Fenicia, F., Freer, J., Gelfan, A., Gupta, H., Hughes, D., Hut, R., Montanari, A., Pande, S., Tetzlaff, D., Troch, P., Uhlenbrook, S., Wagener, T., Winsemius, H., Woods, R., Zehe, E., Cudennec, C., 2013. A decade of Prediction in Ungauged Basins (PUB) – a review. Hydrol. Sci. J. 58, 1198–1255.
Kankam-Yeboah, K., Amisigo, B., Obuobi, E., 2012. Climate Change Impacts on Water Resources in Ghana. Technical Report. Ghana National Commission for UNESCO.
Kankam-Yeboah, K., Obuobie, E., Amisigo, B., Opoku-Ankomah, Y., 2013. Impact of climate change on streamflow in selected river basins in Ghana. Hydrol. Sci. J. 58, 773–788.
Kumagai, T., Saitoh, T.M., Sato, Y., Takahashi, H., Manfroi, O.J., Morooka, T., Kuraji, K., Suzuki, M., Yasunari, T., Komatsu, H., 2005. Annual water balance and seasonality of evapotranspiration in a Bornean tropical rainforest. Agric. For. Meteorol. 128, 81–92.
Legesse, D., Vallet-Coulomb, C., Gasse, F., 2003. Hydrological response of a catchment to climate and land use changes in Tropical Africa: case study South Central Ethiopia. J. Hydrol. 275, 67–85.
Li, Y., Chang, J., Luo, L., Wang, Y., Guo, A., Ma, F., Fan, J., 2019. Spatiotemporal impacts of land use land cover changes on hydrology from the mechanism perspective using SWAT model with time-varying parameters. Hydrol. Res. 50, 244–261.
Lofgren, B., Gronewold, A., 2014. Climate Change in the Midwest: A Synthesis Report for the National Climate Assessment. Island Press, pp. 224–237 (Chapter 12).
McMillan, H., Krueger, T., Freer, J., 2012. Benchmarking observational uncertainties for hydrology: rainfall, river discharge and water quality. Hydrol. Process. 26, 4078–4111.
Me, W., Abell, J., Hamilton, D., 2015. Effects of hydrologic conditions on SWAT model performance and parameter sensitivity for a small, mixed land use catchment in New Zealand. Hydrol. Earth Syst. Sci. 19, 4127–4147.
Moriasi, D., Arnold, J., Van Liew, M., Bingner, R., Harmel, R., Veith, T., 2007. Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. Trans. ASABE 50, 885–900.
Mukheibir, P., 2007. The impact of climate change on small municipal water resource management: the case of Bredasdor, South Africa. Energy Res.
Nie, W., Yuan, Y., Kepner, W., MS, N., Jackson, M., Erickson, C., 2011. Assessing impacts of landuse and landcover changes on hydrology for the upper San Pedro watershed. J. Hydrol. 407, 105–114.
Oudin, L., Andréassian, V., Perrin, C., Michel, C., Le Moine, N., 2008. Spatial proximity, physical similarity, regression and ungaged catchments: a comparison of regionalization approaches based on 913 French catchments. Water Resour. Res. 44.
Pachauri, R.K., Allen, M.R., Barros, V.R., Broome, J., Cramer, W., Christ, R., Church, J.A., Clarke, L., Dahe, Q., Dasgupta, P., et al., 2014. Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. IPCC.
Parker, D.J., 2017. Meteorology of Tropical West Africa: The Forecasters' Handbook. John Wiley & Sons.
Pokhrel, B., 2018. Impact of land use change on flow and sediment yields in the Khokana Outlet of the Bagmati River, Kathmandu, Nepal. Hydrology 5, 22.
Puno, R., Puno, G., Talisay, B., 2019. Hydrologic responses of watershed assessment to land cover and climate change using soil and water assessment tool model. Glob. J. Environ. Sci. Manag. 5, 71–82.
Rathjens, H., Bieger, K., Srinivasan, R., Chaubey, I., Arnold, J., 2016. CMhyd User Manual.
Sanderson, M., Santini, M., Valentini, R., Pope, E., 2010. Relationships Between Forests and Weather. Technical Report. Met Office: Hadley Centre.
Schuol, J., Abbaspour, K., 2006. Calibration and uncertainty issues of a hydrological model (SWAT) model applied to West Africa. Adv. Geosci. 9, 137–143.
Sharma, T.C., 1988. An evaluation of evapotranspiration in tropical Central Africa. Hydrol. Sci. J. 33, 31–40.
Shope, C., Maharjan, G., Tenhunen, J., Seo, B., Kim, K., Riley, J., Arnhold, S., Koellner, T., Ok, Y., Peiffer, S., Kim, B., Park, J., Huwe, B., 2014. Using the SWAT model to improve process descriptions and define hydrologic partitioning in South Korea. Hydrol. Earth Syst. Sci. 18, 539–557.
Sood, A., Muthuwatta, L., McCartney, M., 2013. A SW, evaluation of the effect of climate change on the hydrology of the Volta River basin. Water Int. 38, 297–311.
Srinivasan, R., Zhang, X., Arnold, J., 2010. Hydrological budget and crop yield predictions in the Upper Mississippi River Basin. Trans. ASABE 53, 1533–1546.
Sudjarit, W., Pukngam, S., Tangtham, N., 2015. Application of SWAT model for assessing effect on main functions of watershed ecosystem in headwater, Thailand. In: Zhang, W. (Ed.), Proceedings of the International Academy of Ecology and Environmental Sciences, pp. 57–69.
Swain, J.B., Patra, K.C., 2017. Streamflow estimation in ungauged catchments using regionalization techniques. J. Hydrol. 554, 420–433.

Taylor, K., Balaji, V., Hankin, S., Juckes, M., Lawrence, B., 2010. CMIP5 Data Reference Syntax (DRS) and Controlled Vocabularies. Version 0.27 ed.CMIP5 Data Reference Syntax (DRS) and Controlled Vocabularies. Version 0.27 ed.

Teutschbein, C., Seibert, J., 2012. Bias correction of regional climate model simulations for hydrological climate-change impact studies: review and evaluation of different methods. J. Hydrol. 456, 12–29.

UCL-Geomatics, 2017. Land Cover CCI: Product User Guide Version 2.0.

UCLouvain, 2017. ESA Climate Change Initiative-Land Cover.

Uzeika, T., Merten, G., Minella, J., Moro, M., 2011. Use of the SWAT model for hydro-sedimentologic simulation in a small rural watershed. Rev. Bras. Ciênc. Solo 36, 557–565.

Van Vuuren, D.P., Edmonds, J., Kainuma, M., Riahi, K., Thomson, A., Hibbard, K., Hurtt, G., Kram, T., Krey, V., Lamarque, J., Masui, T., Meinshausen, M., Nakicenovic, N., Smith, S., Rose, S., 2011. The representative concentration pathways: an overview. Clim. Change 109, 5.

Water Resource Commission, G., 2012a. National Integrated Water Resource Management (IWRM) Plan.

Water Resource Commission, G., 2012b. Pra River Basin: Integrated Water Resources Management Plan.

WaterBase, 2016. http://www.waterbase.org/resources.html. (Accessed 27 May 2016).

Welde, K., Gebremariam, B., 2017. Effect of land use land cover dynamics on hydrological response of watershed: case study of Tekeze Dam Watershed, Northern Ethiopia. Int. Soil Water Conserv. Res. 5, 1–16.

White, M.J., Harmel, R.D., Arnold, J.G., Williams, J.R., 2014. SWAT check: a screening tool to assist users in the identification of potential model application problems. J. Environ. Qual. 43, 208–214.

Worqlul, A., Dile, Y., Bizimana, J.C., Jeong, J., Gerik, T., Srinivasan, R., Richardson, J., Clarke, N., 2018. Multi-dimensional evaluation of simulated small-scale irrigation intervention: a case study in Dimbasinia watershed, Ghana. Sustainability 10, 1531.

WRB, I.W.G., 2014. World Reference Base for Soil Resources 2014: International Soil Classification System for Naming Soils and Creating Legends for Soil Maps. World Soil Resources Report.

Yeboah, F., Awotwi, A., Forkuo, E., Kumi, M., 2017. Assessing the land use and land cover changes due to urban growth in Accra, Ghana. J. Basic Appl. Res. Int. 22, 43–50.

Zhang, W., Miranda, J., Matsuo, T., Gore, L., Makin, I., Rogers, C., 2014. Kingdom of Bhutan: Adapting to climate change through Integrated Water Resources Management. Technical Report. Asian Development Bank.