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ORIGINAL PAPER

Separation and attribution of impacts of changes in land use and climate on hydrological processes

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Abstract

This study aims to assess, compare, and attribute the effects due to separate and combined land use/land cover (LULC) and climate changes on hydrological processes in a tropical catchment. The Soil and Water Assessment Tool (SWAT) model is set up and calibrated for a small contributing sub-basin of the Tana River Basin (TRB) in Kenya. The model is then applied to simulate the hydrological components (i.e., streamflow (FLOW), evapotranspiration (ET), soil water (SW), and water yield (WYLD)) for different combinations of LULC and climate scenarios. Land use data generated from Land Satellite 5 Thematic Mapper (Landsat 5TM) images for two different periods (1987 and 2011) and satellite-based precipitation data from the African Rainfall Climatology version 2 (ARC2) dataset are utilized as inputs to the SWAT model. The Nash–Sutcliffe model efficiency (NSE), coefficient of determination (R^2), percent bias (PBIAS), and the ratio of root mean square error to the standard deviation (RSR) for daily streamflow were 0.73, 0.76, 3.16%, and 0.51 in calibration period, respectively, and 0.45, 0.54, 12.53%, and 0.79 in validation period, respectively, suggesting that the model performed relatively good. An analysis of the LULC data for the catchment showed that there was an increase in agricultural, grassland, and forested land with a concomitant decrease in woodland and shrubland. Simulation results revealed that change in climate had a more significant effect on the simulated parameters than the change in LULC. It is shown that changes in LULC only had very minor effects in the simulated parameters. The monthly mean FLOW and WYLD decreased by 0.02% and 0.11%, respectively, while ET and SW increased by a monthly mean of 0.2% and 2.2%. Varying the catchment climate and holding the land use constant reduced FLOW, ET, SW, and WYLD by an average monthly mean of 43.2%, 21%, 13%, and 70%, respectively, indicating that climate changes have more significant effects on the catchment hydrological processes than changes in LULC. Thus, it is necessary to evaluate and identify the isolated and combined effects of LULC and climatic changes when assessing impacts on the TRB's hydrological processes.

1 Introduction

Hydrological resources and flow regimes around the globe are significantly being affected by changes in LULC and climatic variables (Haghighi et al. 2020). Land use refers to the state of human activities on land (e.g., urban/built up, industrial, farmland, forested land (natural/managed), shrubland), while the physical appearance of a land surface refers to land cover (Camara et al. 2019). It is known that hydrologic processes in a watershed (e.g., evapotranspiration, surface runoff, groundwater recharge, and streamflow) are directly affected by LULC dynamics. The information on LULC gives distinctive features of the land's surface (e.g., surface permeability, solar reflectance, type of vegetation, the structure of the built-environment), which may be included in the parameterization of environmental models (Fang et al. 2012).

Human activities in the environment are considered the leading agent influencing change in LULC in the world (Xu et al. 2022). LULC changes influence the compartmentalization of water into the various pathways such as interception, evapotranspiration, infiltration, soil moisture, and runoff, which in turn causes variations in frequency and severity of floods, base flow, and/or streamflow (Liu et al. 2020; Yin et al. 2017; Wang et al. 2014). On the other hand, changes in climate can affect the flow routine, peak flows, and volume (De Niel and Willems 2018; Shooshtari et al. 2017). As such, LULC changes are likely to exacerbate the effects due to climatic

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variations on hydrologic resources in a watershed. Some studies have suggested that it is possible that global changes in LULC may have a more severe effect on surface flows than changes in climatic conditions (Yin et al. 2017; Vörösmarty et al. 2000; Franczyk and Chang 2009). Therefore, a comprehensive plan for managing water resources requires a good understanding of hydrologic feedback of watersheds to changes in LULC and climatic variables (Mango et al. 2011). Various studies have demonstrated that land use and climate can greatly influence the hydrologic balance and biogeochemical processes of watershed systems (Stonestrom et al. 2009; Talib and Randhir 2017; Lu et al. 2015). A study conducted in northwest Iran observed that by reducing the land under grassland by 34.5% and increasing the land under shrubland and rain-fed agriculture by 13.9% and 12.1%, respectively, increased runoff by 33% and reduced groundwater recharge by 22% (Ghaffari et al. 2010). Mango et al. (2011) demonstrated using SWAT that forest cover changes had less profound impacts on discharge and other hydrologic components than variations in rainfall and temperature. Lu et al. (2015) showed that forested land, grassland, and farmland contributed the largest to the catchment total water yield, with up to about 39%, 38%, and 21%, respectively.

Recent studies have shown that LULC and climate changes may compromise water supplies availability in Africa, mainly because of the increasing incidence of floods and prolonged droughts (Palamuleni et al. 2011). Moreover, the changes will have significant impact on Kenya because the country is highly vulnerable to climatic changes and is already experiencing acute freshwater scarcity. The TRB catchment is the primary source of hydroelectric power in Kenya and the major contributor of water to Nairobi. Recently the TRB has been experiencing significant LULC transformations mainly due to the expansion of agriculture, industrial and commercial activities, and an increasing population. The need to meet the competing interests for water demand has weighed heavily on water availability, which at times leads to conflicts among water consumers in the basin. Rockström et al. (2002) underscored the need to recognize the association between hydrological regimes and prevailing LULC changes in catchments in the face of enhanced anthropogenic activities vis-à-vis water conflicts. Similarly, DeFries and Eshleman (2004) recognized the need to continuously establish the impact of changes in LULC on water resources. Furthermore, it is appreciated that LULC data is an integral element in environmental management which is necessary for driving environmental models such as SWAT.

Despite the many studies focusing on understanding the impacts due to variations in LULC and climate on hydrological systems, the nature and magnitude of their merged effects and proportional significance are yet to be understood, hard to pinpoint, and separate or may change according to individual cases (Qi et al. 2009; Liu et al. 2010; D'Agostino et al. 2010). Application of catchment experiments to investigate the impacts due to variations of LULC on the hydrological processes, viz., runoff, as applied in a number of previous investigations, have produced either variable or contradictory results. This is because such endeavors for investigating feedbacks to changes in LULC are tedious and laborious, forcing many studies to focus on hydrological models to investigate the impacts. The application of hydrological models is advantageous because of the possibility of assessing previous and probable future impacts (Li and Zhang 2008, Hou et al. 2019). SWAT, in particular, has proven to be highly suitable in assessing hydrologic impacts (Gassman et al. 2007) and has been adequately applied in watersheds fraught with data scarcity (Ndomba et al. 2008; Stehr et al. 2008). Various works, such as in Iran (Ghaffari et al. 2010), Korea (Im et al. 2009), China (Li et al. 2009), and the USA (Miller et al. 2002), have utilized SWAT to study the impacts LULC and climate on water availability. However, hydrologic modeling, especially in ungauged catchments, is usually hampered by the paucity of precipitation data and corresponding discharge measurements with sufficient temporal and spatial extent. The availability of high temporal and spatial resolution data allows for adequate calibration and validation and may enhance model precision.

The current paper aims to assess and isolate the impacts of the change in LULC and climate on the hydrological parameters of a small mountainous sub-catchment in the headwaters of the TRB. To achieve this, we intend (1) to set up, calibrate, parameterize and validate the SWAT model; (2) to simulate the catchment hydrological parameters such as surface runoff (FLOW), evapotranspiration (ET), soil water (SW), and water yield (WYLD) under different land use and climate scenarios; and (3) to examine and attribute the impacts on simulated FLOW, ET, SW, and WYLD to either the isolated or combined changes in LULC and climate in the watershed. A detailed literature search revealed that there had not been any study of similar nature undertaken in the TRB. Moreover, most studies undertaken in tropical catchments have focused solely on streamflow simulation as opposed to determining the isolated and combined effects caused by changes in LULC and climatic variables on the individual parameters of the hydrological cycle.

2 Materials and methods

2.1 Description of the study area

The study area (Fig. 1) is a small contributing sub-catchment of the larger Tana River Basin (TRB) with a drainage area of about 500 km^2. The catchment has a complex topography with elevation ranging between 500 and 4000 m above sea level. The sub-catchment was chosen because

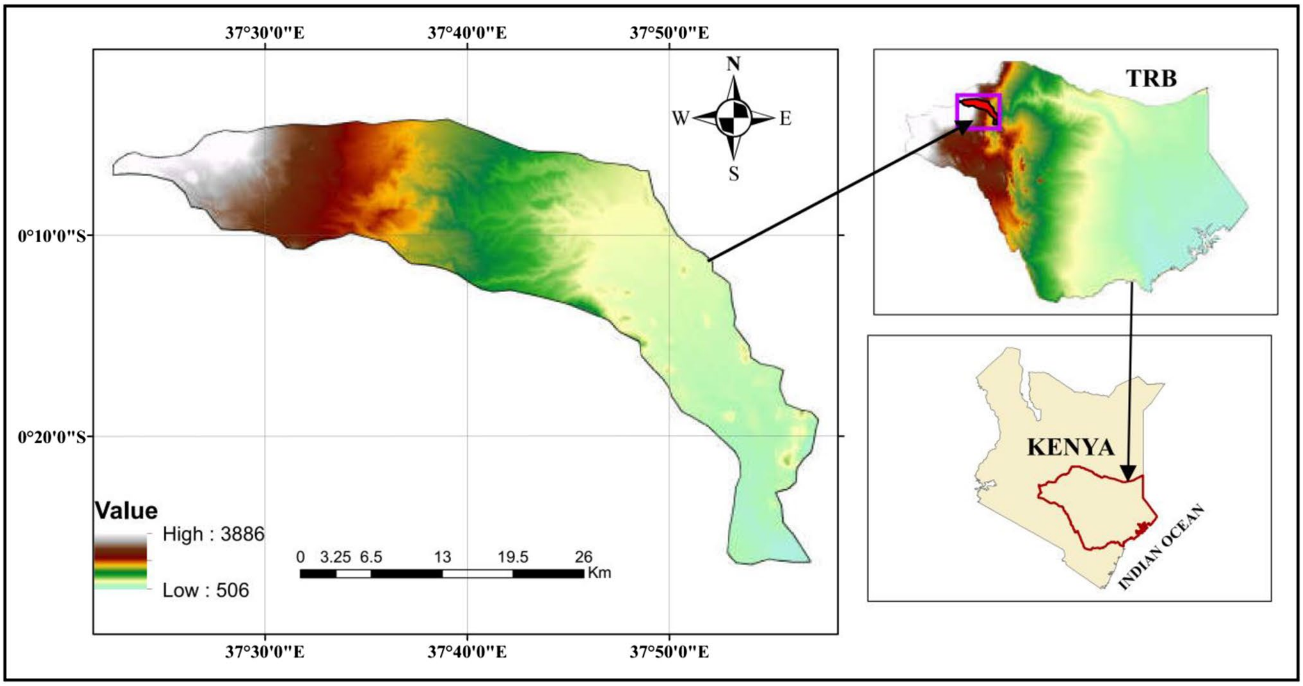

Fig. 1 Study area map shows the topography (left panel) of the Tana River Basin (top right) and the location of the Tana River Basin in Kenya (bottom right)

it is one of the few sub-catchments that has a functioning gauging station. Moreover, the sub-catchment is relatively less affected by human activities such as construction of dams and water diversion. The climate of the TRB shows a close correlation of elevation and climate zones such that it varies from humid on the higher altitudes to arid and semi-arid in the lowlands. The precipitation regime in the sub-catchment follows the larger basin's bimodal pattern and is primarily influenced by topography (Kerandi et al. 2016). There are two wet periods throughout the year, with most of the rain occurring from March to May and another one occurring from September to November with less rainfall. The duration between the two wet periods receives very light rainfall, thereby diminishing the amount of available water in the catchment (Jacobs et al. 2007). The soils existing in the catchment include Andosols, Nitosols, Ferallsols, and Vertisols. Land use is dominated by grassland, forests, woodlands, shrubland, and croplands.

2.2 The SWAT model

2.2.1 Model description

SWAT is a comprehensive, physically based semi-distributed watershed model intended to simulate hydrology, sedimentation, and agricultural chemical yields at various scales in complex watersheds (Arnold et al. 1998; Neitsch et al. 2005; Gassman et al. 2007). The SWAT model is advantageous in that it has high computational efficiency and has the ability of extended continuous simulations. This model considers the effect of factors that may influence a catchment's hydrology, such as soil properties, land use, and issues of management of water resources. SWAT simulates the catchment hydrology by dividing the catchment into multiple sub-basins and further subdividing the sub-basins into hydrologic response units (HRUs), which have unique topographical, land use, and soil characteristics. In addition to that, SWAT allows for the simulation of various physical processes occurring in a catchment. It considers the water cycle routines, viz., vadose zone processes that consist of such as evaporation, infiltration, lateral flow, plant uptake, and percolation. The equation of water balance forms the basis for hydrological simulation in the SWAT model is as follows:

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

where SW_t (mm) is the final soil water content; SW_0 (mm) is the initial soil water content on day i, and t (days) is time; R_{day} (mm) is the precipitation amount on day i; Q_{surf} (mm) is the amount of surface runoff on day i; ET_i (mm) is the evapotranspiration (ET) amount on day i:

W_{seepi}(mm) is the amount of water entering the vadose zone from the soil profile on day i, and Q_{gw} (mm) is the amount of return flow on day i.

2.2.2 Model setup

Modeling using SWAT needs data with detailed geographic and spatial information, including climate data, digital elevation model (DEM) data, soil properties, and land use data. The building and parameterization of the model were performed using the ArcSWAT 2012 interface available in ArcGIS software. A total of 34 discrete sub-basins were delineated using the DEM and stream network of the catchment and setting the threshold drainage area of 10 km^2. The sub-basin was further subdivided into 218 homogenous hydrological response units (HRUs) by fixing a threshold value of 10% slope, 10% soil, and 20% land use type, which ensures that areas smaller than the threshold are integrated into larger ones using an area-weighted scheme. Individual HRUs in the model is considered to be homogenous entities in which the water balance is calculated. The DEM data of the study domain is shown in Fig. 1.

Hydrometeorological data Meteorological data (precipitation, maximum and minimum temperature, relative humidity, solar radiation, and wind speed) are required by SWAT for effective simulation. Confidence in hydrologic modeling is increased by the availability of precipitation data with high spatial and temporal resolution. However, watershed modeling in developing countries has traditionally been hampered by the paucity of precipitation data due to the non-existing or highly sparse and poorly maintained rain-gauge network. Consequently, many studies have used the widely available satellite-based precipitation products (SPPs) to overcome the challenge posed by insufficient and inconsistent in situ precipitation measurements. Because of the absence of rain gauges in the catchment, this study used the recently completed high temporal and spatial resolution African Rainfall Climatology version 2 (ARC2) (Novella and Thiaw 2013) as a substitute to the rain-gauge measurements. The ARC2 dataset is a new gridded, daily 30-year precipitation estimation dataset centered over Africa at 0.1 that was developed in 2012. The ARC2 is consistent with the operational Rainfall Estimation, version 2, algorithm (RFE2), and uses inputs from two sources: (1) 3-hourly geostationary infrared (IR) data centered over Africa from the European Organization for the Exploitation of Meteorological Satellites (EUMETSAT) and (2) quality controlled Global Telecommunication System (GTS) gauge observations reporting 24-h rainfall accumulations over Africa. The main difference between with ARC2 resides in the recalibration of all Meteosat First Generation (MFG) Infra-Red (IR) data (1983–2005). Validation and inter-comparison results show that ARC2 is consistent with other long-term historical datasets such as Global Precipitation Climatology Project (GPCP) and Climate Prediction Center Merged Analysis of Precipitation (CMAP) (Novella and Thiaw 2013). The data set was among three other high-resolution satellite-based precipitation products (PERSIANN-CDR, TRMM-3B42, and CHIRPS) which were evaluated in an earlier study and found to be more superior in detecting rainfall over the basin. Meteorological data were acquired from the National Centres for Environmental Prediction (NCEP) (http://globalweather.tamu.edu/). The daily flow data was provided by the Water Resources Management Authority (WRMA) for the Mutonga gauging station (station no. 4EA06).

Digital elevation model The NASA Shuttle Radar Topography Mission Global 1 arc second V003 (SRTMGL1) digital elevation model data with a 30-m resolution (NASA JPL 2013) was used to generate the topography of the watershed.

Soil data The data used for the classification of soil was generated from the Kenya Soil and Terrain (KENSOTER) database (KSS and ISRIC 2007) and Soil Property Estimates of the Upper Tana (SOTWIS-Kenya-UpperTana v1) (Batjes 2011). It was further supplemented with data from the Harmonized World Soil Database (FAO 2012). The dominant soil types in the sub-catchment include andosols (volcanic ash), nitisols, regosols, and leptisols (Hunink et al. 2010). The parameters related to soil physical and chemical properties which are required for running SWAT are texture, soil hydrologic groups, maximum rooting depth, fraction of porosity, moist bulk density, available water capacity, saturated hydraulic conductivity, organic carbon content, electrical conductivity, USLE equation soil erodibility factor, sand, silt, and rock fragment contents. Classification of the soil types in the basin using the available databases showed that there were some missing soil parameters which were filled using the Pedo-transfer functions techniques described in Droogers et al. (2001). Specifically, the saturated hydraulic conductivity was calculated using Jabro's model (Jabro 1992). The soil data for the watershed is given in Fig. 2 (b).

Land use/land cover change mapping LULC data was generated from the multi-temporal and multi-spectral 30-m grid spatial resolution United States Geological Survey (USGS) Land Satellite 5 Thematic Mapper (Landsat 5TM) images (http://www.earthexplorer.usgs.gov/). Considering that high-quality images for developing LULC database may not be available at the archive for all periods, we adopted the stratagem of choosing Landsat imagery based on their availability, the vegetation phenology, multi-temporal images, and image quality (cloudiness, haze) (Palamuleni et al. 2011). The study ensured that the cloud and haze-free images obtained from the archive were taken at the same month of the year for the three different periods to account for the varying plant phenology. In this case, we chose images taken during February of both 1987 and 2011. The unsupervised classification method with maximum likelihood clustering was

Fig. 2 The map of the delineated watershed (**a**), soil properties (**b**), land use for 1987 (**c**), and 2011 (**d**)

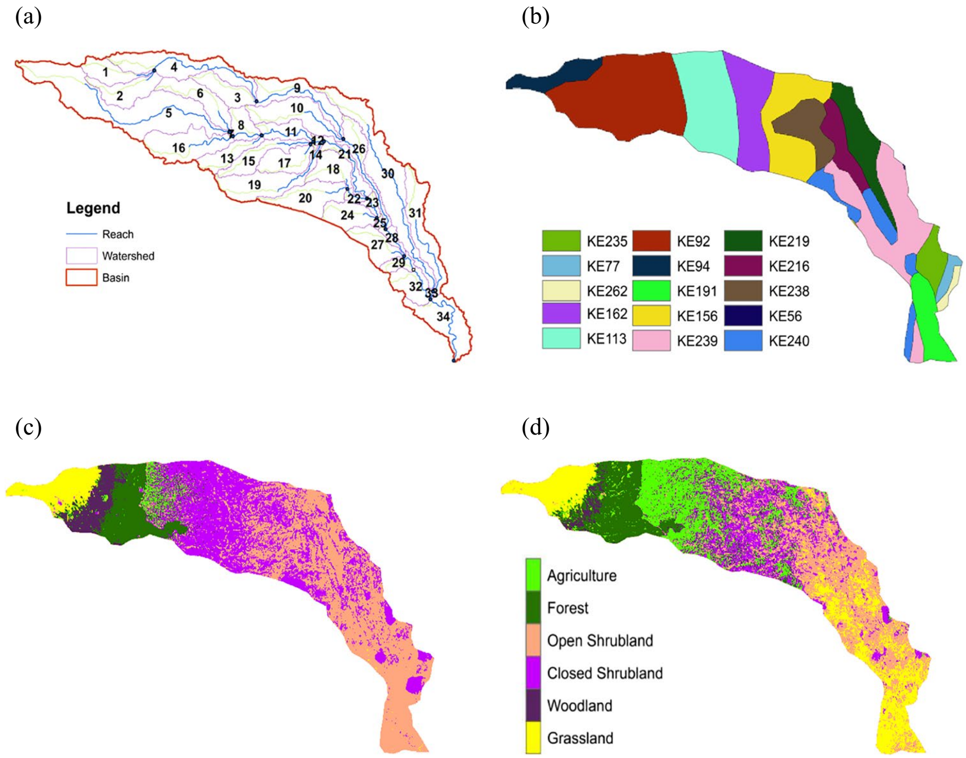

Table 1 The coverage area of the land use types (hectares) in the study area based on the delineated watershed from 1987 land use map

Land use type	Area coverage (Ha)	
	1987	2011
Agriculture	2857.05	16,020.81
Forest	6820.83	8554.14
Open Shrub land	29,252.25	16,201.98
Closed Shrub land	27,129.33	16,039.26
Woodland	3579.21	1148.58
Grassland	4872.24	16,546.14

used to assign land cover classes to spectrally similar areas. In view of the lack of mapped ground truth data, we used the MODIS land use data and the DEM of the catchment to compare with the generated classes. The images were finally merged into six classes: agriculture, forest, open shrubland, closed shrubland, woodland, and grassland. The types of LULC classes occupying the sub-catchment are given in Table 1, while Fig. 2 (c and d) shows the spatial extent of each of the classes in the watershed during the two periods.

2.2.3 SWAT model parameterization and sensitivity/uncertainty analysis

SWAT contains numerous hydrological parameters which might not all have a significant impact on the output. As such, a sensitivity analysis was proposed to be able to choose the most critical parameters that influence the hydrologic processes in the catchment. The basic operational of the SWAT model is the hydrological response units (HRUs). The HRUs is the fundamental spatial unit that consists of homogeneous land use, management, topographical, and soil characteristics upon which SWAT simulates the water balance and is the basis for hydrologic cycle simulation in SWAT. To understand how closely the model simulates the hydrological processes within a watershed, it is critical to examine the influence of different parameters. To run a physically based distributed hydrological model, such as SWAT, various parameters must be calibrated because of measurement difficulties. Sensitivity analysis is the computation of the most sensitive parameters for a given watershed. Sensitivity analysis describes the procedure of calculating the rate at which the model outputs vary when the input parameters to the model are varied (Arnold et al. 2012). This procedure helps in replacing the less sensitive parameters with those deemed to be more sensitive while also indicating to the modelers how to precisely handle the chosen parameter (Uniyal et al. 2015). The sensitivity analysis was performed using the global sensitivity approach in the Sequential Uncertainty Fitting (SUFI-2) algorithm (Abbaspour et al. 2007). The SUFI-2 algorithm is provided in the software package of SWAT-Calibration and Uncertainty Procedures (SWAT-CUP) (Abbaspour 2015). The advantage of using SWAT-CUP relies on the possibility of using different kinds of parameters including those responsible for surface runoff, water quality parameters, crop, parameters, crop rotation and management parameters, and weather generator parameters. The global sensitivity analysis method calculates the sensitivity of one input parameter in relation to the other in order to highlight their statistical significance. In the SUFI-2 algorithm, all sources of uncertainties (conceptual model, driving variables, measured data, and parameters) are depicted onto the ranges of parameters, which then calibrated to bracket most of the measured data in 95% prediction uncertainty (95PPU) in an iterative process (Abbaspour et al. 2007). Thereafter, the Latin hypercube sampling is performed to get the 2.5% and 97.5% levels of the cumulative distribution of the output variable at 95PPU. A detailed description of the SUFI-2 algorithm and the calibration protocol is found in Abbaspour et al. (2015). Table 2 shows the streamflow parameters that were tested for their sensitivity.

2.2.4 SWAT calibration, validation, and performance evaluation

The reasons for calibrating and validating the model are to minimize the effects of the intricate nature of processes occurring in watersheds and reduce the uncertainty inherent in both modeling parameters and inputs data (Gyamfi et al. 2016). There are many challenges involved in calibrating and validating hydrological models, and at times, it may render the process to be subjective. By calibrating the model, we endeavor to minimize the prediction uncertainty by matching the input parameters to the local conditions occurring in the catchment, while during validation, we demonstrate that a given site-specific model is capable of making sufficiently accurate simulations (Arnold et al. 2012). The objective of calibrating and validating the model is to ensure that the simulation reflects the natural conditions. In this study, the model was calibrated and validated using daily discharge data measured at Mutonga gauging station (station no. 4EA06). There were many gaps in the data record, which made it difficult to construct a relatively long series of uninterrupted records. Nevertheless, we endeavored to minimize the uncertainty during model calibration and validation by choosing the periods with relatively fewer gaps and fill the missing data using the WaterData package available in R-programme (Ryberg and Vecchia 2017). The streamflow record from 2000 to 2002 was used for calibrating and the record for 2003 to 2004 for validating.

SWAT performance during calibration and validation were evaluated according to the protocol developed by Moriasi et al. (2007). The simulated (predicted) values are compared with the observed values based on four statistical indexes that include the Nash–Sutcliffe efficiency (NSE), the percent bias (PBIAS), the coefficient of determination (R^2), and the ratio of mean squared error to the standard deviation of the measured data (RSR). The coefficient of determination (R^2) describes the degree of collinearity between simulated and measured data. The values range from 0 to 1, with higher values indicating less error variance (i.e., fitting effect is better as R^2 approaches 1.0), and the values of R^2 higher than 0.5 are considered to be acceptable (Moriasi et al. 2007). The NSE indicates how the observed and simulated values fit into 1:1 line. It lies between $-\infty$ and 1.0, with NSE = 1.0 being the optimal value, and thus the best fit. Moriasi et al. (2007) suggested that in general, model simulation can be judged as satisfactory if NSE > 0.5. Values ≤ 0.0 show that the mean observed value is a reliable predictor than the simulated

Table 2 Sensitivity analysis parameters for the SWAT model (Shen et al., 2008)

Parameter	Definition
ALPHA_BF	Base-flow alpha factor (days)
ALPHA_BNK	Base-flow alpha factor for bank storage (dimensionless)
CH_K2	Effective hydraulic conductivity in main channel alluvium (mm/h)
CH_N2	Manning's "n" value for the main channel
CN2SCS	runoff curve number (dimensionless)
ESCO	Soil evaporation compensation factor (dimensionless)
GW_DELAY	Groundwater delay (days)
GW_REVAP	Groundwater "revap" coefficient (dimensionless)
GWQMN	Threshold depth of water in the shallow aquifer required for return flow to occur (mm)
RCHRG_DP	Deep aquifer percolation fraction (dimensionless)
REVAPMN	Threshold depth of water in the shallow aquifer for "revap" to occur (mm)
SOL_AWC	Available water capacity of the soil layer (mm H2O/mm soil)
SOL_BD	Moist bulk density (Mg/m^3)
SOL_K	Saturated hydraulic conductivity (mm/h)
SOL_Z	Depth of soil (mm)
SURLAG	Surface runoff lag coefficient (dimensionless)

value and therefore is unacceptable model performance. The PBIAS measures the average tendency of the simulated data to be larger or smaller than their observed counterparts (Gupta et al. 1999). The performance ratings of a model is considered to be good if a value of < 10% to < 15% is achieved for PBIAS and is considered to be unsatisfactory if a value > 25% is achieved (Moriasi et al. 2007; Van Liew et al. 2007).

The equations for calculating the performance metrics are as in Eqs. (2) to (5).

$$\mathrm{NSE} = 1 - \left[\frac{\sum_{i=1}^{n} (O_i - S_i)^2}{\sum_{i=1}^{n} (O_i - \overline{O})^2} \right] \tag{2}$$

$$R^2 = \frac{\left[\sum_i^n \left(O_i - \overline{O} \right)(S_i - \overline{S}) \right]^2}{\sum_i^n (O_i - \overline{O})^2 * \sum_i^n (S_i - \overline{S})^2} \tag{3}$$

$$PBIAS = \frac{\sum_{i=1}^{n} (O_i - S_i)}{\sum_{i=1}^{n} (O_i)} * 100 \tag{4}$$

$$RSR = \frac{RMSE}{STD_{obs}} = \frac{\sqrt{\sum_{i=1}^{n} (O_i - S_i)^2}}{\sqrt{\sum_{i=1}^{n} (O_i - \overline{O})^2}} \tag{5}$$

where O_i is the observed and S_i is the simulated data.

2.3 Assessing effects of LULC change and climate variability

The effects due to alterations in LULC and climate on the hydrological processes of the watershed were evaluated using the approach of varying one factor at a time while holding the others constant (Li et al. 2009; Yin et al. 2017). The SWAT model was run with each of the land use maps (1987 and 2011) and driven by climate data from two different time slices (1983–1992 and 2003–2012). The impacts of LULC and climate change were assessed by comparing the SWAT outputs of the four (4) scenarios (e.g., in Yin et al. 2017). Four different scenarios were simulated, with each representing 1 decade, and each simulation required a LULC map and meteorological data set as described in the numerical experiment. To demonstrate the effects of change in a particular variable, the variable was substituted with another for a different period while all the others are maintained (Li et al. 2009; Yin et al. 2017). The effects of LULC and climate change were assessed and quantified by comparing the SWAT outputs of the four scenarios based on the following four numerical experiments.

2.3.1 The numerical experiments

The responses of the hydrological processes to changes in LULC and climate in the catchment were evaluated based on the following experiments:

Baseline scenario Both land use and climate were held constant, i.e., simulation using the 1987 land use and 1980s (1983–1992) climate data. This will be referred to as baseline simulation:

Scenario A: Holding the land use constant and changing the climate, i.e., simulation using the 1987 land use and 2000s (2003–2012) climate data.
Scenario B: Changing the land use while the climate is held constant, i.e., simulation using the 2011 land use and the 1980s climate change data.
Scenario C: Changing both land use and climate, i.e., simulation using the 2011 land use and 2000s (2003–2012) climate change data.

The effects due to changes in LULC alone are estimated by comparing the baseline and scenario B; the impacts due to the occurrence of changes in climate alone are appraised by comparing the outputs from the baseline scenario and scenario A, while the impacts associated to both changes in LULC and climate are calculated by comparing the baseline and scenario C.

3 Results

3.1 Results of model parameterization and sensitivity analysis

The SUFI algorithm which is incorporated in the SWAT-CUP (Abbaspour 2015) was used to perform the global sensitivity analysis by undertaking 500 iterations. In this study, it is shown that twelve (12) parameters were the most sensitive. The parameters in order of their ranking as obtained by means of LH-OAT analysis together with the fitted values are shown in Table 3. The ranking order is such that the most sensitive parameters are ranked 1 while the least sensitive is ranked last. It is observed that the CN2 followed by ALPHA_BF and GW_DELAY were the most sensitive parameters in the model. CN2 takes into consideration the overall effect of precipitation, hydrologic soil group, and land uses to estimate the volume of runoff from a precipitation occurrence. The most sensitive parameters for this particular catchment were those governing the responses to surface runoff, base flow generation (sub-surface response), and those governing the basin responses. Some other studies

Table 3 List of sensitive parameters and their calibrated values

Rank	Parameter	Parameter range	Fitted value
1	R_CN2.mgt	−0.2–0.05	−0.18863
2	V_ALPHA_BF.gw	0–0.0664	0.010724
3	V_GW_DELAY.gw	201.267–295.0181	294.69
4	V_GWQMN.gw	1.6464–2.4379	1.805127
5	V_GW_REVAP.gw	0.16086–0.18696	0.174627
6	V_ESCO.hru	0.8–0.97929	0.892782
7	V_CH_N2.rte	0.09909–0.143952	0.141911
8	V_CH_K2.rte	91.54037–100.7115	95.96545
9	V_ALPHA_BNK.rte	0.01–0.15	0.08287
10	R_SOL_AWC(..).sol	0.105215–0.173819	0.152312
11	R_SOL_K(..).sol	−0.46667 to −0.20587	−0.36717
12	R_SOL_BD(..).sol	−0.29911 to −0.1481	−0.22972

X_ gives the identifier code to indicate the type of change to be applied to the parameter:

R__ means an existing parameter value is multiplied by a ratio

V__ means the existing parameter value is to be replaced by a given number

(e.g., Mango et al. 2011; Anaba et al. 2017) undertaken over East Africa reported similar results.

3.2 Results of model calibration, validation, and performance evaluation

SWAT was calibrated and validated with daily streamflow data provided by WRMA for the only available gauging station (4EA06) in the watershed. The hydrographs of the observed and simulated daily streamflow utilized when calibrating and validating SWAT are shown in Fig. 3. The statistics used to gauge how SWAT performed (R^2, NSE, PBIAS, and RSR) are shown in Table 4. It is shown that the simulated and observed streamflow matched well in the calibration period with R^2 = 0.757 and NSE = 0.726. When the model was validated, the R^2 and NSE were 0.542 and 0.454, respectively. The existence of gaps (missing values) in the data is the likely cause of the relatively lower values of R^2 and NSE when validating the model. The PBIAS was for the calibrated model was 3.16% and 12.53% for the validation. This indicates that there was a slight underestimation of flow during both periods. As suggested by some studies (Abbaspour et al. 2015; Anaba et al 2017; Qiu et al. 2012), it is possible that uncertainties inherent in the catchment such as unaccounted for wetland processes, quality of input data, lack of sufficient precipitation measurements, and undocumented for wastewater discharges from point sources may have played a role in underestimating flow in the catchment.

Table 4 Statistical results of the calibration and validation of streamflow (at the daily time step) for the SWAT model

Evaluated statistic	Calibration period	Validation period
R^2	0.757	0.542
NSE	0.726	0.454
PBIAS	3.156	12.53
RSR	0.512	0.785

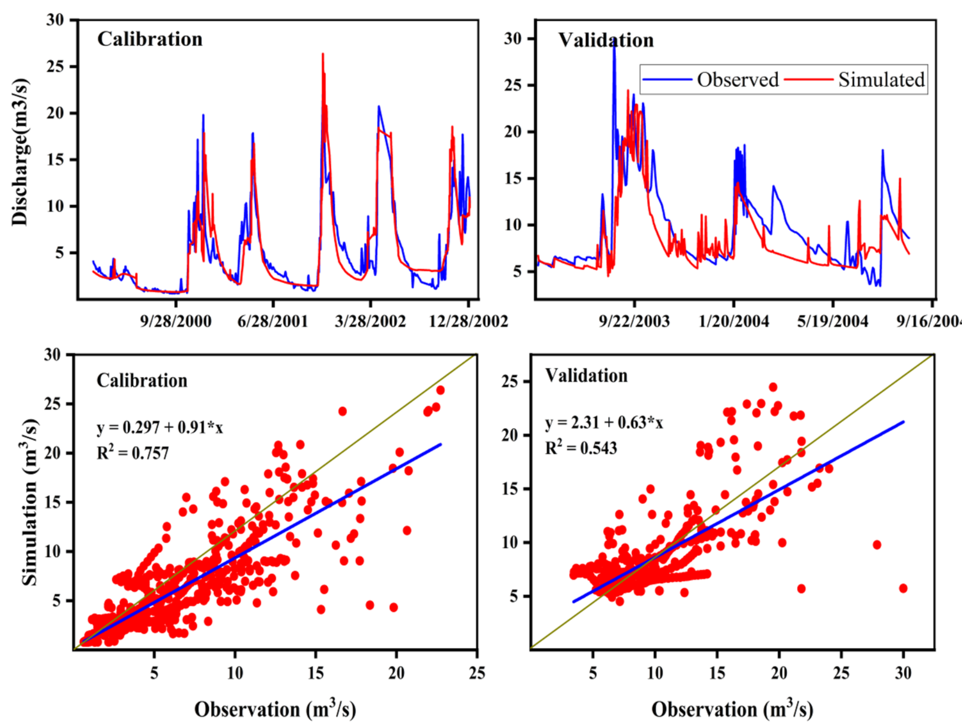

Fig. 3 The results of the calibration and validation of the SWAT model for the sub-catchment

Qiu et al. (2012) noted that streamflow in the SWAT model simulations might partly be underestimated or overestimated if CN2 is unable to give an accurate prediction of runoff for days with several storms. The value of the RSR when calibrating the model was 0.512 and 0.785 when validating. Therefore, considering the criterion put forward by Moriasi et al. (2007), the SWAT model is deemed to have performed relatively good in the calibration period and its performance is deemed to be satisfactory in the validation period. Hence, SWAT was capable of simulating the hydrological processes and can thus be applied to conduct further hydrological studies in the basin. Experience has shown that by minimizing the uncertainties inherent in a catchment will likely enhance the capability of predicting flow in a catchment by a well calibrated SWAT model.

where R is the relative change in the parameters and V is the substitution of a parameter value by another value in the given range.

3.3 Results of LULC and climate change effects

3.3.1 Effects due to LULC changes from 1987 to 2011

The maps for LULC during the two periods (1987 and 2011), which were employed as LULC data for the SWAT, are shown in Fig. 2 (c & d). The area coverage changes of the various types/classes of LULC between the two periods are given in Table 5. By comparing the two LULC maps, it is observed that the major changes were the conversion of woodland and shrubland to agriculture and grassland. Between the two periods, the land use for agriculture, grassland, and forest increased by 460.75%, 239.6%, and 25.4%, respectively. The land use classes for woodland, open shrubland, and closed shrubland decreased by a margin of 41 to 68% concurrently. Changes in LULC classes at the sub-basin level were calculated as the variation from the area coverage of land use class in 2011 and 1987, expressed as a percentage. The change in the spatial distribution of in individual LULC classes is shown in Fig. 4. It is shown in Fig. 4 (a) that between 20 and 80% of the LULC use in the upper sub-basins of the catchment was converted to agriculture.

Table 5 The percentage change in land use between 1987 and 2011

Land use type	Land use area coverage (Ha)		Land use change (%) (2011–1987)
	1987	2011	
Agriculture	2857.05	16,020.81	**460.75**
Forest	6820.83	8554.14	**25.41**
Open Shrub land	29,252.25	16,201.98	**−44.61**
Closed Shrub land	27,129.33	16,039.26	**−40.88**
Woodland	3579.21	1148.58	**−67.91**
Grassland	4872.24	16,546.14	**239.6**

Similarly, Fig. 4 (c) shows that woodland and closed shrubland (classified as RNGB in the SWAT model) reduced considerably in the same sub-basins. Forest land use type increased slightly in the upper part, as shown in Fig. 4 (b), while grassland and open shrubland reduced by a bigger margin around the middle part of the catchment. It is possible that the changes in LULC in the catchment potentially resulted from population growth which could lead to the expansion of agricultural activities.

3.4 Impacts of changes in LULC and climate on hydrological processes

The effects of changes due to LULC and climate were analyzed by contrasting the simulated hydrological components (FLOW, ET, SW, and WYLD) obtained from the three scenarios with the baseline period. To get a clear picture of the effects of LULC and/or climate changes, we calculated the percentage difference between the scenario simulations and the baseline. Table 6 shows the percentage monthly mean difference between the simulations based on the change scenarios and the baseline period. The isolated impacts due to change in LULC alone (scenario B) are depicted in Fig. 5. The impacts are shown in the form of monthly mean differences between the changing scenario and the baseline. The results show that the change in LULC caused SW to increase in all the months while FLOW, ET, and WYLD showed temporal fluctuations throughout the year. The variation in the monthly FLOW and WYLD could be attributed to the monthly variation of temperature, leading to changes in ET. Therefore, the rise in the monthly FLOW and WYLD in June, July, August, September, and October could be attributed to the reduction in evapotranspiration, while lower FLOW and WYLD during the other months may be due to increased evapotranspiration rates.

To compare the impacts due to both alterations in LULC and climate, we computed the annual mean difference (in percentage) between the change scenarios (A, B, and C) and the baseline scenario as depicted in Fig. 6. The association between changes in the simulated parameters and changes in the LULC types at the sub-basin level can be visualized by comparing Fig. 4 with Fig. 6. The results show that the difference in the simulated annual mean FLOW, ET, SW, and WYLD was small. Also, Figs. 7, 8, and 9 give a spatial comparison (at the sub-basin scale) of the change in the distribution of monthly mean ET, SW and WYLD under the three different LULC and climate scenarios. From Fig. 4, which is based on scenario B, the monthly mean FLOW and WYLD decreased by a monthly average of 0.02% and 0.11%, respectively. The monthly mean FLOW and WYLD showed slight increases mainly in the months without rain and slight

Fig. 4 The spatial distribution of the percentage change in land use types between 1987 and 2011 at sub-basin scale

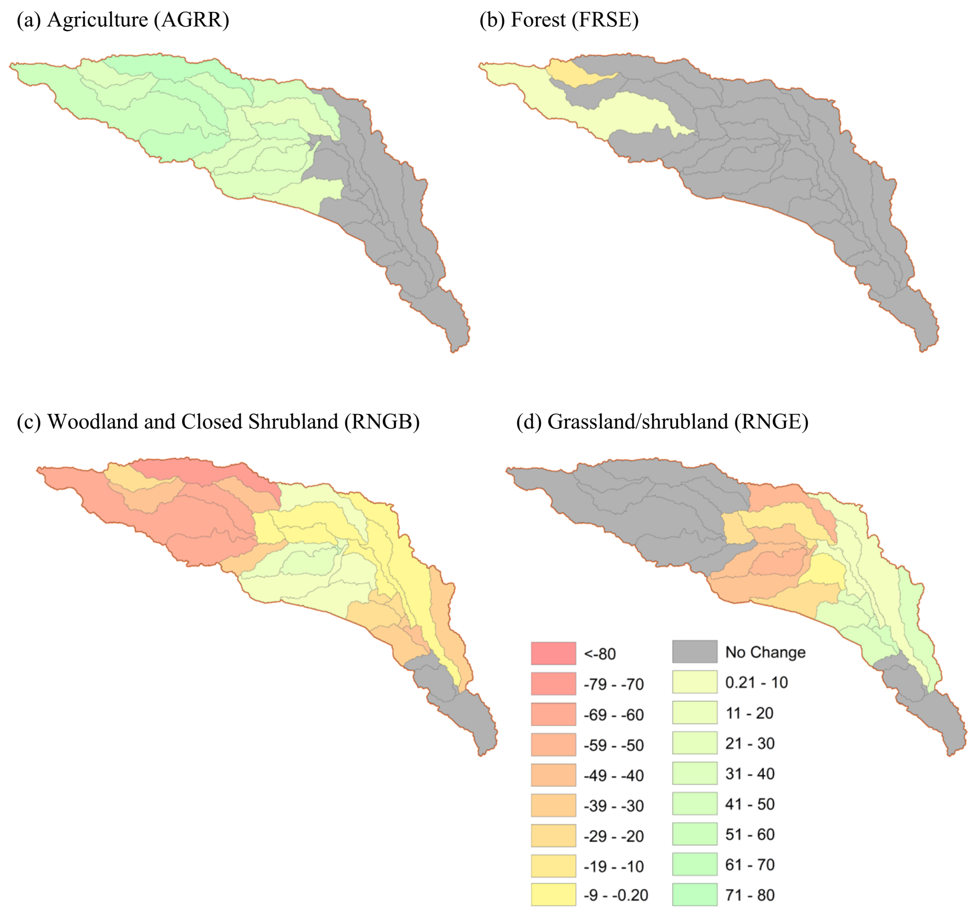

Table 6 Percent difference in the monthly mean parameters (FLOW, ET, SW, and WYLD) simulated from a combination of different land use and climate scenarios and the baseline simulation

Simulated parameter	Simulated scenarios	Mean monthly difference (%) between scenarios and baseline simulation											
		Jan	Feb	March	April	May	June	July	August	Sept	Oct	Nov	Dec
FLOW	A	−43.79	−58.72	−52.21	−39.8	−33.33	−39.41	−49.78	−54.29	−56.88	−36.55	−8.42	−44.88
	B	−0.24	−0.4	0.03	−0.41	−0.58	0.2	0.57	0.7	0.81	0.49	−0.48	−0.67
	C	−43.8	−58.54	−52.02	−40.21	−33.87	−39.51	−49.51	−53.91	−56.4	−36.82	−9.02	−45.11
ET	A	−26.75	−33.14	−22.31	−14.4	−19.02	−24.41	−32.68	−25.63	−37.87	4.77	−0.92	−21.71
	B	0.66	1.4	0.55	0.51	0.39	0.63	−0.13	−0.58	−0.11	−0.12	−0.22	−0.2
	C	−26.13	−31.9	−21.87	−13.79	−18.57	−24.36	−32.84	−25.99	−37.73	4.61	−1.14	−21.83
SW	A	−13.37	−9.88	−18.7	−5.06	−15.31	−19.85	−23.97	−29.81	−45.23	12.43	2.43	−0.77
	B	2.29	1.89	1.73	1.26	1.42	1.57	1.98	2.96	3.8	2.54	2.09	2.34
	C	−11.14	−7.94	−17.01	−3.9	−14.27	−18.48	−22.27	−27.36	−42.32	14.93	4.46	1.54
WYLD	A	−81.66	−85.25	−77.6	−50.22	−61.27	−82.11	−83.95	−80.36	−84.68	−32.4	−47.74	−76.17
	B	−0.12	−0.23	−0.17	−0.8	−0.37	0.61	0.47	0.47	0.31	−0.35	−0.65	−0.49
	C	−81.6	−85.22	−77.67	−50.92	−61.62	−81.83	−83.68	−80.2	−84.45	−33.34	−48.29	−76.31

The parameters were simulated based on A, holding land use constant and changing climate; B, changing land use and holding climate constant; and C, changing both land use and climate

decreases in the wetter period. The comparison of annual mean ET and SW between scenario B and the baseline showed an increase of about 0.2% and 2.2%, respectively. Therefore, based on this analysis and by comparing Fig. 4 with Fig. 5, it is observed that conversion of land use from woodland and closed shrubland to agriculture and grassland

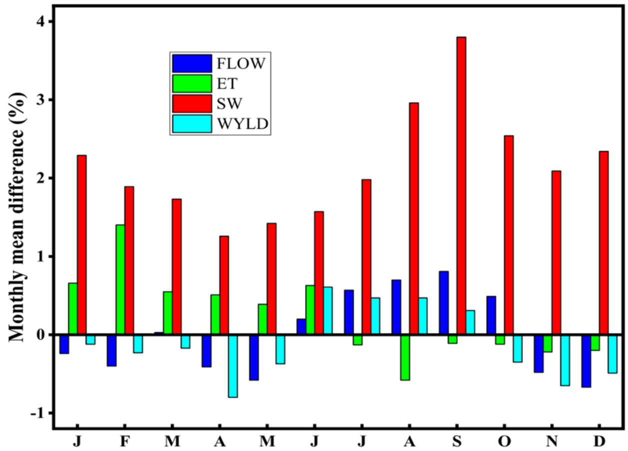

Fig. 5 The impact due to changes in LULC on the hydrological processes in the catchment (defined as the monthly mean difference (%) between scenario B and the baseline scenario)

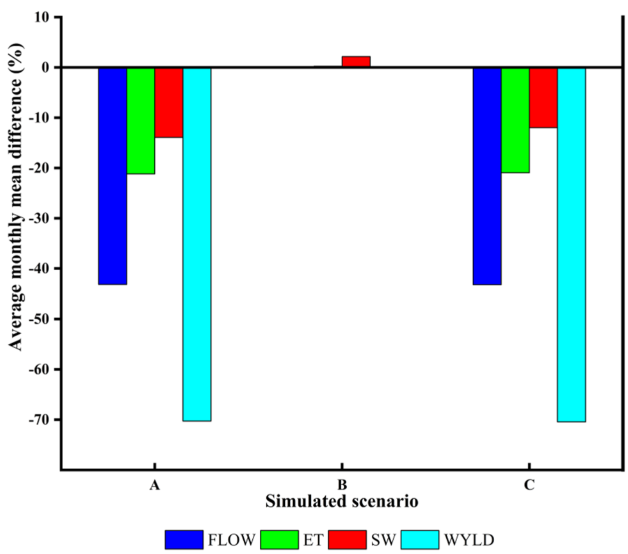

Fig. 6 The annual mean difference (%) of FLOW, ET, SW, and WYLD for the three different scenarios (i.e., the changing scenario minus the baseline scenario)

led to a small decrease in the volume of simulated FLOW and WYLD and a small increase in ET and SW. However, varying the climate used for simulation produced significant differences between the values simulated in the different scenarios and those simulated based on the baseline scenario. All the simulated parameters decreased when the climate was changed from the 1980s (baseline) to the 2000s. This reduction in the simulated parameters could be an indication of reduced rainfall during this particular decade when compared with the baseline period. Although the analysis of rainfall variation in the sub-basin was not within the scope of this particular study, a study by Polong et al. (2019) conducted over the Tana River Basin (TRB) found that there was a period of enhanced drought conditions over the highlands in the basin during the 2000 decades compared to the decade preceeding it. However, the outcomes arising from altering both LULC and climate on the simulated parameters were slightly higher than the climate change-only effect. In both scenarios A and C, the average annual mean FLOW decreased by about 43.2%, ET by about 21%, SW by about 13%, and WYLD by over 70%. The difference between scenario A (changing climate only) and scenario C (changing both land use and climate) was very small, implying that climate changes had a dominant impact on watershed hydrologic dynamics. Further analysis of SWAT output indicated that converting land use type to agriculture and/or grassland decreased the simulated parameters' values. It is also shown that the apparent increase in the forest class had a negligible effect on the simulated hydrological parameters. This is probably due to the concomitant large increase in land use classes for agriculture and grassland. Like the study by Zuo et al. (2016), this scenario indicates that the effect of LULC change on the simulated parameters may not be apparent because the effects of climate change play a dominant role. A study by Li et al. (2015) in the Heihe River Basin found that by expanding forest and grassland caused a significant decrease in the quick response runoff, which caused an overall decrease in the water yield. Wagner et al. (2013) found a positive correlation between an increase in cropland and ET.

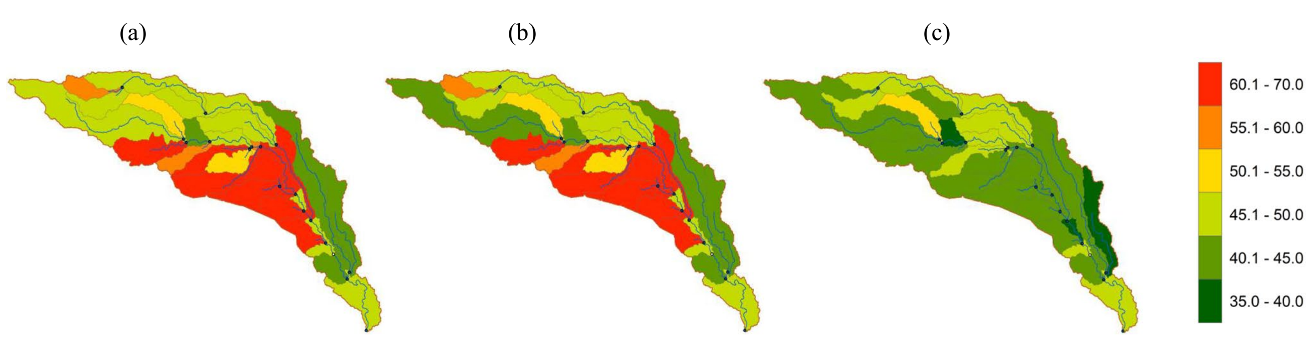

Fig. 7 The spatial variability of monthly ET under 3 different scenarios: (**a**) 1987 land use and 1980s climate, (**b**) 2011 land use and 1980s climate, and (**c**) 2011 land use and 2000s climate

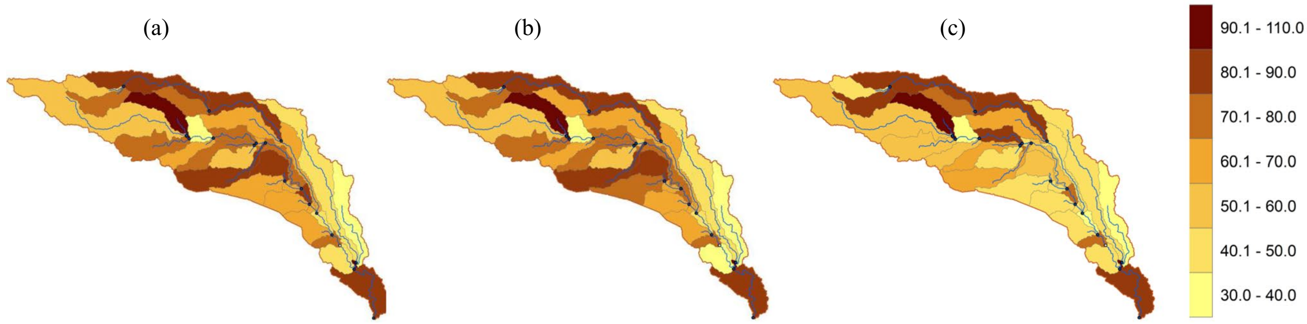

Fig. 8 Spatial variability of monthly SW under 3 different scenarios: (**a**) 1987 land use and 1980s climate, (**b**) 2011 land use and 1980s climate, and (**c**) 2011 land use and 2000s climate

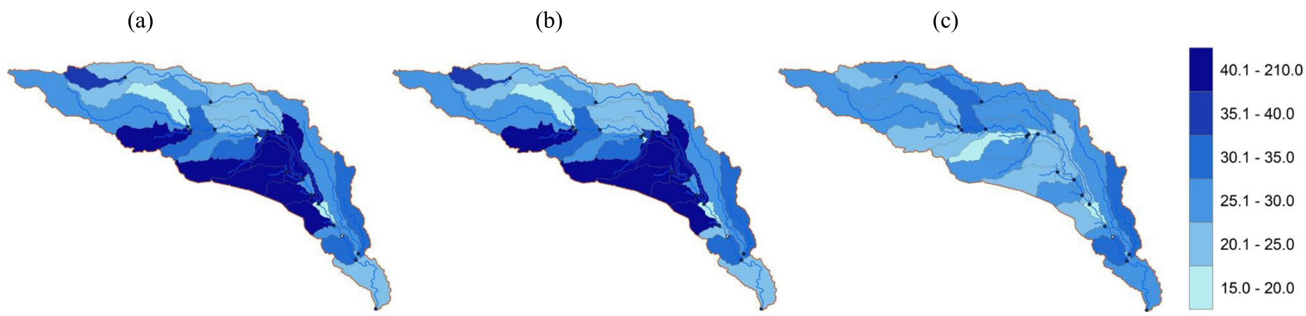

Fig. 9 Spatial variability of monthly WYLD under 3 different scenarios: (**a**) 1987 land use and 1980s climate, (**b**) 2011 land use and 1980s climate, and (**c**) 2011 land use and 2000s climate

4 Discussion

A small contributing sub-catchment of the Tana River Basin was chosen to assess, contrast, and attribute the impacts arising from alterations in LULC and climate on hydrological processes. The SWAT model was utilized to assess and contrast the simulated hydrological model outputs from an initial period (baseline) with outputs from three (3) different LULC and climate scenarios. The process of calibrating and validating SWAT produced relatively good results despite the relatively poor quality of the measured data in the catchment, which is a common problem in the African river basins. Abbaspour et al. (2007) observed that calibrating hydrological models for catchment scale is arduous and impeded by unpredictability, which may be associated with hidden processes not visible to the modeler eludes the model, and also when the model over-simplifies the modeling processes. The problem is far more critical in Africa because of the acute scarcity of measured data, despite the region being the most desirous of scientific information to inform and back up efforts of catchment water resource management and planning. In hydrologic modeling studies, it is expected that uncertainties in the model would result from model structure, parameter values, and input data. Kavetski et al. (2006) noted that uncertainties associated with precipitation and runoff data (input/output data) as well as errors inherent in the model might significantly affect the capability of hydrological models to estimate parameters. The availability of good quality and continuous daily discharge measurements is necessary for calibration, which is imperative as a sign of an apt-performing model. Also, this study used input data based on satellite estimates (for precipitation) and reanalysis data (for temperature, solar radiation, and wind), which may introduce significant uncertainties in the model results. This is because data biases are often introduced during field measurements, inventorying processes, data aggregation, and when spatially analyzing extended series of space and time data (Kavetski et al. 2006; Verburg et al. 2011).

Moreover, there is a possibility of errors being introduced to the model during the process of interpreting remote-sensed imagery. Model performance could also be affected by the calibrated parameters that may not necessarily depict the catchment's actual conditions. The difference between SWAT achievement during the calibration and validation periods could be attributed to differences in climatic conditions existing in the two periods. It is appreciated that uncertainties compromise hydrological modeling and may potentially yield biased and misleading results. Nevertheless, this study shows that SWAT achievement was considered good for modeling of the catchment hydrological processes as per the protocol developed by Moriasi et al. (2007).

Changes in LULC between 1987 and 2011 mainly increased in the area under agriculture and clearing of woodland and shrubland through unsustainable energy conversion activities (e.g., charcoal burning). The modest increase in forest cover in the upper part of the catchment could be attributed to the government's recent sustained efforts to conserve forest resources. The changes in LULC had far fewer effects on hydrologic conditions of the catchment when contrasted with changes in climate. These findings are consistent with Lahmer et al. (2001), which showed that moderate variations in LULC in mesoscale catchment produce only minimal changes in the hydrological components of the water balance. Zheng et al. (2016) noted that the catchment evapotranspiration increases, and streamflow declines when forestland is expanded, and cropland is reduced. They observed that an increase in the total water loss in the catchment is probably due to rising air temperature, leading to an increase in potential evapotranspiration in the catchment. Like Welde and Gebremariam (2017), the observed monthly mean differences in the simulated parameters could be caused by LULC dynamics in the catchment. We found the results of this study to be comparable with the findings by Ghaffari et al. (2010), which deduced that because of the effect of enhanced ET, the rate of loss of water is higher in grassland than shrubland, agricultural land, and bare ground. Their study which was undertaken in the Zanjanrood Basin of Northwest Iran showed that when the area under rain-fed agriculture was increased by 12% between 1967 and 2007, then by 2007, there occurred a 43% increase in mean annual land surface flow. Conversion of woodland and closed shrubland (which have a more closed canopy) to agriculture and grassland (more open/bare) made the catchment to be more susceptible to surface runoff. Hence, the increase in FLOW and WYLD mainly during the dry season could be due to low interception of rainfall and a higher curve number because the soils are either poorly covered or bare.

This study shows that when variations in both LULC and climate occur in tandem, they exacerbate the magnitude of change in hydrological conditions in the watershed. The enhanced effects of LULC and climate changes could be attributed to the varied responses of the different land use patterns to rainfall-runoff relationships. For this study, it is expected that FLOW and WYLD will increase, considering that agriculture and grassland increased at the expense of woodland and closed shrubland. Li et al. (2009) observed that runoff decreased when grassland was converted to woodland but increased when the woodland cover was reduced and increased land. It is apparent that different patterns of LULC generate different amounts of FLOW and WYLD, and thus, it can be deduced that the reason for the increases in both FLOW and WYLD in this catchment is that woodland and closed shrubland has been replaced by agriculture and grassland. Some studies have suggested that the varied response among the different types of LULC could be associated with changes in canopy structure, the curve number (CN) value, and surface roughness (Ghaffari et al. 2010). Marhaento et al. (2018) observed that hydrological responses in the catchment are mainly affected by variations in the curve number (CN) whenever there is a change in LULC, whereby streamflow increases and ET decreases when the curve number increases. When changes in both LULC and climate (scenario C) are considered, it is observed that the volumes of the simulated parameters are slightly amplified. This scenario brings out the critical role of the synergy observed when both LULC and climate changes occur concurrently and the impacts on the catchment hydrological processes. Similar to the observations of Hu et al. (2005), this study has shown that significant changes in the surface hydrology of a catchment may occur when both LULC and climate changes occur in the catchment.

Moreover, such changes may significantly affect the aquatic as well as terrestrial ecosystems in a basin. It is observed that the generation of hydrological processes in the catchment is influenced by the variable spatial disposition of different LULC types. This study's findings are similar to Yin et al. (2017), which reported that variations in surface runoff arose because of the modification of SW and ET brought about by LULC changes occurring in the catchment. For our case, there is a possibility that by converting woodland and closed shrubland to agriculture enhanced infiltration and soil moisture in the catchment. The findings in this study suggest that the fluctuations of the hydrological parameters are influenced less by changes in LULC and more by variations in climate.

5 Conclusion

This study assessed the impacts of isolated and combined changes in LULC and climate on hydrological processes in a small noubtainous catchment situated in the Tana River Basin. The catchment area has a rugged and complex topography because of its mountainous nature, and measurement data were acutely scarce. The SWAT model was applied to quantify and isolate the effects due to a changing LULC and climate regime as represented by the simulated hydrological components in the sub-catchment. The model performance metrics proved the suitability of the SWAT model as a reliable tool for capturing the impacts of environmental changes in catchments. R^2, NSE, PBIAS, and RSR for daily streamflow were 0.76, 0.73, 3.16%, and 0.51 when calibrating period and 0.54, 0.45, 12.5%, and 0.79 when validating, respectively, which is an indication that SWAT performance was good.

During the study period, the significant changes in LULC were the increase in agriculture and grassland and the reduction in woodland and shrubland. The findings of this study demonstrate that separate (individual) changes in LULC and climate action are the driving force to the changing catchment hydrological processes, although it is observed that the impacts are more pronounced when the two drivers act concurrently (i.e., in combination). Simulation results revealed that climate change had a more significant effect on the simulated parameters than the change in LULC. The study showed that by altering both LULC and climate on the simulated parameters was slightly higher than the climate change-only effect. In both scenarios A (changing climate) and C (changing both climate and LULC), the average annual mean FLOW decreased by about 43.2%, ET by about 21%, SW by about 13%, and WYLD by over 70%. The difference between scenario A (changing climate only) and scenario C (changing both land use and climate) was very small, implying that climate changes had a dominant impact on watershed hydrologic dynamics. Further analysis of SWAT output indicated that converting land use type to agriculture and/or grassland decreased the simulated parameters' values. It is also shown that the apparent increase in the forest class had a negligible effect on the simulated hydrological parameters. This is probably due to the concomitant large increase in land use classes for agriculture and grassland.

Suffice to say that the application of SWAT with generally available data allowed for adequate assessment, quantification, and attribution of impacts due to LULC and climate changes upon catchment hydrological processes in a data-scarce catchment like the TRB. It is envisioned that knowledge gained will enhance our understanding of impacts arising from changes in LULC and climate on hydrologic conditions in the TRB. Also, from an application perspective, the findings may be valuable to watershed managers for decision-making, especially in the light of a changing LULC and climate regime in the TRB. Furthermore, the use of remote-sensed data with reliable precision and high resolution (e.g., precipitation and LULC data) might reduce uncertainty and accuracy improvement of the hydrological model and prediction in the data-scarce catchments. The relatively subdued effects of LULC on the hydrological processes may partly be attributed to the small size of the catchment, which renders the extent of the overall change in total acreage to be very small. Nevertheless, with the recent significant changes in LULC patterns in the wider TRB catchment, the effect of changes associated with LULC is of immediate concern when assessing impacts on water resources. This study has demonstrated the possibility of utilizing satellite-based data (precipitation estimates and land use data) as alternative sources of data required by SWAT for modeling in an ungauged and data-scarce catchment such as the TRB.

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Authors Contribution Francis Polong: project administration, conceptualization, writing—original draft, software, formal analysis, visualization. Khidir Deng, Quoc Bao Pham, Nguyen Thi Thuy Linh, S.I. Abba, Ali Najah Ahmed: formal analysis; writing—original draft, visualization. Khaled Mohamed Khedher: data curation, writing, review and editing. Duong Tran Anh, Ahmed El-Shafie: supervision, writing, review, editing.

Data availability The data that support the findings of this study are available from Quoc Bao Pham, phambaoquoc@tdmu.edu.vn, upon reasonable request.

Code availability Code is available from Quoc Bao Pham, phambaoquoc@tdmu.edu.vn, upon reasonable request.

Declarations

Ethics approval Not applicable.

Consent to participate Not applicable.

Consent for publication Not applicable.

Conflict of interest The authors declare no competing interests.

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