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Land use and climate change impacts on the hydrology of the upper Mara River Basin, Kenya: results of a modeling study to support better resource management

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Abstract. Some of the most valued natural and cultural landscapes on Earth lie in river basins that are poorly gauged and have incomplete historical climate and runoff records. The Mara River Basin of East Africa is such a basin. It hosts the internationally renowned Mara-Serengeti landscape as well as a rich mixture of indigenous cultures. The Mara River is the sole source of surface water to the landscape during the dry season and periods of drought. During recent years, the flow of the Mara River has become increasingly erratic, especially in the upper reaches, and resource managers are hampered by a lack of understanding of the relative influence of different sources of flow alteration. Uncertainties about the impacts of future climate change compound the challenges. We applied the Soil Water Assessment Tool (SWAT) to investigate the response of the headwater hydrology of the Mara River to scenarios of continued land use change and projected climate change. Under the data-scarce conditions of the basin, model performance was improved using satellite-based estimated rainfall data, which may also improve the usefulness of runoff models in other parts of East Africa. The results of the analysis indicate that any further conversion of forests to agriculture and grassland in the basin headwaters is likely to reduce dry season flows and increase peak flows, leading to greater water scarcity at critical times of the year and exacerbating erosion on hillslopes. Most climate change projections for the region call for modest and seasonally variable increases in precipitation (5–10 %) accompanied by increases in temperature (2.5–3.5 °C). Simulated runoff responses to climate change scenarios were non-linear and suggest the basin is highly vulnerable under low (−3 %) and high (+25 %) extremes of projected precipitation changes, but under median projections (+7 %) there is little impact on annual water yields or mean discharge. Modest increases in precipitation are partitioned largely to increased evapotranspiration. Overall, model results support the existing efforts of Mara water resource managers to protect headwater forests and indicate that additional emphasis should be placed on improving land management practices that enhance infiltration and aquifer recharge as part of a wider program of climate change adaptation.

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1 Introduction

Water is a critical resource in Kenya, central to the conservation of ecosystems but also to the development of agriculture, industry, power generation, livestock production, and other important economic activities. However, with an annual average rainfall of just 630 mm and population approaching 40 million people, Kenya is also categorized as a water scarce country (WRI, 2007). The scarcity of this crucial resource requires that it be managed properly, and proper management requires reliable information on flows and models that can be used to evaluate scenarios of changing land use and climate.

Understanding the hydrologic response of watersheds to physical (land use) and climatic (rainfall and air temperature) change is an important component of water resource planning and management (Vorosmarty et al., 2000). Land use change in Africa included the conversion of 75 million hectares of forest to agriculture and pasture between the years 1990 and 2010, a rate second only to that in South America (FAO, 2010). In East Africa, nearly 13 million hectares of original forest were lost over the same 20 year period, and the remaining forest is fragmented and continually under threat (FAO, 2010). The impacts of land use change on river basin hydrology are interlinked with impacts of climate change. Observed climatic changes in Africa include warming of 0.7 °C over the 20th century, 0.05 °C warming per decade and increased precipitation for East Africa. Future projections by the Intergovernmental Panel on Climate Change (IPCC) include warming from 0.2 °C (low scenario) to more than 0.5 °C per decade (high scenario), 5–20 % increase in precipitation from December-February (wet months) and 5–10 % decrease in precipitation from June–August (dry months) (Hulme et al., 2001; IPCC, 2001, 2007). Overall, annual mean rainfall in East Africa is projected to increase during the first part of the century (Christensen et al., 2007).

Effective planning of water resource use and protection under changing conditions requires the use of basin runoff models that can simulate flow regimes under different scenarios of change. Accurately modeling future runoff regimes is challenging in African catchments with limited current and historical runoff data, but an increasing number of model applications suggest that useful simulations are possible. Using coarse resolution datasets such as a 90 m resolution Shuttle Radar Topography Mission (SRTM) DEM, a 1:50 000 scale land use map and incomplete rainfall data, Setegn et al. (2009, 2011) used the Soil Water Assessment Tool (SWAT) model to simulate the hydrology and impact of climate change on the hydroclimatology of the Lake Tana Basin in Ethiopia. Similarly, Jayakrishnan et al. (2005) used the SWAT model to model runoff in the Sondu River basin in Kenya. In the upper Tana River catchment in Kenya, Jacobs et al. (2007) used SWAT to test the effectiveness of alternative land use interventions. This was done using coarse soil data sets (1:1 000 000). Mulungu and Munishi (2007) used the SWAT model to parameterize the Simiyu catchment, Tanzania, with a view of using the baseline results for application in similar areas around the country and ungauged watersheds for land/water management studies. And Mutie at al. (2006) applied the USGS Geo Streamflow Model to determine the extent and effect of land use and land cover change on the flow regime of the transboundary Mara River in Kenya and Tanzania. While caution must be applied when interpreting and communicating the results of these modeling efforts, and value must be measured in both heuristic and algorithmic terms, their development positively contributes to water resource planning efforts.

In this study, we seek to build upon past experiences in runoff modeling in East African river basins and inform water resource planning in one of East Africa's most valued river basins, the Mara Basin of Kenya and Tanzania. The Mara is typical of many East African basins in the mix of land use, climate, and socioeconomic change that challenge water resource managers. The Mara River also has a higher international profile as the only year-round source of surface water to two renowned conservation areas, Masai Mara National Reserve and Serengeti National Park (Gereta et al., 2002).

The specific objectives of this study are to assess the sensitivity of land use change, rainfall and air temperature variation on the water flux of the upper Mara River in Kenya. For this purpose, plausible scenarios of land use change are developed based on trends and information from the area, and climate change predictions are considered based on the IPCC Fourth Assessment Report (2007). The results of this research not only help water resource planning efforts, they also provide an evaluation of the application of semi-distributed, physically-based hydrological models such as the SWAT to data-scarce African watersheds with highly variable precipitation patterns.

2 Methodology

2.1 Study area

The transboundary Mara River basin is shared between Kenya and Tanzania and is located in East Africa between longitudes 33.88372° and 35.907682° W and latitudes −0.331573° and −1.975056° S (Fig. 1). It covers 13 750 km^2 and is 395 km long. The Mara River flows from its source at 3000 m in the Mau Forest in Kenya across different landscapes and drains into Lake Victoria at Musoma Bay in Tanzania. Major tributaries are the Nyangores, Amala, Talek, Sand and Engare Engito on the Kenyan side, and the Bologonja River on the Tanzanian side. The Nyangores and Amala sub-basins form the upstream part of the Mara River basin and are the main source of water throughout the year; the Nyangores River is the focus of this study. The Mara River is impacted by widespread human activities such as deforestation and subsequent cultivation of land beginning at the headwaters in the Mau forest complex (Fig. 1). Middle and lower sections of the Mara River Basin include human settlements, agricultural areas, protected areas such as the Masai Mara National Reserve and Serengeti National Park, and wetlands that are dependent on the availability of fresh water in adequate quality and quantity (Gereta et al., 2002; Mati et al., 2005).

2.2 SWAT model

SWAT is a semi-distributed model that can be applied at the river basin scale to simulate the impact of land management practices on water, sediment and agrochemical yields in large watersheds with varying soils, land use and agricultural conditions over extended time periods of time (Arnold

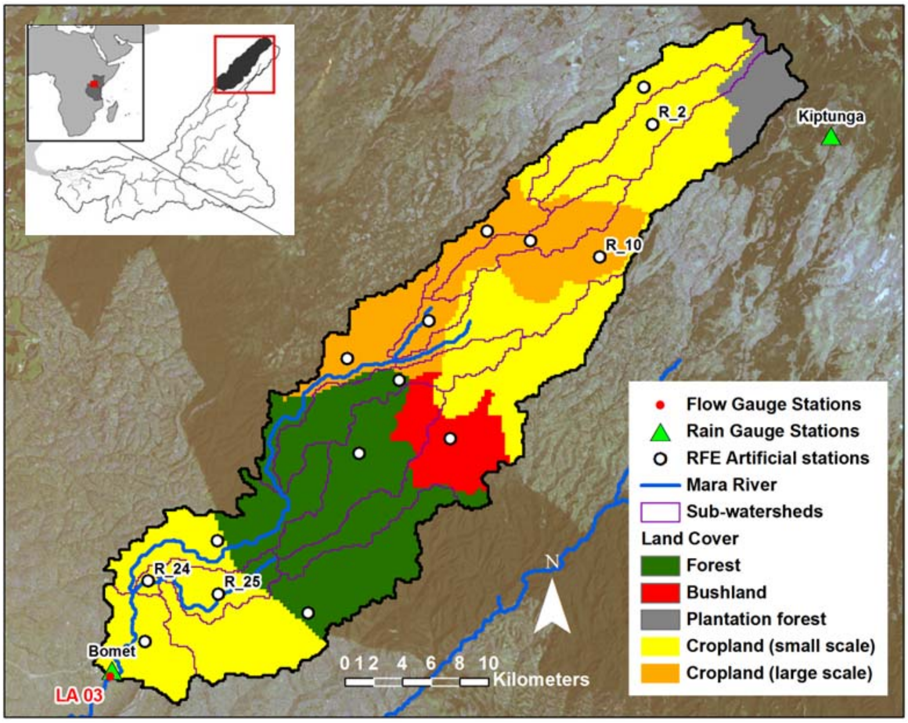

Fig. 1. Nyangores sub-basin, upper Mara River basin, Kenya.

et al., 1998). The design of SWAT makes it useful in modeling ungauged watersheds and, more importantly, simulating the impact of alternative input data such as changes in land use, land management practices and climate (Neitsch et al., 2005; Arnold et al., 1998). The interface in geographical information system (GIS) is convenient for the definition of watershed hydrologic features and storage, as well as the organization and manipulation of the related spatial and tabular data (Di Luzio et al., 2002). While specialized processes can be simulated if sufficient input data are available, SWAT also runs with minimum data inputs, which is advantageous when working in areas with limited data. SWAT is computationally efficient and therefore able to run simulations of very large basins or management practices without consuming large amounts of time or computational resources. Lastly, SWAT is a continuous time model able to simulate long-term impacts of land use, land management practices and build-up of pollutants (Neitsch et al., 2005). These qualities of the SWAT model aid in the quantification of long term impacts of land use changes and variations in rainfall and air temperature on the hydrology of the Mara River basin.

The SWAT model application can be divided into six steps: (1) data preparation, (2) sub-basin discretization, (3) HRU definition, (4) parameter sensitivity analysis, (5) calibration and validation, and (6) uncertainty analysis. The flowchart showing the modeling steps is shown in Fig. 2.

2.2.1 Data preparation

Hydrological modeling using SWAT requires the use of spatially explicit datasets for land morphology or topography, land use or land cover, soil parameters for hydrological characteristics, and climate and hydrological data on a daily time-step (Schuol and Abbaspour, 2007). While general global, continental or regional datasets exist, they often lack sufficient spatial and temporal resolution or sufficient continuity in the time series records. In the case of the Mara River basin, available large-scale datasets for land use and rainfall were judged to be unacceptable for SWAT modeling. Thus, new, basin-specific datasets were developed from raw data sources for land use/land cover and for precipitation. A complete list of variables and utilized data sources is presented in Table 1. The preparation of data is described in the following sections.

Land use/land cover data

Land use and management is an important factor affecting different processes in the watershed, such as surface runoff, erosion, recharge and evapotranspiration. The land cover data were generated from the 30 meter resolution Landsat Thematic Mapper data acquired in 2008. Following the basic principles of the USGS land use/land cover classification system (LULCCS) for use with remote sensor data level classification (Anderson et al., 1976), a schema was formulated that

Table 1. Variables used in the SWAT model and data sources.

Variables	Data source
Land use/land cover map	Landsat 5 Thematic Mapper (USGS/ GLOVIS)
Soil map	Soil Terrain Database of East Africa (SOTER) Database
Digital Elevation Model	Shuttle Radar Topography Mission (SRTM)
Measured streamflow	Lake Victoria South Water Resource Management Authority
Measured rainfall	Lake Victoria South Water Resource Management Authority
Measured temperature	Lake Victoria South Water Resource Management Authority

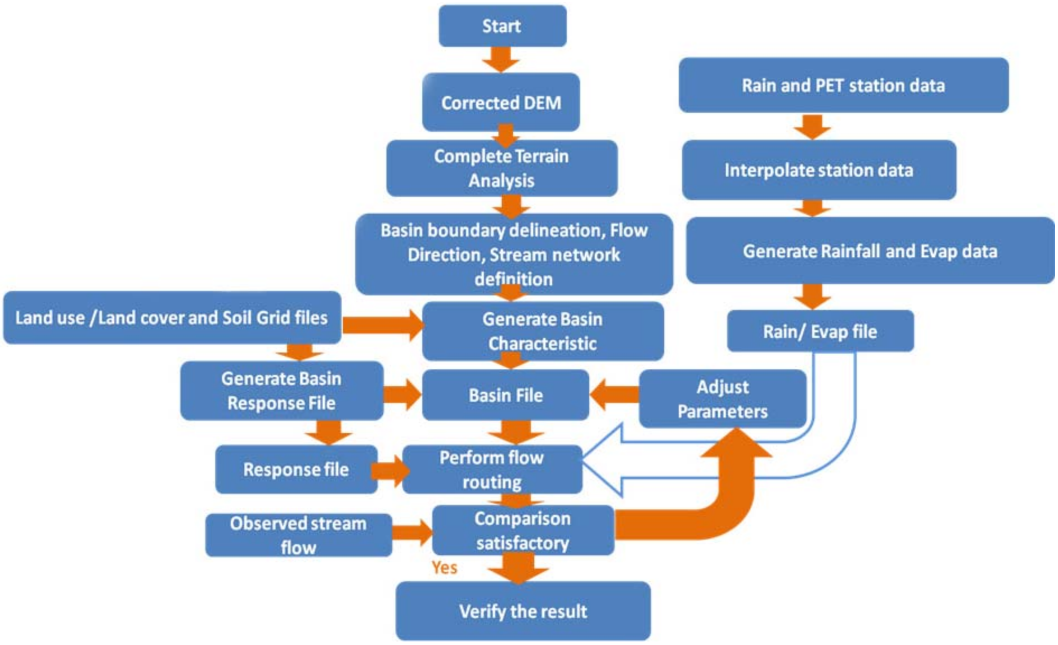

Fig. 2. Flow chart of the modeling process, inputs and outputs.

would adequately represent the land cover/land use within the Mara River basin and at the same time allow for reclassification to match classes that are comparable to the SWAT land cover and land use database (Table 2). For the purpose of this study, the land cover classes generated for the study area are (1) bushland including shrubs, (2) forest composed of primary and secondary forest including forestry plantations, (3) water and (4) cropland which was annual plants mainly general crops including small scale and large scale agriculture and (5) cropland tea consisting of small and large scale tea plantations. This distinction for cropland was established based on the fact that annual crops undergo a yearly cycle that leaves plots barren for part of the year. The cropland class includes plots at all stages of the cycle including bare soil.

The image classification was performed using a supervised machine learning procedure that uses a binary recursive partitioning algorithm in a conditional inference framework (Hothorn et al., 2006) c-tree procedure in the party

Table 2. Land use/land cover type reclassification into SWAT LU/LC classes.

Landsat image classification	Refined Land Cover Type	SWAT LU/LC Type
Forest	Plantation forest	Forest Deciduous
	Forest	Forest Evergreen
Bushland	Bushland	Forest Mixed
Cropland	Cropland (small scale)	Agricultural Land Close Grown
	Cropland (large scale and plantations)	Agricultural Land Generic
Cropland Tea	Tea Plantations	
Water	Water	Water

Table 3. Land cover classification accuracies as provided by binary recursive partitioning algorithm in conditional inference framework. comError = proportional error of commission, omError = proportional error of omission.

Reference Data	Cropland	Cropland Tea	Bushland	Forest	Water	Row Total	ComError	ComError (%)
Cropland	439	3	13	4	0	459	0.04	4.4
Cropland Tea	2	35	0	0	0	37	0.05	5.4
Bushland	26	0	74	19	0	119	0.38	37.8
Forest	1	2	14	203	1	221	0.08	8.1
Water	0	0	0	1	6	7	0.14	14.3
Column Total (pixels)	468	40	101	227	7	843		
OmError	0.06	0.13	0.27	0.11	0.14			
OmError (%)	6.2	12.5	26.7	10.6	14.3			
Accuracy (%)	93.8	87.5	73.3	89.4	85.7			
Overall Accuracy (%)	89.8							
Kappa Coeff.	83.2							

package of the statistical software R. Estimates for class specific and overall accuracy were performed on the training set with 843 samples. The resultant error matrix gave a Kappa coefficient value of 83 % while the overall classification accuracy for the classification was 90 % (Table 3). The class with the highest accuracy is cropland (93.8 %) followed by forest (89.4 %), cropland tea (87.5 %), water (85.7 %) and bushland (73.3 %). The highest omission and commission errors were associated with bushland. The resulting classification was then refined to a finer classification that was made possible using data from a field ground referencing study in order to better represent the land cover in the study area. This was then reclassified to the SWAT land use/land cover type.

Climate data

Climate data used in the SWAT model consist of daily rainfall, temperature, wind speed, humidity and evapotranspiration data. The weather variables used were the daily precipitation values obtained from the Bomet and Kiptunga stations. The minimum and maximum air temperature values for the period of 1996–2003 from the Kericho Hail Research and Narok Meteorological weather stations (Fig. 1) were obtained from the Ministry of Water Resources of Kenya and the Lake Victoria South Water Resource Management Authority in Kenya. The daily rainfall records from these stations were complete and had no data values missing. The spatial location of these 2 stations, however, was a cause of concern in this study and raised the question of whether the data would be sufficient to accurately represent the rainfall received across the entire watershed. Based on these concerns, additional data were sought to augment the rainfall dataset.

Augmentation of the rainfall data record for the hydrological modeling was achieved by utilizing rainfall estimates derived from remotely sensed data as provided by the Famine Early Warning System (FEWS) daily Rainfall Estimate (RFE). RFE data are derived from Meteosat infrared data and stationary rain gauges generating daily rainfall estimates at a horizontal resolution of 10 km (Xie and Arkin, 1997). The rainfall time series for the SWAT model was obtained by calculating daily area weighted averages across all 30 delineated sub-catchments that form the Amala and Nyangores sub-basins. The continuous and complete time series was then applied to the virtual rain gauges represented by the centroids of the delineated sub-watersheds (Fig. 1). The rainfall estimates were processed for the time period from 1 January 2002, to 31 December 2008. A comparison of the RFE estimates with the observed rainfall records was carried out using stations that were in the same locations and for the same period of time. The data from these stations were plotted and exhibited similarities in trend. The two different sources differed in magnitude with different peaks in rainfall amounts and this can be attributed to spatial location and the nature of point estimation of rainfall that makes it difficult to capture variations in amounts of rainfall in an area especially without a dense network of ground stations.

Soil data

The response of a river basin to a rainfall event depends on the nature and conditions of underlying soils (Shrestha et al., 2008). The SWAT model requires soil property data such as the texture, chemical composition, physical properties, available moisture content, hydraulic conductivity, bulk density and organic carbon content for the different layers of

Table 4. Texture of the soils in the Upper Mara (FAO Soil Database).

Soil type code	Clay %	Silt %	Sand %
KE200	31	29	40
KE196	42	42	16
KE386	41	29	30
KE45	9	67	24
KE187	38	35	27
KE183	30	26	44
KE190	10	28	62
KE192	20	48	32

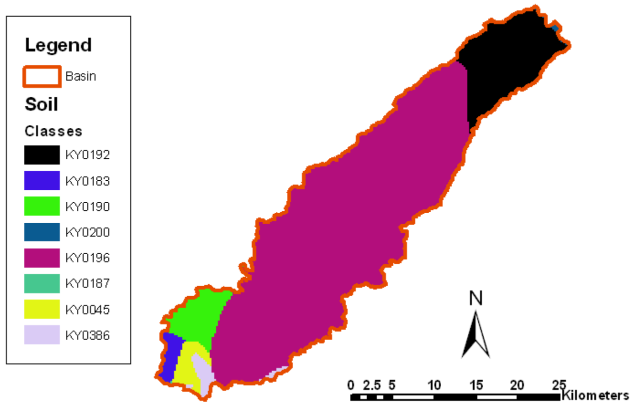

Fig. 3. Nyangores sub-basin soil types (FAO Soil database).

each soil type (Setegn et al., 2009). Soil data were obtained from the 1:2 000 000 Soil Terrain Database of East Africa (SOTER) and the spatial distribution of classes are shown in Fig. 3. The most widespread soil class in the Nyangores sub-basin (KE196) consists of 42 % clay, 42 % silt, and 16 % sand. A soil property table (Table 4) specific for the Mara River basin soils was appended to the SWAT database because the soil types found in the study area are not included in the US soils database provided with SWAT.

River discharge

Daily river discharge data were obtained for the Nyangores River from the Bomet gauging station (LA03) located at the outlet of the basin (Fig. 1). The discharge values for the Nyangores River were used for calibration and validation of the model. The available discharge data for the Bomet gauging station ran from the year 1996 to the year 2008. For the period 1996–2003, the gauging record was >99 % complete. For the period from 2002–2008, the record was 93.4 % complete. Missing data values were replaced statistically by similar day averages for the previous years where there were existing data values. This approach was judged better than using the weather generator embedded in the SWAT model.

2.2.2 Sub-basin discretization

Topography is a necessary input in the SWAT model and is used in the delineation of the watershed and analysis of the land surface characteristics and drainage patterns. It influences the rate of movement and direction of flow over the land surface (Shrestha et al., 2008). The digital elevation model (DEM) with 90 m by 90 m horizontal resolution from the SRTM of NASA was used in this analysis.

2.2.3 Definition of hydrological response units

Hydrologic response units (HRUs) are portions of a sub-basin possessing unique combinations of land use, management or soil attributes and are incorporated into the SWAT model to account for the complexity of the landscape within the sub-basin (Neitsch et al., 2005). Watershed and sub-watershed delineation was carried out using the DEM and included various steps including: DEM setup, stream definition, outlet and inlet definition, watershed outlets selection and definition and calculation of sub-basin parameters. The resulting sub-watersheds were then divided into HRUs based on their combinations of land use, soil and slope combinations.

2.2.4 Sensitivity analysis

Twenty seven hydrological parameters were tested for identifying sensitive parameters for the simulation of stream flow using the Automated Latin Hypercube One-factor-At-a-Time (LH-OAT) global sensitivity analysis procedure (Van Griensven and Meixner, 2006). The ten most sensitive parameters (Table 5) were chosen for calibration of the model. These parameters were; baseflow alpha factor (ALPHA_BF), threshold water depth in the shallow aquifer for flow (GWQMN), soil evaporation compensation factor (ESCO), channel effective hydraulic conductivity (CH_K2), initial curve number (II) value (CN2), available water capacity (SOL_AWC), maximum canopy storage (CANMX), soil depth (SOL_Z), maximum potential leaf area index at the end of the time period (BLAI), and the water in the shallow aquifer returning to the root zone in response to a moisture deficit during the time step (mm H_2O). This also includes water uptake directly from the shallow aquifer by deep tree and shrub roots (GW_REVAP) and (REVAPMN) (Neitsch et al., 2005).

2.2.5 Model calibration and validation

The auto-calibration and uncertainty analysis were done using two different algorithms, i.e. Parameter Solution (ParaSol) (Van Griensven and Meixner, 2006) that is incorporated in SWAT and Sequential Uncertainty Fitting (SUFI-2) (Abbaspour et al., 2004, 2007).

Table 5. Sensitivity ranking of parameters for the SWAT modeling of flow using gauge data and estimated data.

Sensitivity Rank	Nyangores Rain Gauge	Nyangores RFE
1	ESCO	ESCO
2	CN2	GWQMN
3	ALPHA_BF	CN2
4	GWQMN	SOL_Z
5	SOL_Z	ALPHA_BF
6	REVAPMN	SOL_AWC
7	SOL_AWC	REVAPMN
8	CH_K2	CANMX
9	BLAI	GW_REVAP
10	CANMX	BLAI

ALPHA_BF = Baseflow alpha factor, GWQMN = threshold water depth in the shallow aquifer for flow, ESCO = Soil evaporation compensation factor, CH_K2 = Channel effective hydraulic conductivity, CN2 = Initial curve number (II) value, SOL_AWC = Available water capacity, CANMX = Maximum canopy storage, SOL_Z = Soil depth, BLAI = Maximum potential leaf area index at the end of the time period, GW_REVAP = the water in the shallow aquifer returning to the shallow aquifer returning to the root zone in response to a moisture deficit during the time step, REVAPMN = Threshold water depth in the shallow aquifer for "revap" to occur.

ParaSol is a multi-objective uncertainty method that is efficient in optimizing a model and providing parameter uncertainty estimates (Van Griensven and Meixner, 2006). It calculates objective functions (OF) based on the simulated and observed time series and aggregates the OFs into a Global Optimization Criterion (GOC). The optimization is done by adapting the Shuffled Complex Evolution Approach for effective and efficient global minimization method (SCA-UA). The SCA-UA algorithm is a global search algorithm for the minimization of a single function that is implemented to deal with up to 16 parameters (Duan et al., 1992).

SUFI-2 (Sequential Uncertainty Fitting) is the calibration algorithm developed by Abbaspour et al. (2004, 2007) for calibration of the SWAT model. In SUFI-2, parameter uncertainty accounts for all sources of uncertainties such as uncertainty in driving variables (e.g. rainfall), parameters, conceptual model, and measured data (e.g. observed flow, sediment).

For the rain gauge data model, out of the 8 years of complete time series datasets, 4 years were used for calibration and the remaining 4 years were used for validation. On the other hand, for the RFE model 4 years were used for calibration and 3 for validation. The length of the simulations was determined by the availability and length of time series data for discharge, air temperature and rainfall which are key pieces in the model simulation. The model was run on a default simulation of 8 years from 1996 to 2003 for the rain gauge data and from 2002 to 2005 for the RFE data. Comparisons were carried out for the datasets obtained. Statistical measures such as the Nash-Sutcliffe Efficiency (NSE) and the Coefficient of Correlation (R^2) were used to describe and compare the different datasets (observed and simulated).

2.2.6 Scenario analysis

Land use

To explore the sensitivity of model outputs to land use/land cover changes, mainly on the discharge of the Nyangores River, land use scenarios were developed and explored. Attempts were made to ensure these were realistic scenarios in accordance to the ongoing trends of land use change within the study area. The land use scenarios included;

1. Partial deforestation, conversion to agriculture (PDA): this scenario involved manipulation of the forest cover reducing it partially by converting the deciduous forest type to small scale or close grown agricultural land.

2. Complete deforestation, conversion to grassland (CDG): this scenario involved replacing all the existing forest cover with grassland to simulate a complete absence of forest cover in the watershed.

3. Complete deforestation, conversion to agriculture (CDA): replacement of forest land by agriculture is a common trend within the study area and is seen to be one of the major causes of erratic river flows and increased sediment load in the Nyangores River. This scenario was carried out by replacing all forest cover with agriculture particularly small scale agriculture.

Climate change scenarios

The climate change scenarios were based on downscaled General Circulation Models, regional projections of climate change based on those documented in IPCC Fourth Assessment Report (2007). The regional averages of temperature and precipitation projections were developed from a set of 21 global models in the MMD (multi-model data set) for the A1B scenario for East Africa shown in Table 6.

The Special Report on Emissions Scenarios (SRES) groups projections into four scenario families (A1, A2, B1 and B2) that explore alternative development pathways, covering a wide range of demographic, economic and technological driving forces and resulting GHG emissions. The A1 storyline assumes a world of very rapid economic growth, a global population that peaks in mid-century and rapid introduction of new and more efficient technologies. The SRES A1B Emissions Scenarios (a scenario in A1 family) describes "a future world of very rapid economic growth, global population that peaks in mid-century and declines thereafter, and rapid introduction of new and more efficient technologies" (IPCC, 2007).

The projections for mean temperature for the MMD-A1B scenario show an increase in the monthly seasons. For precipitation, the model ensemble shows an increase in rainfall

Table 6. Regional averages of temperature and precipitation projections from a set of 21 global models for the A1B scenario for East Africa (12° S, 22° E; 18° N, 52° E) (IPCC, 2007).

Season	Temperature Response (°C)					Precipitation Response (%)				
	Min	25*	50	75	Max	Min	25	50	75	Max
Dec–Feb		2.6	3.1	3.4	4.2	−3	6	13	16	33
Mar–May	1.7	2.7	3.2	3.5	4.5	−9	2	6	9	20
Jun–Aug	1.6	2.7	3.4	3.6	4.7	−18	−2	4	7	16
Sep–Nov	1.9	2.6	3.1	3.6	4.3	−10	3	7	13	38
Annual	1.8	2.5	3.2	3.4	4.3	−3	2	7	11	25

*25, 50 and 75 refer to quartiles.

in East Africa, extending into the Horn of Africa. The projected increase is robust, with 18 of 21 models projecting an increase in the core of this region, east of the Great Lakes. This East African increase is also evident in Hulme et al. (2001) and Ruosteenoja et al. (2003). Based on these projections, climate scenarios were explored for changes in temperature and changes in precipitation. Table 6 shows the minimum, maximum, median (50 %), and 25 % and 75 % quartile values among the 21 models, for temperature (°C) and precipitation (%) changes for East Africa. Based on the reported changes in temperature and precipitation, the hydrological model was run for minimum, median and maximum change scenarios. The climate change projections were applied by adjusting the monthly precipitation and temperature files in the model for the different seasons (December to February, March to May, June to August and September to November) and running the simulations with the best parameters acquired from the model calibration process.

3 Results and discussion

The results of this study provide new insights about modeling runoff in data-scarce African river basins and also suggest differing responses of land-use and climate change that will be helpful for water resource managers. Regional rainfall estimates from the FEWS Network were found to improve model performance compared to rainfall taken from the few local measuring stations in the vicinity of the catchment. This finding has ramifications for improved modeling of runoff over large areas of Africa where precipitation stations are lacking but estimated rainfall data are available. Use of the calibrated model to explore the potential impacts of continued land use change and future climate change indicates that any additional conversion of forest to agriculture or grassland will adversely affect runoff at critical low-water times of the year and during droughts, increase peak flows and associated hillslope erosion, and increase the vulnerability of the basin to future climate change. Simulations of runoff responses to projected increases in precipitation and temperature during this century indicate nonlinear responses over the range of potential changes. These observations are consistent with trends reported from the basin and support water managers in their efforts to protect headwater forests and promote improved land management in the basin. Each of these findings is considered in more detail in the flowing sections.

3.1 Model performance using gauged versus RFE rainfall data

The observed rainfall from local precipitation stations and RFE data were plotted for comparison and show similarities in trend but also large differences (Fig. 4). The resulting hydrographs from preliminary SWAT discharge results also show similarities in trend (Fig. 5) and results based on both datasets were evaluated further. The ten most sensitive parameters were chosen for calibration of the models and the five most sensitive parameters (Rank 1–5) were the same for both rainfall sources. These are mainly associated with soil, surface and ground water parameters (Table 5). In the case of the Nyangores rain gauge data model, however, there was a clear underperformance and the low NSE and R^2 values of −0.53 and 0.085, respectively, for the calibration period were considered poor (Table 7). The poor model performance using data from limited rain gauges was attributed mainly to the very coarse spatial distribution of climate stations in the catchment. Results for the model using RFE data indicated a better, but still only fair, agreement between the observed and simulated discharge and resulted in an NSE value of 0.43 and an R^2 value of 0.56 for the calibration period.

Validation was carried out to determine the suitability of the models for evaluating the impacts of land use and climate change scenarios. For the RFE model, an NSE value of 0.23 was obtained for validation. This NSE value is better than the −0.06 obtained from the rain gauge data model but not good enough that the model could be used to accurately simulate hydrological processes in the basin. Taking into consideration errors that may have been introduced by missing data values, the SWAT model was, however, considered suitable to explore basic responses of Mara River flow to

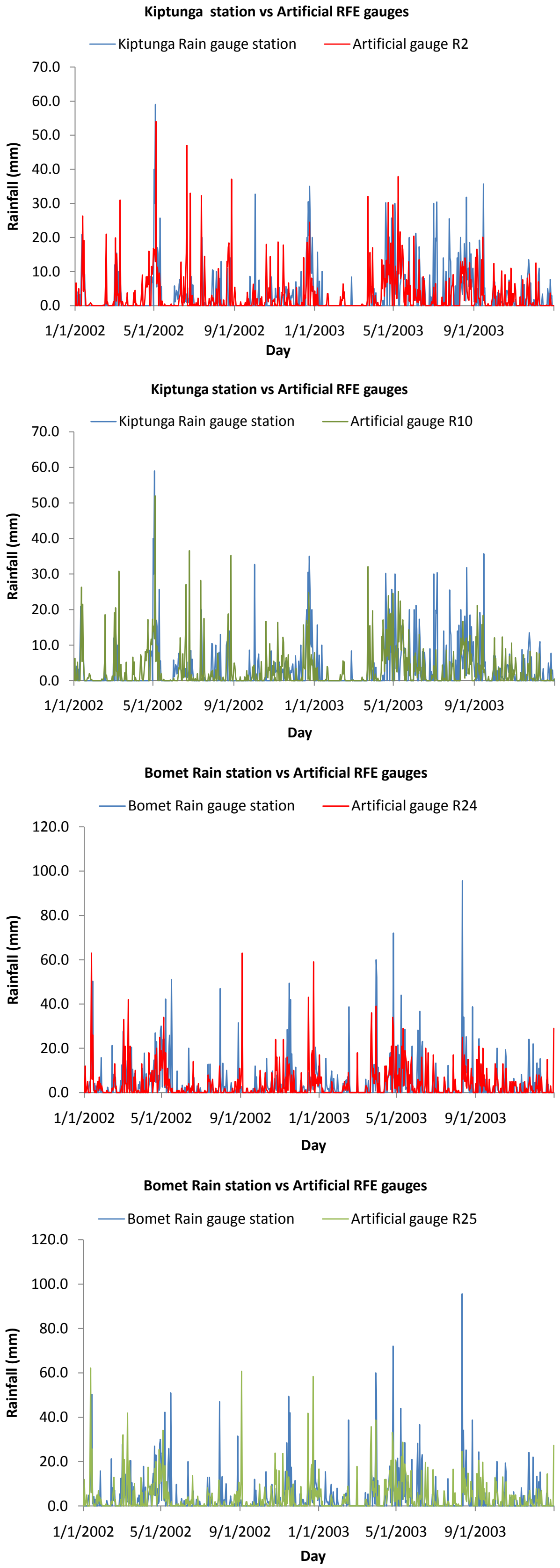

Fig. 4. Comparison between the daily rain gauge and artificial RFE gauge data.

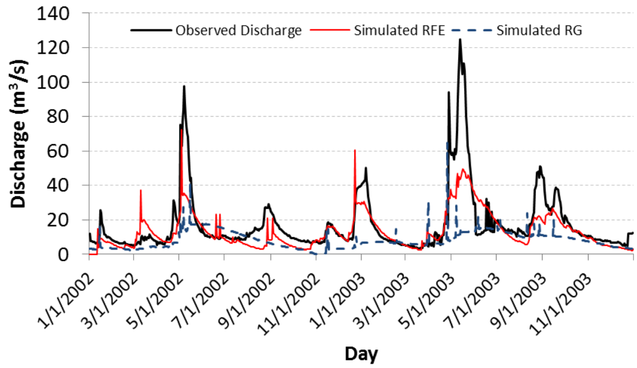

Fig. 5. Simulated daily discharge (RG and RFE Models) for different rainfall sources for Nyangores River plotted with observed discharge.

climate and land use changes. The resulting annual average water balance components for both the rain gauge and RFE simulations are shown in Table 8 and indicate the general apportioning of water as it moved through the watershed.

The finding that the performance of the runoff model was improved using satellite based rainfall data is quite significant. Even with its limitations, the RFE model enables researchers to provide, for the first time, useful guidance to the planning efforts of water resource managers in the Mara River Basin. Continued research efforts can now focus on improving the model and the guidance it enables. Across Africa, an increasing number of studies have sought to take advantage of the recently available and virtually uninterrupted supply of satellite based rainfall information as an alternative and supplement to ground-based observations. Li et al. (2009) made use of TRMM-based satellite data for operational flood prediction system in Nzoia Basin of Lake Victoria in East Africa, producing acceptable results for flood prediction. Studies such as those done by Wilk et al. (2006), have described the development of a combined gauge and satellite long-term rainfall dataset with the necessary spatial and temporal resolution for hydrological modeling applications in river basins such as the Okavango in Botswana. Wilk et al. (2006) also noted that in cases of different datasets that are not representative because of their geographical location, the hydrological model itself can be a useful tool to establish the most appropriate gauge dataset. Use of satellite based artificial rainfall estimations offers the possibility of extending hydrological simulation efforts across large areas of Africa, providing water managers – who currently have no information on flow dynamics in these regions – with information on runoff characteristics and, potentially, on vulnerabilities of runoff and water resources to local, regional and global changes.

Table 7. Model evaluation statistics for monthly discharge simulation result.

Statistics	Nyangores Sub-basin			
	RFE		Rain gauge	
	Cal	Val	Cal	Val
NSE[a]	0.43	0.23	−0.53	−0.06
R^{2}[b]	0.56	0.43	0.09	0.32
r[c]	0.803	0.57	0.29	0.57

[a] NSE = Nash-Sutcliffe Efficiency, [b] R^2 = Coefficient of determination,
[c] r = Correlation coefficient

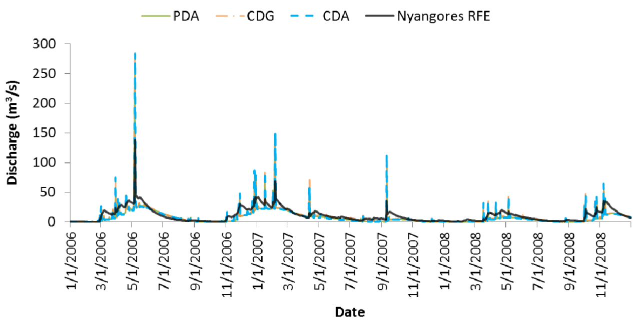

Fig. 6. Nyangores River simulated daily discharge for land use scenarios. PDA = Partial Deforestation, Conversion to Agriculture, CDG = Complete Deforestation Conversion to Grassland, and CDA = Complete Deforestation Conversion to Agriculture.

3.2 Land use change scenarios

Simulations under all land use change scenarios indicated reduced baseflow and average flow over the period of simulation (Figs. 6 and 7), but differences were observed in the percent changes to individual water balance components relative to RFE model results (Fig. 8). In the PDA scenario, 66 km^2 of deciduous and mixed forest – approximately 10 % of the basin area – were converted to agricultural land use (Table 9). Under this scenario, overland flow (SURQ) increased by 7 % and evapotranspiration (ET) increased by approximately 1 %. Large percent increases in tributary water losses (TLOSS) were estimated in this and other scenario simulations, but tributary losses represent only 0.1 % of the basin water balance and thus even large percent changes have little effect on the basin water balance. These changes are therefore omitted from further consideration. All other water balance components decreased, including a 4 % decrease in groundwater discharge (GW_Q) and 2 % decrease in total water yield (WYLD) from the basin.

In the CDG scenario, 248 km^2 of forest – approximately 36 % of the basin area – were converted to grassland. Under this scenario, overland flow increased by 20 %, but evapotranspiration decreased by approximately 2 %. This was the only scenario resulting in a decrease in evapotranspiration and thus an increase in total water yield. Despite the increase in total water yield, a small decrease in groundwater discharge was still observed, indicating decreased baseflow during low water periods. The largest impacts on water balance components in the basin occurred in the CDA scenario, in which all existing forest cover was converted to agricultural land uses. This scenario resulted in a 31 % increase is overland flow and 2 % increase in evapotranspiration. Groundwater discharge decreased by more than 9 % and total water yield decreased by 3 % under this scenario.

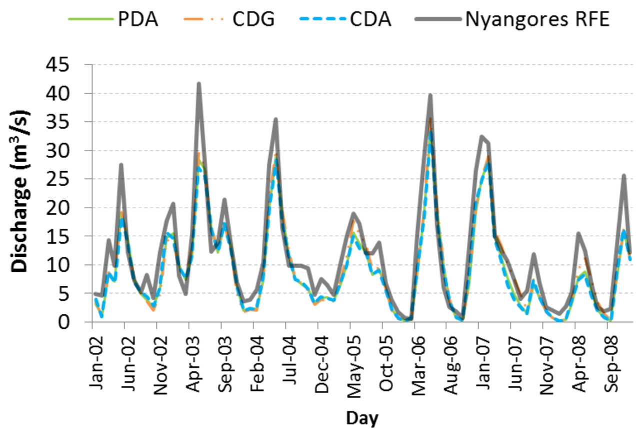

Fig. 7. Nyangores River simulated monthly discharge for land use scenarios. PDA = Partial Deforestation, Conversion to Agriculture, CDG = Complete Deforestation Conversion to Grassland, and CDA = Complete Deforestation Conversion to Agriculture.

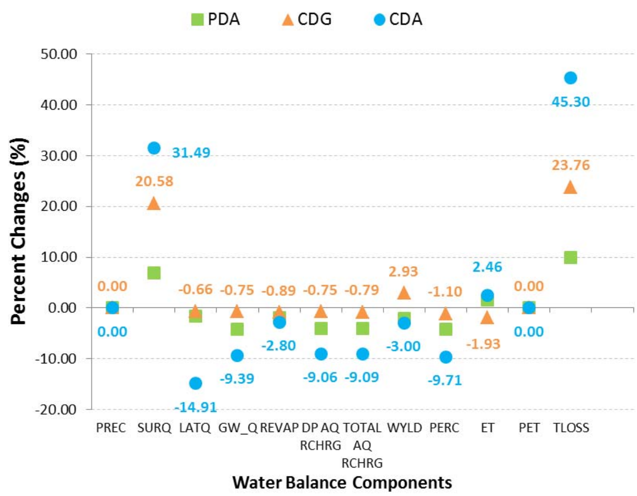

Fig. 8. Percent changes in water balance components for simulated land use change scenarios in the Nyangores subbasin. PDA = Partial Deforestation, conversion to Agriculture, CDG = Complete Deforestation, conversion to Grassland, CDA = Complete Deforestation, conversion to Agriculture.

Table 8. Annual average water balance components for the calibrated Nyangores sub-basin models.

Parameters	Nyangores RG 1996–2003	Nyangores RFE 2002–2008
PRECIP (mm yr^{-1})	1330	1097
SURQ (mm yr^{-1})	15.0	11.5
LATQ (mm yr^{-1})	61	43
GW_Q (mm yr^{-1})	355	48
REVAP (mm yr^{-1})	22	3.5
DA_RCHG (mm yr^{-1})	22	25
GW_RCHG (mm yr^{-1})	449	507
WYLD (mm yr^{-1})	429	535
PERC (mm yr^{-1})	450	509
ET (mm yr^{-1})	789	530
PET (mm yr^{-1})	1150	1179
TLOSS (mm yr^{-1})	1.0	0.8
SEDYLD (T ha^{1} yr^{1})	0.7	0.7

PRECIP = Average total precipitation on sub basin (mm H_20), PET = Potential evapotranspiration (mm H_20), ET = Actual evapotranspiration (mm H_20), PERC = Amount of water percolating out of the root zone (mm H_20), SURQ = Surface runoff (mm H_20), GW_Q = Groundwater discharge into reach or return flow (mm H_20), WYLD = Net water yield to reach (mm H_20), TLOSS = Amount of water removed from tributary channels by transmission (mm H_20), DA_RCHG = Amount of water entering deep aquifer from root zone (mm H_20), REVAP = Water in shallow aquifer returning to root zone (mm H_20), GW_RCHG = Amount of water entering both aquifers (mm H_20), SEDYLD = Sediment yield (metric t ha^{-1}), LATQ = Lateral flow contribution to reach (mm H_20).

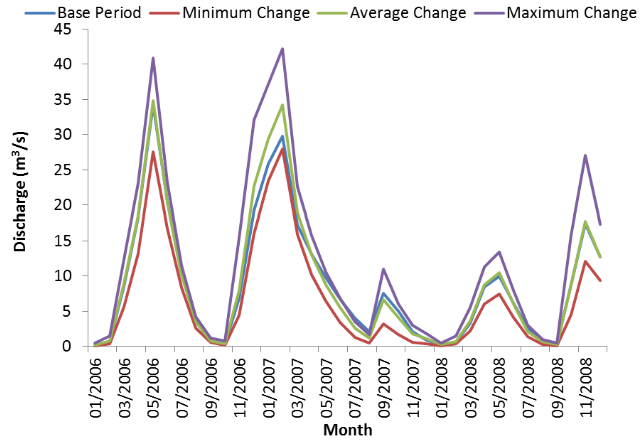

Fig. 9. Nyangores monthly discharge for base period (2006–2008) and climate change scenarios. Different scenarios are described in Table 6.

Although the modest performance of the RFE model in calibration and validation does not justify detailed analysis of differences between land use change scenarios, trends and relative magnitudes of impacts are evident. Model simulations suggest that any additional deforestation in the Nyangores sub-basin of the Mara River Basin will result in increased overland flow and decreased baseflow. These results confirm and bolster the findings of related efforts from the larger Mara River Basin and the adjacent Nyando River Basin (Mati et al., 2008; Olang and Fürst, 2011). The magnitude of impact appears to be greater when forest is converted to agricultural land use in comparison with grassland. These results are also consistent with observed changes in the basin over the past four decades. An estimated 32 % of the Mara River Basin was deforested between 1973 and 2000, representing a loss of 319 km^2 of forest; over the same time the coverage of agricultural land use is estimated to have increased by 1678 km^2, which also includes conversion of grasslands (Mati et al., 2008). Analysis of discharge records from subcatchments of the basin between 1964 and 1993 indicates that subcatchments subjected to higher rates of deforestation exhibit increased flood flows and decreased dry season baseflows relative to subcatchments with less deforestation (Melesse et al., 2008). Moreover, local residents report increasing sediment loads and decreasing dry-season flows over the same period (D. Ombara, personal communication, 2008).

The current catchment management strategy of Kenyan water authorities in the Mara River Basin calls for strict protection of remaining forests and this is supported by complimentary initiatives at the national level (KWRMA, 2008; GoK, 2009). The findings of this study provide additional scientific justification for these conservation efforts. Even if these efforts are successful, water managers face three inter-related challenges: (1) improving existing agricultural land management practices, (2) regulating water allocation to maintain an environmental flow regime in the river, and (3) adapting to possible impacts of climate change. Responses to the first two challenges may be formulated with existing tools and information, but adaptation to climate change requires information on potential future runoff regimes.

3.3 Climate change scenarios

Most climate change projections for East Africa call for increased temperature and precipitation during this century (Anyah and Qiu, 2011; IPCC, 2007). Projections for changes in precipitation range from a 3 % reduction in annual precipitation to a 25 % increase, with considerable variability depending on season (Table 6, Fig. 9). The mean for all projections is for a 7 % increase in annual precipitation by 2099. Examination of these scenarios using the RFE model illustrates nonlinear responses in water balance components that have important management implications. A 3 % reduction in annual precipitation resulted in a 25 % reduction in mean discharge (Table 10). This seemingly disproportionate decrease in mean discharge illustrates the predominance of evapotranspiration in the water balance of the Nyangores sub-basin. The projection of a 3 % decrease in precipitation

Table 9. Areal coverage of land use and percentages in the Nyangores sub-basin for the 2008 cover as well as cover under three scenarios of future land use change.

Land Use Scenario/ Basin	Land use/Land cover (2008) (km^2) (%)	Partial Deforestation, Conversion to Agriculture (PDA) (km^2) (%)	Complete Deforestation Conversion to Grassland (CDG) (km^2) (%)	Complete Deforestation Conversion to Agriculture (CDA) (km^2) (%)
Forest Evergreen	182 (26.3)	182 (26.3)	0	0
Forest Deciduous	26 (3.7)	0	0	0
Forest Mixed	40 (5.9)	0	0	0
Agricultural Land Generic	121 (17.5)	161 (23.3)	121 (17.5)	121 (17.5)
Agricultural Land Close Grown	323 (46.6)	349 (50.4)	323 (46.6)	571 (82.5)
Range Grasses	0	0	248 (35.9)	0
Total (km^2) (%)	692 (100)	692 (100)	692 (100)	692 (100)

Table 10. Changes in average stream flow for the years 2080–2099 with respect to minimum, median and maximum changes to temperature and precipitation in East Africa projected by models used in scenario A1B (IPCC, 2007).

Flow for reference period; 2002–2008 (m^3 s^{-1})	Median change scenario (2080–2099) (m^3 s^{-1})	Min change scenario (2080–2099) (m^3 s^{-1})	Max change scenario (2080–2099) (m^3 s^{-1})
8.9	9.1	6.6	12.0
Change in m^3 s^{-1}	0.2	−2.3	3.1
Changes in %	2.8	−25.3	35.7

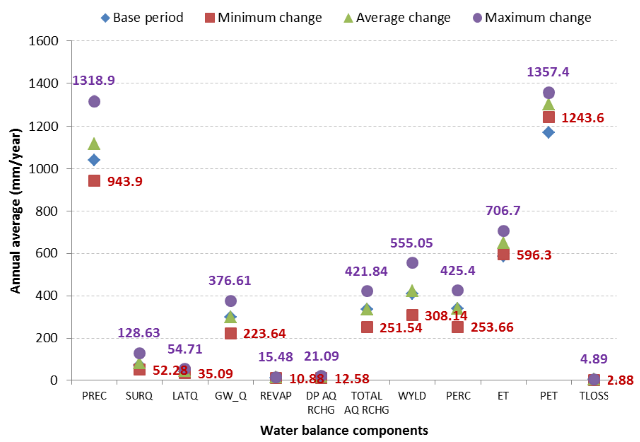

Fig. 10. Nyangores water balance components for the base period (2006–2008) and climate change scenarios. Different scenarios are described in Table 6.

is accompanied by a projected increase in temperature of 1.8 °C, which increases both potential and actual evapotranspiration. Thus, runoff is reduced both by the reduction in precipitation and increase in evapotranspiration. This dynamic is also evident in the simulation of runoff using the median projection in precipitation change, which is a 7 % increase (Table 6). Simulated mean discharge under this scenario increased by just 3 %, as the accompanying projection for a 3.2 % increase in temperature increased evapotranspiration, limiting increases in runoff. It is only under the maximal projected change scenario of a 25 % increase in annual precipitation and 4.3 °C increase in temperature that a large increase in mean runoff is observed (Table 10, Fig. 10). Mean annual runoff increased by 36 % under this scenario, again indicating a nonlinear response, this time skewed toward increased runoff.

The results of the simulations suggest that even small decreases in seasonal and annual precipitation linked to climate change may have large impacts on river discharge and water availability in the Nyangores sub-basin and larger Mara River Basin. Conversely, small increases in precipitation are likely to have little impact due to the buffering effect of increases in evapotranspiration linked to warming temperatures. It is only under the most extreme scenarios of precipitation increase (25 %) that large accompanying changes in runoff are projected. Most models considered in the IPCC process predict modest increases in precipitation in East Africa over this century. However, the few simulations of climate change impacts on river runoff in the region have more often focused on scenarios of reduced seasonal and annual precipitation (Legesse et al., 2003; Setegn et al., 2011). It is important to highlight that because of increased evapotranspiration linked to rising temperatures, river runoff and water availability may be reduced even in cases of no change in annual precipitation or small increases. Surface water resources are thus highly vulnerable to impacts from rising temperatures, which are predicted in all models examining future climate change scenarios in East Africa (IPCC, 2007). One should also consider, however, that inter-annual climate variability is high in East Africa and occasionally severe droughts remain a significant threat irrespective of modest increases in the long term precipitation (Hulme et al., 2001). Periods of excessive rainfall and potentially intense flooding are also likely (Shongwe et al., 2011).

4 Conclusions

Catchment scale runoff model calibration is challenging and is impeded by uncertainties like processes unknown to the modeler, processes not captured by the model and simplification of the processes by the model (Abbaspour et al., 2007). The challenge is even greater in data scarce regions of Africa. But these regions are often those most in need of scientific guidance to inform and back up the efforts of catchment water resource managers and other decision makers. This study has demonstrated that the set-up and calibration of a semi-distributed hydrological model such as SWAT in a poorly-gauged rural African catchment with variable land cover, soils and topography can yield useful results given new satellite-based rainfall estimates, minimal additional input data, and proper attention to manual or automatic calibration. In this study, the modeling exercise produced fair but not good results and it is therefore considered an exploratory analysis and evaluation of trends describing the response of the Mara River basin to future land use and climate change scenarios.

The model was used to explore likely impacts of deforestation on basin water balance components in the Nyangores sub-basin. Much of the original forest in the Mara Basin has already been converted to agricultural lands, and water managers are arguing for protection of remaining forests. Our analysis concluded that any additional forest conversion, whether to agriculture or pasture lands, is likely to reduce dry-season flows and intensify peak flows. These changes would exacerbate already serious problems related to water scarcity in dry periods and hillslope erosion during wet periods. Long-term planning in the basin is also complicated by uncertainties related to projected climate change. Most projections call for modest increases (5–10 %) in precipitation during this century. While these projections may suggest greater future availability of water resources in the basin, our analysis concluded that accompanying increases in evapotranspiration, driven by rising temperature, will limit increases in aquifer recharge and runoff. Water balance components showed strongly nonlinear responses to changes in climate. Even small decreases in precipitation may produce large reductions in runoff due to the compound effects of reduced runoff and increased evapotranspiration. These results emphasize the importance of building adaptation to climate change into current and future planning efforts.

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References

Abbaspour, K. C., Johnson, C. A., and van Genuchten, M. T.: Estimating uncertain flow and transport parameters using a sequential uncertainty fitting procedure, Vadose Zone J., 3(4), 1340–1352, 2004.

Abbaspour, K. C., Yang, J., Maximov, I., Siber, R., Bogner, K., Mieleitner, J., Zobrist, J., and Srinivasan, R.: Modelling hydrology and water quality in the pre-alpine/alpine Thur watershed using SWAT, J. Hydrol., 333, 413–430, 2007.

Anderson, R. J., Hardy, E. E., Roach, J. T., and Witmer, R. E.: A Land Use and Land Cover Classification System for use with remote sensor data, United States Geological Survey, United States Government Printing Office, Washington, DC, 1976.

Anyah, R. O. and Qiu, W.: Characteristic 20th and 21st century precipitation and temperature patterns and changes over the Greater Horn of Africa, Int. J. Climatol., 31, doi:10.1002/joc.2270, in press, 2011.

Arnold, J. G., Srinivasan, R., Muttiah, R. S., and Williams, J. R.: Large area hydrologic modeling modeling and assessment, Part I: Model development, J. Am. Water Resour. Assoc., 34, 73–89, 1998.

Christensen, J. H., Hewitson, B., Busuioc, A., Chen, A., Gao, X., Held, I., Jones, R., Kolli, R. K., Kwon, W. T., Laprise, R., Magaña Rueda, V., Mearns, L., Menéndez, C. G., Räisänen, J., Rinke, A., Sarr, A., and Whetton, P.: Regional Climate Projections, in: Climate Change: The Physical Science Basis, Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, edited by: Solomon, S., Qin, D., Manning, M., Chen, Z., Marquis, M., Averyt, K. B., Tignor, M., and Miller, H. L., Cambridge University Press, Cambridge, UK and New York, NY, USA, 2007.

Di Luzio, M., Srinivasan, R., and Arnold, J. G.: Integration of Watershed Tools and the SWAT Model into BASINS, J. Am. Water Resour. Assoc., 38(4), 1127–1141, 2002.

Duan, Q. Y., Sorooshian, S., and Gupta V.: Effective and efficient global optimization for conceptual rainfall-runoff models, Water Resour. Res., 28(4), 1015–1031, 1992.

FAO – Food and Agriculture Organization of the United Nations: Global Forest Resources Assessment Main report, FAO Forestry

Paper 163, Food and Agriculture Organization of the United Nations, Rome, 2010.

Gereta, E., Wolanski, E., Borner, M., and Serneels, S.: Use of an ecohydrology model to predict the impact on the Serengeti ecosystem of deforestation, irrigation and the proposed Amala Weir water Diversion Project in Kenya, Ecohydrol. Hydrobiol., 2(1–4), 135–142, 2002.

GoK – Government of Kenya: Report of the Prime Minister's Task Force on the Conservation of the Mau Forests Complex, available online: http://www.kws.go.ke/export/sites/kws/info/maurestoration/maupublications/Mau_Forest_Complex_Report.pdf, last access: 15 June 2009.

Hothorn, T., Hornik, K., and Zeileis, A.: Unbiased Recursive Partitioning: A Conditional Inference Framework, J. Comput. Graph. Stat., 15(3), 651–674, 2006.

Hulme, M., Doherty, R. M., Ngara, T., New, M. G., and Lister, D.: African climate change: 1900–2100, Clim. Res., 17, 145–168, 2001.

IPCC – Intergovernmental Panel on Climate Change: Climate Change 2007, Synthesis Report, Cambridge Press, Cambridge, 2007.

IPCC – Intergovernmental Panel on Climate Change: The Science of Climate Change, Cambridge University Press, Cambridge, 2001.

Jacobs, J. H., Angere, J., Vitale, J., Srinivasan, R., and Kaitho, R.: Mitigating Economic Damage in Kenya's Upper Tana River Basin: An Application of Arc-View SWAT, J. Spat. Hydrol., 7(1), 23–46, 2007.

Jayakrishnan, R., Srinivasan, R., Santhi, C., and Arnold, J.: Advances in the application of the SWAT model for water resources management, Hydrol. Process., 19, 749–762, 2005.

KWRMA – Kenya Water Resource Management Authority: Catchment Management Strategy Lake Victoria South Catchment Area, Water Resource Management Authority, Nairobi, Kenya, 2008.

Legesse, D., Vallet-Coulomba, C., and Gasse, F.: Hydrological response of a catchment to climate and land use changes in Tropical Africa: case study South Central Ethiopia, J. Hydrol., 275, 67–85, 2003.

Li, L., Hong, Y., Wang, J., Adler, R. F., Policelli, F. S., Habib, S., Irwn, D., Korme, T., and Okello, L.: Evaluation of the real-time TRMM-based multi-satellite precipitation analysis for an operational flood prediction system in Nzoia Basin, Lake Victoria, Africa, Nat. Hazards, 50(1), 109–123, 2009.

Mati, B. M., Mutie, S., Home, P., Mtalo, F., and Gadain, H.: Land Use Changes in the Transboundary Mara Basin: A Threat to Pristine Wildlife Sanctuaries in East Africa, A Paper presentation at the: 8th International River Symposium, Brisbane, Australia, 6–9 September, 2005.

Mati, B. M., Mutie, S., Gadain, H., Home, P., and Mtalo, F.: Impacts of land-use/cover changes on the hydrology of the transboundary Mara River, Kenya/Tanzania, Lake. Reserv. Manage., 13, 169–177, doi:10.1111/j.1440-1770.2008.00367.x, 2008.

Melesse, A. M., McClain, M., Abira, M., and Mutayoba, W.: Hydrometeorological Analysis of the Mara River Basin, Kenya/Tanzania, Proceedings of the World Environmental and Water Resources Congress 2008, ASCE Conf. Proc. doi:10.1061/40976(316)589, 2008.

Mulungu, D. M. M. and Munishi, S. E.: Simiyu River catchment parameterization using SWAT model, Phys. Chem. Earth, 32, 1032–1039, 2007.

Mutie, S., Mati, B., Gadain, H., and Gathenya, J.: Evaluating land use change effects on river flow using USGS geospatial stream flow model in Mara River basin, Kenya, A Paper presentation at the 2nd Workshop of the EARSeL SIG on Land Use and Land Cover, Bonn, 28–30 September, 2006.

Neitsch, S. L., Arnold, J. G., Kiniry J. R, and Williams, J. R.: Soil and Water Assessment Tool, Theoretical Documentation: Version, Agricultural Research Service and Texas A & M Blackland Research Center, Temple, TX, USDA, 2005.

Olang, L. O. and Fürst, J.: Effects of land cover change on flood peak discharges and runoff volumes: model estimates for the Nyando River Basin, Kenya, Hydrol. Process., 25, 80–89, 2011.

Ruosteenoja, K., Carter, T. R., Jylhä, K., and Tuomenvirta, H.: Future climate in world regions: an intercomparison of model-based projections for the new IPCC emissions scenarios, The Finnish Environment vol. 644, Finnish Environment Institute, 83 pp., 2003.

Schuol, J. and Abbaspour, K. C.: Using monthly weather statistics to generate daily data in a SWAT model application to west Africa, Ecol. Model., 201(3–4), 301–311, 2007.

Setegn, S. G., Srinivasan, R., Melesse, A. M., and Dargahi, B.: SWAT model application and prediction uncertainty analysis in the Lake Tana Basin, Ethiopia, Hydrol. Process., 23(26), 3738–3750, 2009.

Setegn, S. G., Rayner, D., Melesse, A. M., Dargahi, B., and Srinivasan, R.: Impact of climate change on the hydroclimatology of Lake Tana Basin, Ethiopia, Water Resour. Res., 47, W04511, doi:10.1029/2010WR009248, 2011.

Shongwe, M. E., van Oldenborgh, G. J., van den Hurk, B. J. J. M., and van Aalst, M. A.: Projected changes in extreme precipitation in Africa under global warming, Part II: East Africa, J. Climate, in press, doi:10.1175/2010JCLI2883.1, 2011.

Shrestha, M. S., Artan, G. A., Bajracharya, S. R., and Sharma, R. R.: Using satellite-based rainfall estimates for streamflow modeling: Bagmati Basin, J. Flood Risk Manage., 1, 89–99, 2008.

Van Griensven, A. and Meixner, T.: Methods to quantify and identify the sources of uncertainty for river basin water quality models, Water Sci. Technol., 53(1), 51–59, 2006.

Vorosmarty, C. J., Green, P., Salisbury, J., and Lammers, R. B.: Global water resources: Vulnerability from climate change and population growth, Science, 289, 284–288, 2000.

Wilk, J., Kniveton, D., Andersson, L., Layberry, R., Todd, M. C., Hughes, D., Ringrose, S., and Vanderpost, C.: Estimating rainfall and water balance over the Okavango River Basin for hydrological applications, J. Hydrol., 331, 18–29, 2006.

WRI – World Resources Institute, Department of Resource Surveys and remote Sensing, Ministry of Environment and Natural resources, Kenya, Central Bureau of Statistics, Ministry of Planning and Development, Kenya; and International Livestock Research Institute: Nature's Benefits in Kenya: An Atlas of Ecosystems and Human Well-Being, World Resources Institute, Washington, DC, and Nairobi, 2007.

Xie, P. and Arkin, P. A.: Global precipitation: A 17-Year monthly analysis based on gauge observations, Satellite Estimates, and numerical model outputs, B. Am. Meteorol. Soc., 78, 112539–112558, 1997.