Environmental Systems Research

The impact of future climate and land use/cover change on water resources in the Ndembera watershed and their mitigation and adaptation strategies

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Abstract

Background: Land use/cover and climate changes have a great influence on the hydrological processes in the watershed. The impacts of land use/cover and climate change are set to increase in the future due to the increased clearance of virgin forest lands for agriculture and the rise of global warming. The way in which the future climate will interact with the land use changes and affect the water balance in the watersheds requires more attention. This study was carried out in the Ndembera river watershed in Usangu basin, Tanzania, whereby the Soil and Water Assessment Tool was used to (i) assess the impact of near future (2010–2039) climate and 2013–2020 land use/cover change on the water balance and streamflow and (ii) evaluate the effectiveness of four land and water management practices as the mitigation and adaptation strategies for the impacts of climate and land use/cover changes. The 2020 land use/cover was predicted using Markov Chain and Cellular Automata models based on 2006 and 2013 land use/covers. The near-future climate scenario was generated from the Coupled Model Intercomparison Project 5 General Circulation Models.

Results: During the period from 2013 to 2020, the agricultural land and evergreen forests will increase by nearly 10 and 7%, respectively. Mixed forests will decrease by 12%. Such land use/cover changes will decrease the total water yield by nearly 13% while increasing evapotranspiration and surface runoff by approximately 8 and 18%, respectively. This moisture balance changes will be aggravated by warmer near-future mean annual temperatures (1.1 °C) and wetter conditions (3.4 mm/year) than in the baseline period (1980–2009). The warmer future climate will increase evapotranspiration and decrease water yield by approximately 35 and 8%, respectively. The management practices such as filter strips can reduce the annual evapotranspiration by 6%, and increase stream-flow by 38% in February.

Conclusion: The future land use/cover changes will interact with the near-future warmer temperatures and reduce water availability in the Ndembera watershed. Land and water management practices have great potential to mitigate the impacts of future climate and land use/cover changes on water resource, thus increasing its availability.

Keywords: Water balance, Soil and Water Assessment Tool, Climate change, Land and water management practices, Usangu catchment, Tanzania

Background

Land use/cover and climate changes have a great influence on the hydrological response of a watershed

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(Kashaigili and Majaliwa 2013; Kirby et al. 2016). The hydrological processes which are affected by such changes include evapotranspiration, infiltration, surface runoff, groundwater flow and stream discharge regime (Natkhin et al. 2015). The effects of the land use/cover and climate change on hydrological processes are set to increase in the future due to the increased clearance of virgin forest lands for agriculture and the rise of global

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warming (Fischer 2013). Thus, the way in which the future climate will interact with the land use changes and affect the water balance in the watersheds requires more attention.

There is evidence to suggest that Tanzania is among the countries in Africa which is most at risk of being impacted by climate change (Hatibu et al. 1999). Further, it is anticipated that the farming sector will experience more impacts resulting in decreased production of different crops due to decreased water availability and the shift of growing seasons (Kangalawe and Lyimo 2013; Laderach and Eitzinger 2012). Although the climate change is predicted to cause adverse impacts on freshwater resources, especially in the dry sub-tropical regions (Pervez and Henebry 2015; Serdeczny et al. 2016), there is a little consideration given to the impacts in the process of planning of future water resource use and management (McCartney et al. 2012). Studies of the impacts of climate change on water resource are, therefore, encouraged to ensure its sustainability.

Usangu catchment, a part of the Rufiji Drainage Basin, is important for rice production in Tanzania. It produces more than 30% of the country's rice and supports over 30,000 rice-producing households on approximately 45,000 ha of irrigated land (SMUWC 2001). Rice and onions have captured good market price in the recent years which, in turn has brought a huge influx of Tanzanians into the catchment area to grow these crops. As a result, forest and wetlands along the rivers including the Ndembera river are converted into small irrigated farms. Kashaigili (2008) showed that there is a clear linkage between land use/cover changes and the changes in the hydrological regime for the Usangu wetlands and the Great Ruaha river in the Usangu catchment. It is therefore important to assess the changes in water balance and river discharge resulting from the land use/cover changes taking place in the Ndembera river watershed.

The historical land use/cover changes and their impacts on water resources in Usangu Catchment have been widely studied (Kikula et al. 1996; Kashaigili et al. 2006a; Kashaigili 2008). For example, Kashaigili et al. (2006a) observed a decline in water inflow into the Usangu Wetland due to the expansion of agricultural activities through forests clearing in the upstream. Indeed, some few land and water management practices have been applied in Usangu Catchment to improve the moisture holding capacity of soils. These practices include afforestation programs (Kashaigili et al. 2009), growing trees and shrubs (Malley et al. 2009) and contour bunds and terraces (Mwanukuzi 2011). Generally, the effectiveness of land and water management practices such as filter strips, contour and terracing and

grassed waterways in improving the moisture holding capacity have been widely studied (Arnold et al. 2013; Fiener and Auerswald 2003; Taniguchi 2012; Wallace 2000). Nevertheless, there is limited information about their effectiveness in reducing the impact of climate and land use/cover change on water resources in Usangu Catchment.

This study was, therefore, carried out to assess the impact of the future (2020) land use/cover change and the near future (2010–2039) climate change effects on water balance and streamflow of the Ndembera river watershed in Usangu basin. Further, the effectiveness of land and water management practices in mitigating the impacts of future climate and land use changes on water balance and streamflow was evaluated.
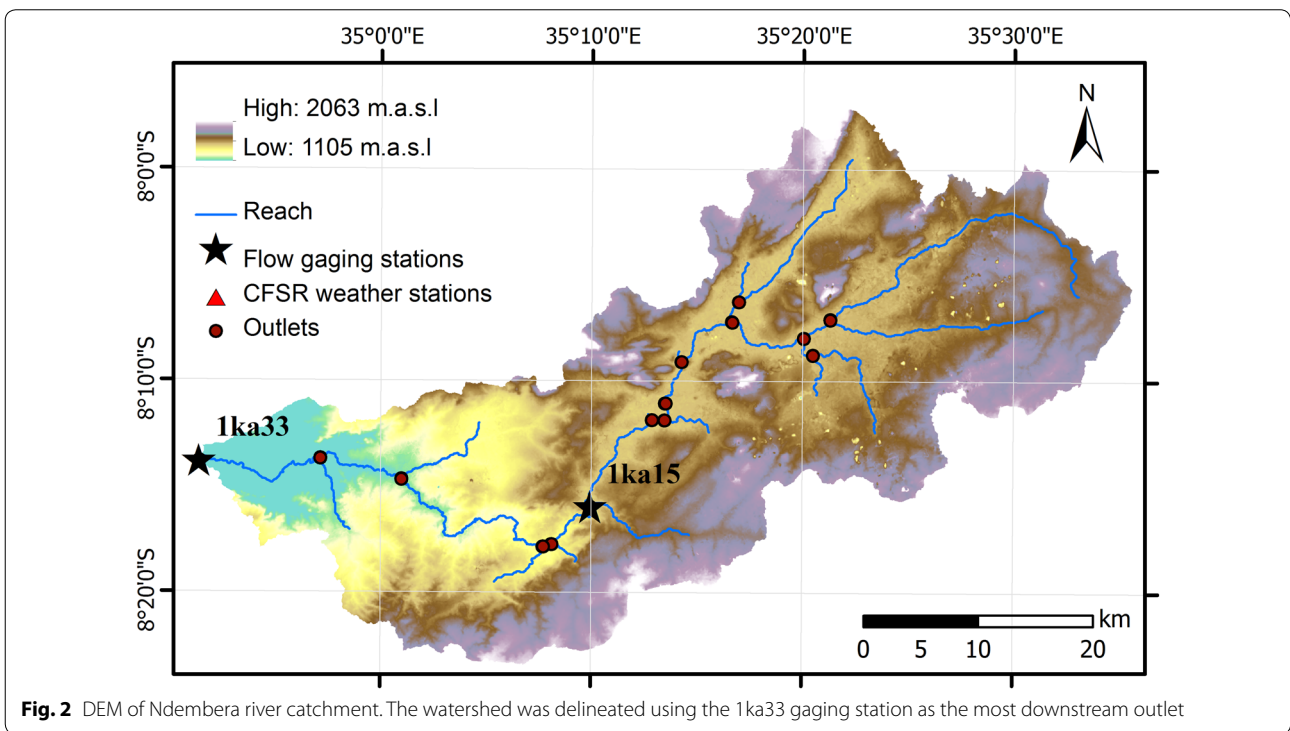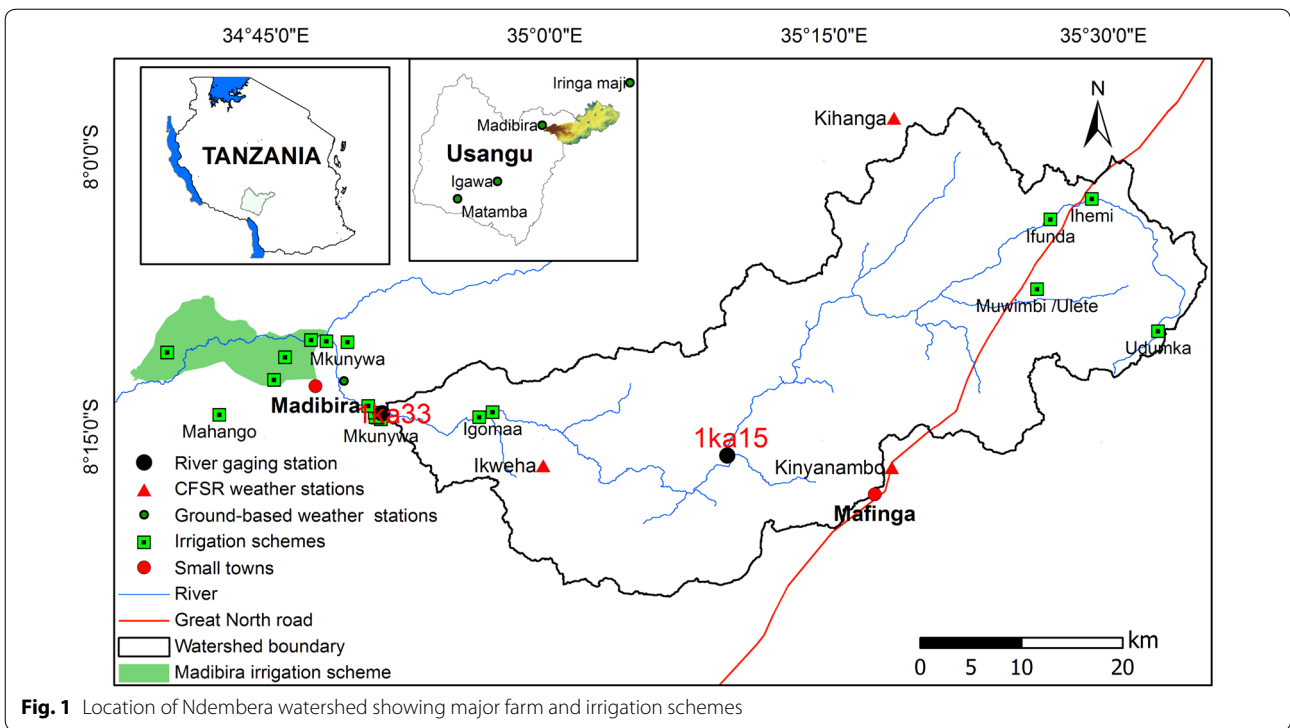
Methods

Study area

The Ndembera river watershed is located in Usangu Basin, in the southern highlands of Tanzania (Fig. 1). It covers an area of about 1705 km^2. Ndembera is one of the five perennial rivers in the Usangu Catchment, in the Rufiji Basin (SMUWC 2001). The river originates from the springs of Udumka Village (Fig. 1), at an elevation of about 2060 meters above sea level (m.a.s.l. This river accounts for about 15% of the total flow of the Great Ruaha river (Elzein 2010). The section of the watershed which is considered in this study drains from Udumka Village to a river gauging station (1ka33). Water from Ndembera river supports about 16 large scale farms and irrigation schemes located at Udumka, Ihemi, Ifunda, Muwimbi, Igomaa, Mkunywa and Mahango villages as well as the Madibira irrigation scheme located near Madibira town (Fig. 1).

The climate of the watershed is seasonal, with one wet period (Early November to the end of April) and one dry period (Early May to the end of October). The precipitation is uni-modal, and its spatial distribution is strongly influenced by topography. The highlands receive precipitation of about 1600 mm/year, while the plains receive around 500–700 mm/year (Shu and Villholth 2012).
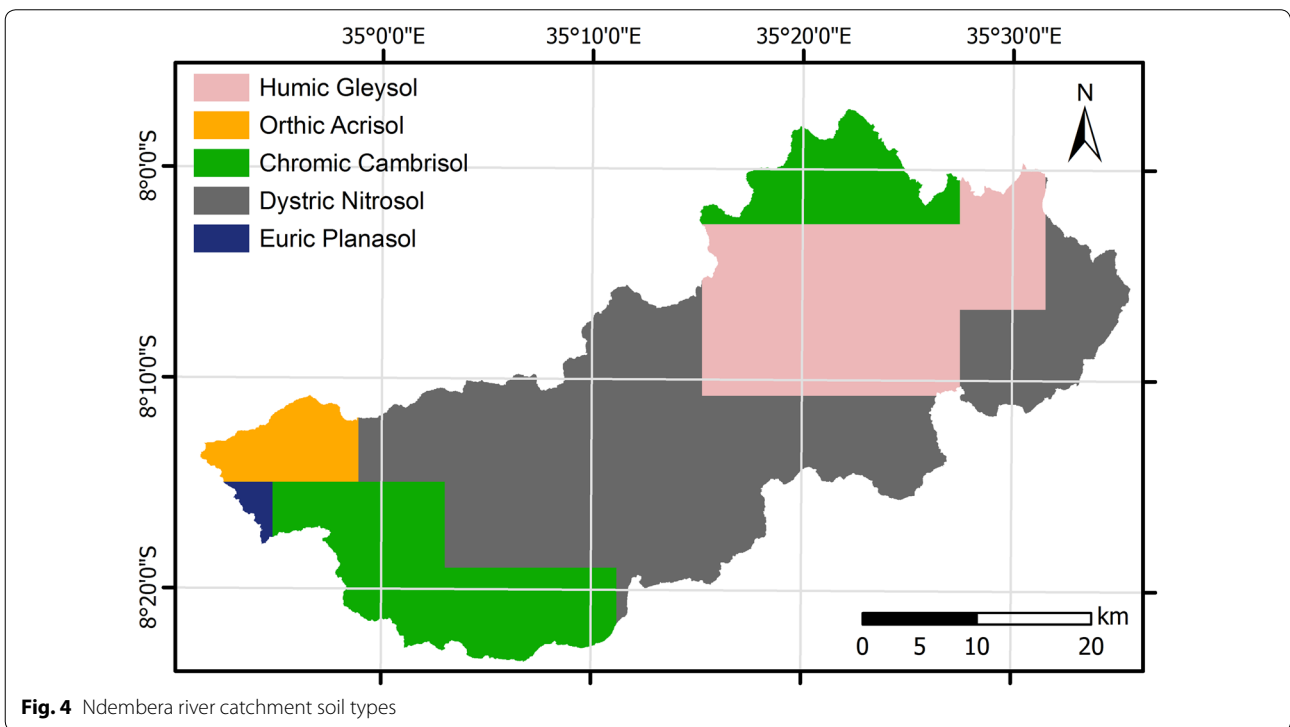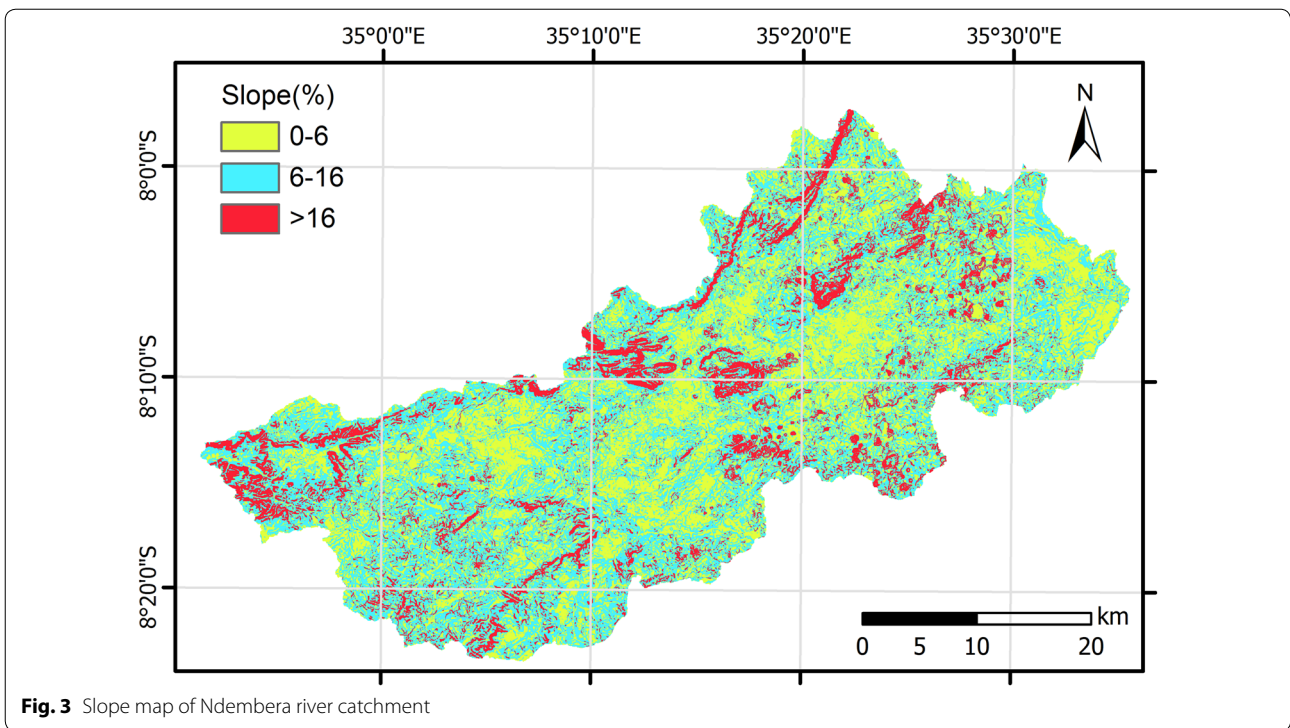
Preparation of the ArcSWAT model inputs

The input data for SWAT model (soil, land use, slope and weather data) were pre-processed in ArcMap 10.1 environment to obtain the data format required by ArcSWAT12 database. The SRTM 30 m Digital Elevation Model (DEM) of the study area (Fig. 2) was downloaded from the USGS database at https://earthexplorer.usgs.gov/. The DEM was used for delineating the study area's watershed and stream networks. The slope map (Fig. 3) was derived from the DEM using the Spatial Analyst tool.

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Fig. 1 Location of Ndembera watershed showing major farm and irrigation schemes

Fig. 2 DEM of Ndembera river catchment. The watershed was delineated using the 1ka33 gaging station as the most downstream outlet

Soil data in Fig. 4 was downloaded from the FAO Harmonized global soils database at http://www.waterbase.org/download_data.html. The watershed boundary was used to extract the soil data from the FAO soil database of the African soils slice. The attributes of these soils in Fig. 4 were updated using a "usersoil" table from the

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Fig. 3 Slope map of Ndembera river catchment


Fig. 4 Ndembera river catchment soil types

MapWindow SWAT12 database due to the fact that the "usersoil" table of ArcSWAT12 soil database contains USA soils only.

The baseline land use/cover map of 2013 (Fig. 5) was prepared by classifying Landsat images obtained from three path and rows (path168/row066, path169/row065

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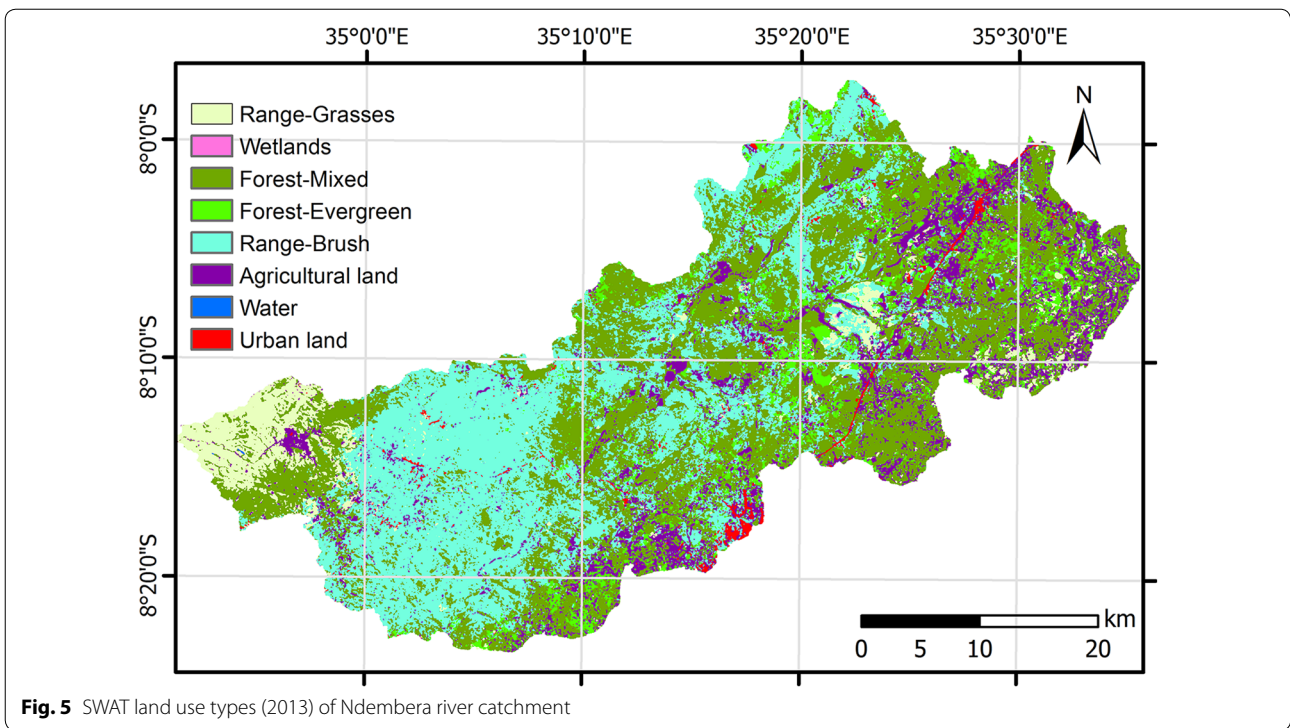
Fig. 5 SWAT land use types (2013) of Ndembera river catchment
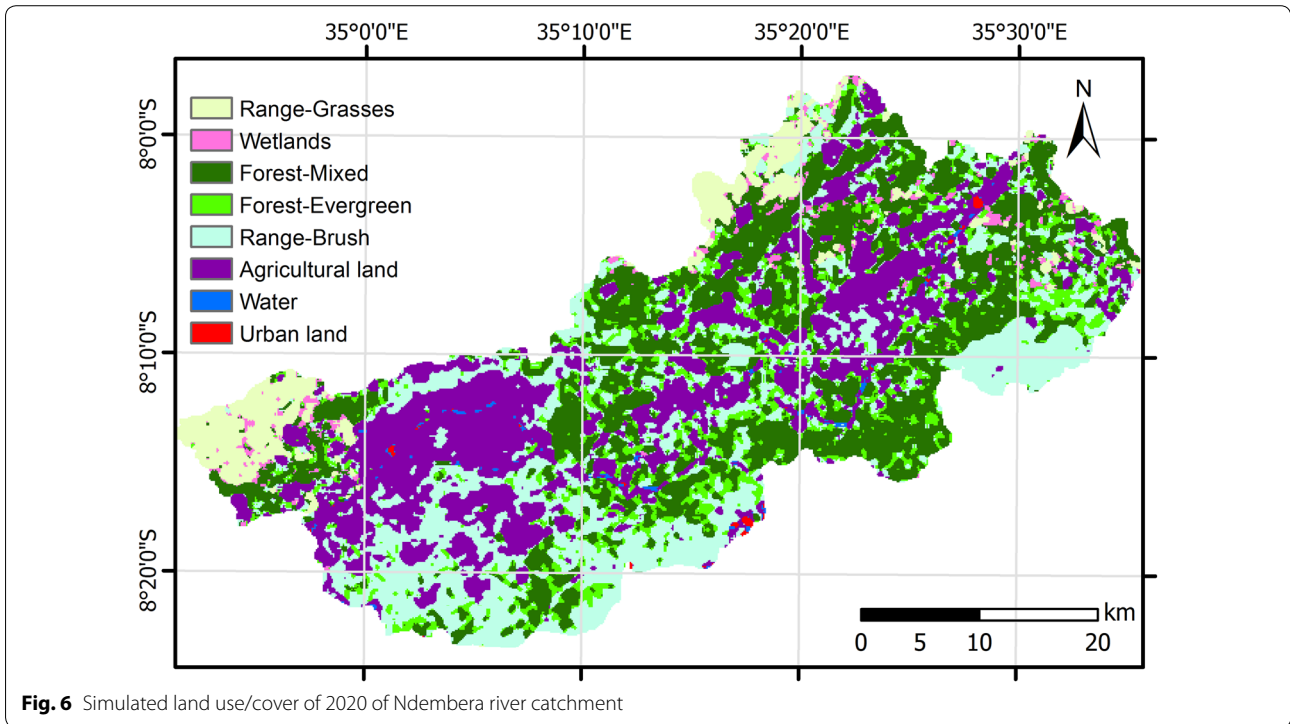
Fig. 6 Simulated land use/cover of 2020 of Ndembera river catchment

and path169/row066). The 2020 land use/cover of the Ndembera river watershed (Fig. 6) was extracted from the 2020 land use/cover of Usangu Catchment which was

predicted using the Markov Chain and Cellular Automata models (CA-Markov) (Hyandye and Martz 2017). The CA–Markov model is one of the spatial transition-based

models whereby the current trends of land use/cover evolution from "$t-1$" to "t" is used to project probabilities of land use and cover changes for the future date "$t+1$" (Behera et al. 2012; Eastman 2012; Houet and Hubert-Moy 2006). CA–Markov model is able to simulate changes in multiple land use types (Houet and Hubert-Moy 2006), hence giving possibilities of simulating the transition from one category of land use and cover to another (Behera et al. 2012).

Weather data was obtained from the ground-based weather gauging station (Iringa Maji) and the Climate Forecast System Reanalysis (CFSR) global weather data for SWAT. The ground-based gauging stations data were provided by the Rufiji Basin Water Organization (RBWO); while the CFSR weather data were downloaded from http://globalweather.tamu.edu/. Since the three operational ground-based weather stations in Usangu Catchment, namely, Matamba, Iringa Maji and Igawa station were located outside Ndembera watershed (Fig. 1), and Ndembera Auto met station located within the Ndembera watershed has not functioned since 2008, it was necessary to use CFSR global rainfall data. This CFSR data was obtained for Ikweha, Kihanga and Kinyanambo stations (Fig. 1). The CFSR data often captures the rainfall pattern very well, however, it often overestimates the gauged rainfall (Worqlul et al. 2014, 2017a); hence, Iringa Maji station data, a nearby weather station which had daily series data from 1962 to 2013, were used to perform bias correction of the CFSR precipitation data. The CFSR of the National Centres for Environmental Prediction (NCEP) readily provides weather data for any geographic location on earth between 1979 and 2014 (Roth and Lemann 2016). The bias of the CFSR data was corrected by a linear bias correction approach which is described by Worqlul et al. (2017b). This approach reduces the volume difference between CFSR and gauged rainfall data while keeping the pattern. The two datasets (uncorrected CFSR and gauged rainfall data) involved in the linear bias correction process covered the same time window (1999–2013). The annual volume difference between the observed and bias corrected data was minimized to zero. In addition, the mean monthly data (observed and corrected CFSR) were highly correlated due to their close mean monthly values as shown in Fig. 7.

The discharge data for model calibration and validation period (2000–2010) for Ndembera river at gauging station (1ka33) was obtained from the Rufiji Basin Water Organisation. Two major challenges were encountered. Firstly, the data series had gaps of up to 6 months, and sometimes for more than a year, as they were observed in 1998–1999. Secondly, the data series had ambiguous data units. It is acknowledged that data at 1ka33 were not of
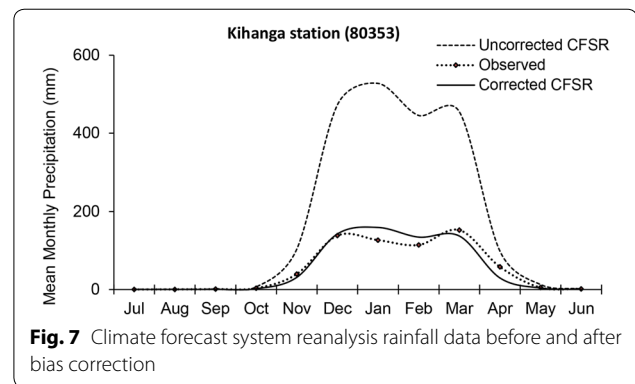
Fig. 7 Climate forecast system reanalysis rainfall data before and after bias correction

good quality due to poor gauge reading (personal communication). Also, during our visit to the station in the dry season, we found out that the water flow was below the gauge, meaning that, in the dry season, the water discharge is not captured. During data processing, the ambiguous data was deleted. Then, the data from the upstream station 1ka15 (Fig. 2) was used to fill data gaps at station 1ka33 for the period from 2000 to 2010 using the simple interpolation and linear regression methods (Koch and Cherie 2013).

SWAT model set-up and parameterization

The whole watershed was divided into 29 sub-basins. A total of 411 and 470 hydrological response units (HRU) were generated for the baseline and future land use scenarios, respectively. The general sub-basin parameters such as initial leaf area index (LAI_INI), plants potential heat units (PHU_PLT) and curve numbers (CN_2) were updated for the respective land covers. Management operations for specific land uses such as agricultural lands were scheduled based on the growing calendar used by farmers in the watershed (Table 1). The crops were auto-irrigated and auto-fertilised. The potential evapotranspiration was estimated using the Hargreaves method while the runoff was estimated using the curve number method.

SWAT model calibration and validation

River discharge data of 1999–2006 and 2007–2010 from the 1ka33 gauging station was used to calibrate and validate the SWAT model, respectively. The calibration and validation were accomplished using a semi-automatic Calibration and Uncertainty Programme; SWAT-CUP SUFI-2 (Arnold et al. 2012). A warm-up period of 3 years (1999–2001) was used for model initialization during model calibration. The calibration process was preceded by the sensitivity analysis of the parameters which control the observed river flows. The sensitivity analysis considered the range of parameters suggested by Holvoet et al. (2005). A total of twenty-three (23) parameters

Table 1 Crops growing calendar in Usangu Basin in a hydrological year

	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct
Cereal and Grains												
Paddy(Rice)												
Maize												
Oil seeds (sunflower and groundnuts)												
Vegetables												
Onions												
Others (Tomatoes, vegetables, potatoes)												

Legend						
Sowing seeds		Farms Preparations		Trans- planting		1st weeding
						2nd weeding
Mid-season		Harvest		Mixed activities		

Hydrological year starts in November and ends in October of the following year. Activities related to tomatoes, vegetables, and sweet potatoes vary from one location to another

pre-selected during manual calibration were used in the SWAT-CUP SUFI2 to run one thousand simulations. A total of nineteen (19) influential parameters of the stream flow were identified for model calibration (Table 2), whereby the sensitivity was evaluated using the t-statistic (t-stat) and p values.

SWAT model performance evaluation

The model performance in predicting the catchment conditions was evaluated using the statistical analysis parameters such as coefficient of determination (R^2), Nash–Sutcliffe efficient (NSE), *r*-factor and *p*-factor (Arnold et al. 2012) and graphical analysis. In addition, the percentage bias (PBIAS) was also considered. The *r*-factor refers to the thickness of the 95% prediction uncertainty envelope, while the p-factor is a percentage of observations covered by the 95% prediction uncertainty.

Calibration and validation of future climate data

The Near-term (2010–2039) climate scenario of precipitation and temperatures was generated from the 29 GCMs using the procedures described in the Guide for Running AgMIP Climate Scenario Generation Tools with R (Hudson and Ruane 2013). These GCMs were sourced from the Coupled Model Intercomparison Project 5 (CMIP5). The GCMs included ACCESS1-0, bcc-csm1-1, BNU-ESM, CanESM2, CCSM4, CESM1-BGC, CSIRO-Mk3-6-0, GFDL-ESM2G, GFDL-ESM2 M, HadGEM2-CC, HadGEM2-ES, inmcm4, IPSL-CM5A-LR, IPSL-CM5A-MR, MIROC5 and MIROC-ESM-CHEM. Others were MPI-ESM-LR,

MPI-ESM-MR, MRI-CGCM3, NorESM1-M, FGOALS-g2, CMCC-CM, CMCC-CMS, CNRM-CM5, HadGEM2-AO, IPSL-CM5B-LR, GFDL-CM3, GISS-E2-R and GISS-E2-H. The models were provided by Sokoine University of Agriculture, Tanzania and the National Aeronautics and Space Administration Goddard Institute for Space Studies (NASA-GISS), USA. The Simple Delta Method was used for statistical downscaling of the GCMs. This method preserves the observed patterns of temporal and spatial variability from the gridded observations (Hamlet et al. 2010).

The statistical downscaling of the 29 GCMs involved the calculation of the change factor (the ratio between a mean value, in the future, and historical run) using the delta change algorithm which was acquired together with the CMIP5-GCMs (Fig. 8). This change factor was then applied to the observed time series (1980–2009) to transform it into a time series representing the future climate. The 2010–2039 climate scenario was analysed under the Representative Concentration Pathway 8.5 Greenhouse Gas Emission scenario. This concentration pathway is characterized by increasing Greenhouse gases emissions over time, a representative of scenarios leading to high Greenhouse gases concentration levels (Chaturvedi et al. 2012).

The sub-selection of the five representative GCMs for hot/wet, hot/dry, cold/wet, cold/dry and middle (Ensemble mean) future climatic conditions was based on a scatter diagram approach (Fig. 9). The diagram represented the changes in mean monthly temperatures against the percentage in mean monthly change in future

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Table 2 Parameters sensitive to streamflow, their default range, fitted value during calibration and final values used in SWAT model for streamflow simulations

Parameter	Description	SUFI2 fitted value	Default SWAT range	Final value in SWAT model
v__SURLAG.bsn	Surface runoff lag time (days)	20.76	0.05 to 24	20.76
v__ESCO.bsn	Soil evaporation compensation factor	0.83	0 to 1	0.83
a__GWQMN.gw	Threshold depth of water in the shallow aquifer for return flow to occur (mm H_2O)	217.08	0 to 5000	1217.08
a__GW_REVAP.gw	Groundwater "revap" coefficient	0.03	0.02 to 0.2	0.05
a__REVAPMN.gw	Threshold depth of water in the shallow aquifer for "revap" to occur (mm H_2O)	236.07	0 to 1000	986.07
v__ALPHA_BF.gw	Baseflow alpha factor (days)	0.83	0 to 1	0.83
v__SHALLST.gw	Initial depth of water in the shallow aquifer	1263.00	0 to 5000	1263.00
v__RCHRG_DP.gw	Deep aquifer percolation fraction	0.63	0 to 1	0.63
v__GW_DELAY.gw	Groundwater delay (days)	18.25	0 to 500	18.25
v__CH_N2.rte	Manning's "n" value for the main channel	0.11	− 0.01 to 0.3	0.11
v__EPCO.hru	Plant uptake compensation factor	0.50	0 to 1	0.50
a__OV_N.hru	Manning's "n" value for overland flow	28.86	0.01 to 30	28.86
a__CANMX.hru	Maximum canopy storage (mm H_2O)	10.78	0 to 100	10.78
a__SLSUBBSN.hru	Average slope length (m)	40.45	10 to 150	131.91
a__HRU_SLP.hru	Average slope steepness (m/m)	0.44	0.3 to 0.6	0.47
a__SOL_AWC().sol	Available water capacity of the soil layer (mm H_2O/ mm soil)	− 0.06	0 to 1	0.04
a__SOL_K().sol	Saturated soil hydraulic conductivity (mm/h)	21.37	0 to 2000	39.02
a__CH_K1.sub	Effective hydraulic conductivity in main channel alluvium (mm/h)	85.56	0 to 300	85.56
a__CN2.mgt	Initial SCS runoff curve number for moisture condition II	− 1.87	35 to 98	83.13

a__means absolute; a given value is added to the existing parameter value during the calibration

v__means replace; the existing parameter value is to be replaced by a given value during the calibration

Fig. 8 Schematic diagram showing the work flow to generate future climate variables
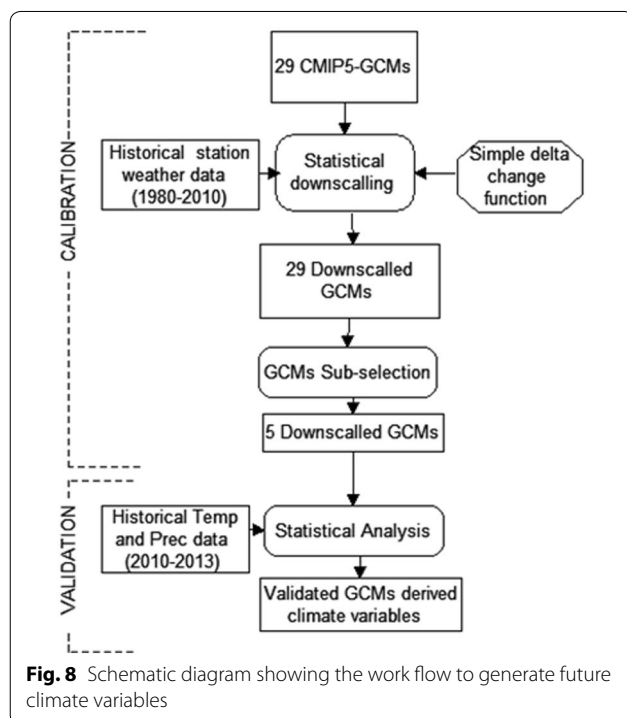
precipitation from the baseline scenario. The GCM falling close to the median of each quadrant was selected according to Subash et al. (2016). The GCMs selected for each weather station in the watershed (Table 3) were averaged to obtain a site specific GCMs-derived climate data (Fig. 9).

The mean GCMs-derived precipitation and temperatures were validated by comparing them with the observed historical station data 1980–2009 and 2010–2013. The validation involved a graphical and statistical analysis. The statistical analysis included the Mean error (ME), correlation (R), Median, Mean and Standard deviation (SD).
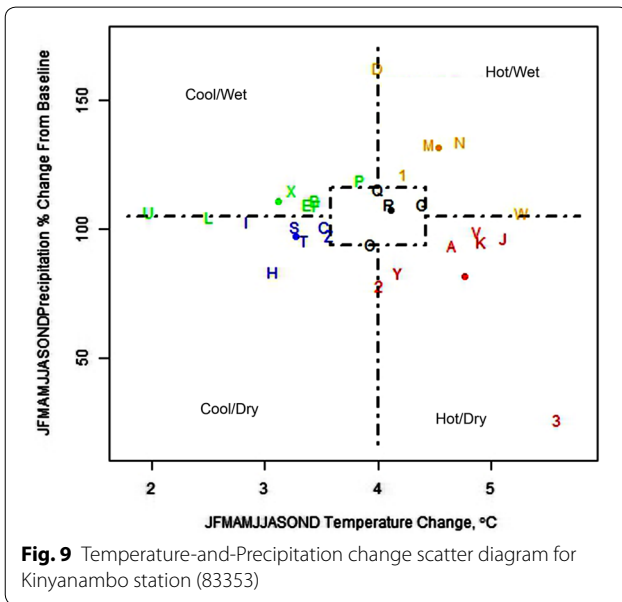
Simulation of the impacts of future land use/cover, climate and land management practices on water balance

The 2020 land use/cover of the Ndembera river watershed was introduced in a calibrated SWAT model to replace the baseline land use/cover of 2013. The model was then run to simulate the water balance conditions using the 2020 land use/cover scenario without changing other SWAT input data (weather, soils, and slope). The following assumptions were made: (i) land use/cover will

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Table 3 Selected CMIP5-GCMs for forcing the SWAT model

Station ID	Local name	Lat	Long	Elevation	GCM ID	GCM name	Future condition
80353	Kihanga	− 7.962	35.313	1589	D	CanESM2	Hot/wet
					B	bcc-csm1-1	Cool/wet
					S	MRI-CGCM3	Cool/dry
					2	GISS-E2-R	Hot/dry
					R	MPI-ESM-MR	Middle
83353	Kinyanambo	− 8.274	35.313	1803	M	IPSL-CM5A-LR	Hot/wet
					X	CNRM-CM5	Cool/wet
					S	MRI-CGCM3	Cool/dry
					A	ACCESS1-0	Hot/dry
					R	MPI-ESM-MR	Middle
83350	Ikweha	− 8.274	35.00	1427	M	IPSL-CM5A-LR	Hot/wet
					F	CESM1-BGC	Cool/wet
					S	MRI-CGCM3	Cool/dry
					R	MPI-ESM-MR	Hot/dry
					Q	MPI-ESM-LR	Middle

Fig. 9 Temperature-and-Precipitation change scatter diagram for Kinyanambo station (83353)

change as expected, and (ii) the hydrological and atmospheric conditions, soils and slope will remain unchanged over the next decade. The future GCMs-derived climate data was then introduced into the Ndembera SWAT model that had been updated with the 2020 land use/cover. This was done in order to simulate the combined effect of future climate and land use/cover changes on water balance. Lastly, the same SWAT model setup containing the 2020 land use/cover and the 2010–2039 GCMs-derived climate data was used to simulate the impacts of land and water management practices on water balance and streamflow. The practices included

terracing and contouring, filter strips, grassed waterways and deep ripper subsoiler tillage. The choice of these management practices was based on the nature of the landscape (slope) and the expected land use/cover and climate changes on water balance in the watershed such as reduced infiltration and increased evapotranspiration.

The effects of the four management practices on water balance were simulated in SWAT by activating the sub-models of the respective management practices. Table 4 shows the parameters and their final values used for water balance simulation under each management practice. These values were applied in the hydraulic response units with agricultural land use only.

Results

Sensitivity analysis results

The top six most sensitive parameters to the river discharge were the groundwater delay factor (GW_DELAY), average slope steepness (HRU_SLP), groundwater "revap" coefficient (GW-REVAP), available water content of the soil (SOL_AWC), average slope length (SLSUBBSN), and the curve number (CN_2) (Fig. 10). Compared to others, these six parameters showed higher t-Statistic values ($|\cong 2$ to $16|$) and lower p values (0 to < 0.05). Four parameters (CN_2, SLSUBBSN, SOL_AWC and HRU_SLP) which are the surface flow response parameters showed high sensitivity while two channel response parameters (CH_K1 and CH_N2) showed very low sensitivity to the river discharge.

Performance of the SWAT model

The coefficients of determination (R^2), the Nash-Sutcliff efficient index (NSE) and PBIAS values showed that

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Table 4 List of SWAT input parameters and values used for each management practice

Management practice	SWAT input table	Parameters	Parameter description	Value
Filter strips	Management (.Mgt)	FILTERW	Width of the edge of field filter strips (m)	30*
	Operations (.Ops)	FILTER_RATIO	Ratio of field area to filter strip area (unitless)	40
	Operations (.Ops)	FILTER_CON	Fraction of the HRU which drains to the most concentrated ten percent of the filters strip area	0.5
	Operations (.Ops)	FILTER_CH	Fraction of the flow within the most concentrated ten percent of the filter strip which is fully channelized (dimensionless)	0
Grassed waterways	Operations (.Ops)	GWATN	Manning's "n" value for overland flow	0.35
	Operations (.Ops)	GWATL	Grass waterway length (km)	1000
	Operations (.Ops)	GWATW	Average width of grassed waterway (m)	10*
	Operations (.Ops)	GWATD	Depth of grassed waterway channel from top of bank to bottom (m)	1
	Operations (.Ops)	GWATS	Average slope of grassed waterway channel	HRU slope × 0.75
Terraces and contour	Operations (.Ops)	TERR_CN	Curve number	62**
	Operations (.Ops)	TERR_SL	Average slope length (m)	61***
	Operations (.Ops)	CONT_CN	Initial SCS curve number II value	62**
Deep ripper subsoiler	Management (.Mgt)	CNOP	SCS runoff curve number for moisture conditions II	62**

* User defined value based on knowledge from the field. ** Adopted from Table 20-1 of runoff curve numbers for cultivated agricultural lands (Arnold et al. 2013).
*** Values from the calibrated SWAT model. Other values without the asterisk (*) were default values from the SWAT database
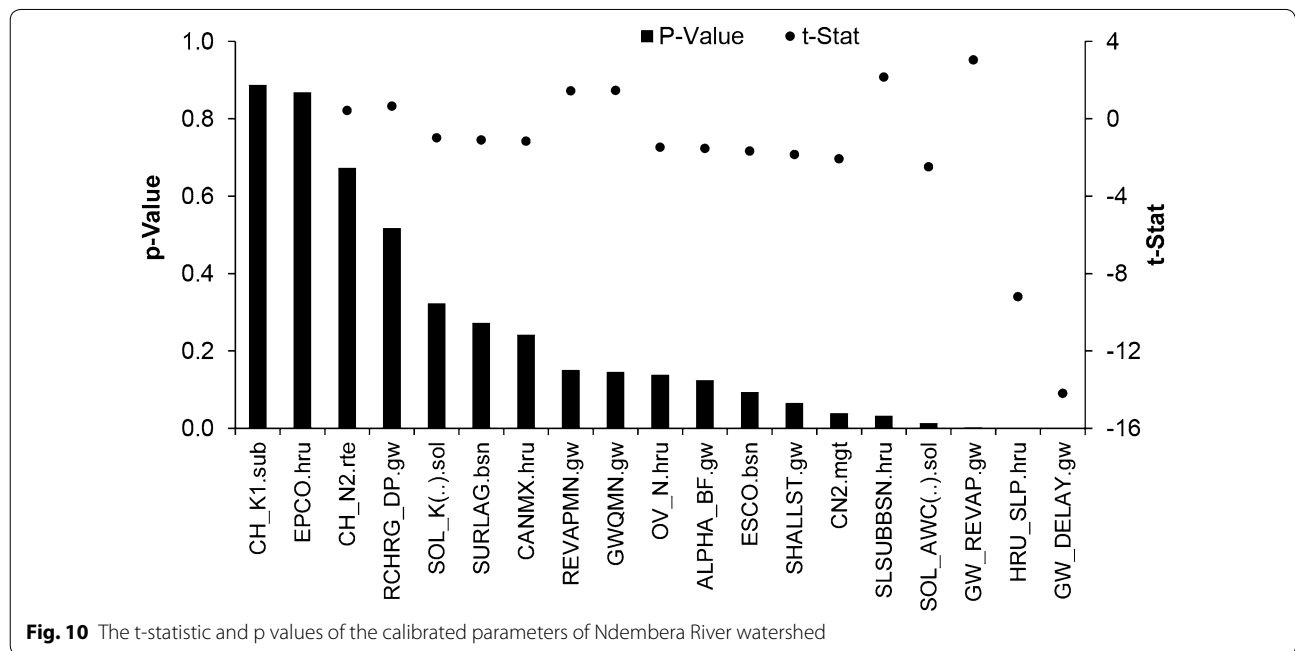
Fig. 10 The t-statistic and p values of the calibrated parameters of Ndembera River watershed

there was a good fit between the observed and the simulated flow both in the calibration and validation period (Table 5). The R^2 for calibration and validation periods were 0.79 and 0.80, respectively. The NSE ranged from 0.78 to 0.76. The respective *p*-factor and *r*-factor statistic were 0.63 and 0.61 for the calibration period and 0.48 and 0.65 for the validation period. The differences between the simulated and observed discharge at 1ka33, expressed as the percentage bias (PBIAS) was very small

for the calibration and validation period (3.8 and −4.6, respectively).

A comparison between SWAT simulated and observed discharge of the Ndembera river at 1ka33 on monthly time step in Fig. 11 showed a good capture of both ascent and recession of the river hydrograph. The hydrograph matched well with the precipitation rhythm of the catchment. The peaks of the simulated streamflow appeared to be underestimated both during the calibration and

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Table 5 SWAT model's calibration and validation statistical analysis results

Parameter	Statistical values	
	Calibration	Validation
NSE	0.78	0.76
R^2	0.79	0.80
p-Factor	0.63	0.48
r-Factor	0.61	0.65
PBIAS	3.8	− 4.6

validation periods except in 2010 where the peak flows of simulated flow were greater than the observed flow. Generally, the simulated streamflow from the calibrated model slightly underestimated the actual streamflow during the low flows. Given the high values for R^2 and NSE and good match hydrographs, the model was considered to be suitable for water balance simulation in this study.

Evaluation of the GCMs-derived climate data

The mean monthly precipitation and temperature from the downscaled GCMs for both the baseline and verification periods showed a good match with the observed data (Figs. 12, 13). In these figures, the curves of the GCMs-derived climate data captured very well the pattern (peaks and troughs) of the inter-annual variations in the observed data series from the three weather stations. Results in Table 6 depicted good linear relationship between observed and GCM-derived climate data (R = 0.92–0.99 for precipitation and 0.77–0.99 for temperature).

The comparison between observed and GCMs-derived temperature in Fig. 13a, b showed a slight underestimation of GCMs-derived temperature while Fig. 13c indicated an overestimation. The degree to which the GCMs-derived climate variables were underestimated or overestimated were denoted by positive and negative mean error values (ME) in Table 6. Kinyanambo station mean error values were 0.95 and 1.24 for the baseline and verification periods, respectively; while, Ikweha station had negative mean error values of − 1.19 and − 0.91, respectively. The mean error values of precipitation from all three weather stations ranged from − 0.19 to 0.05. Generally, the mean error values for both temperature and precipitation were relatively small. In addition, the distribution parameters, the mean, standard deviation (SD) and median of the GCMs-derived climate data were close to those from the observed station data.

Current and future trends of mean climate in the watershed

The annual mean precipitation and mean monthly temperature of the Ndembera watershed for the past three decades (1980–2009) showed an increasing trend (Figs. 14a, 15a). The same trend was observed in the near-future period (Figs. 14b, 15b). Whereas the annual mean precipitation increase from 1980–2009 was about 2.4 mm/year (Fig. 14a), that of the near-term period was about 3.2 mm/year (Fig. 15a). Based on the regression equation in Fig. 14b, the watershed annual mean precipitation was shown to be about 801.4 mm/year at the end of 2039. Regarding temperature, the watershed mean monthly temperature changed from 16.8 °C in 1980 to about 17.6 °C at the end of 2009 (Fig. 15a), an increase
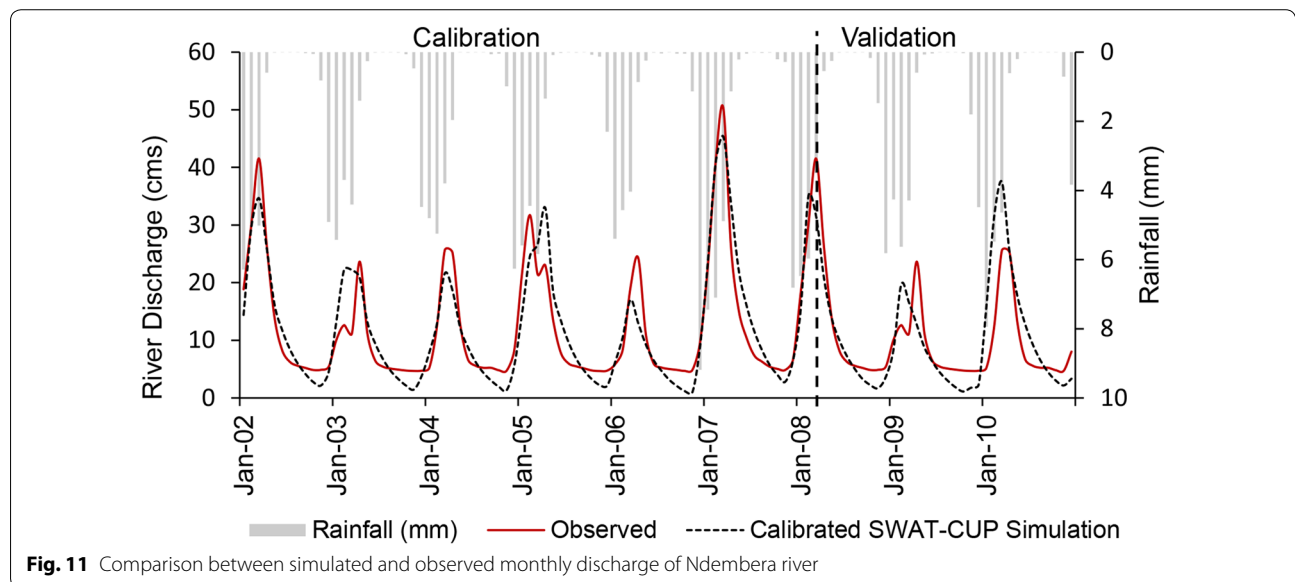
Fig. 11 Comparison between simulated and observed monthly discharge of Ndembera river

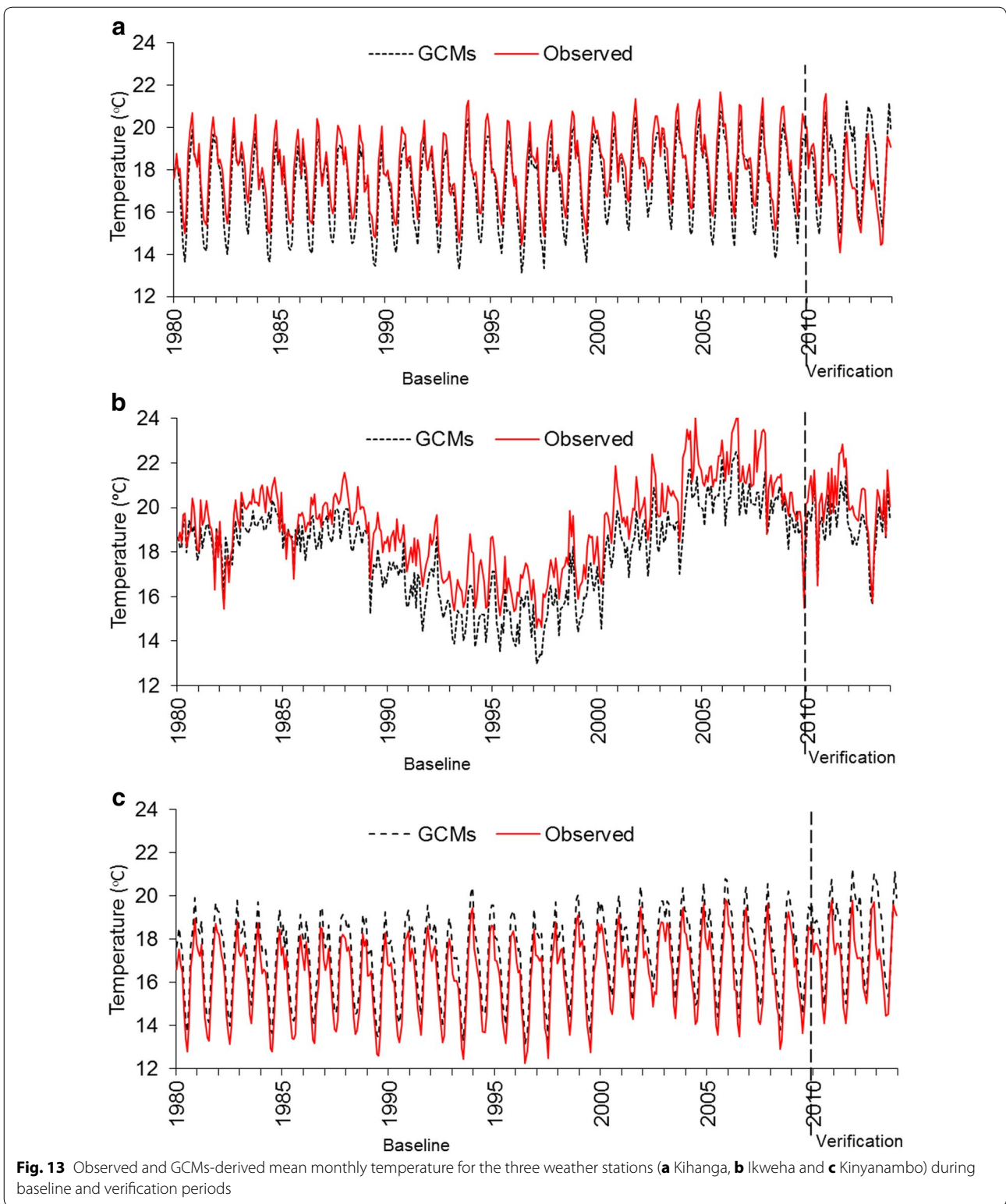Hyandye *et al. Environ Syst Res* (2018) 7:7

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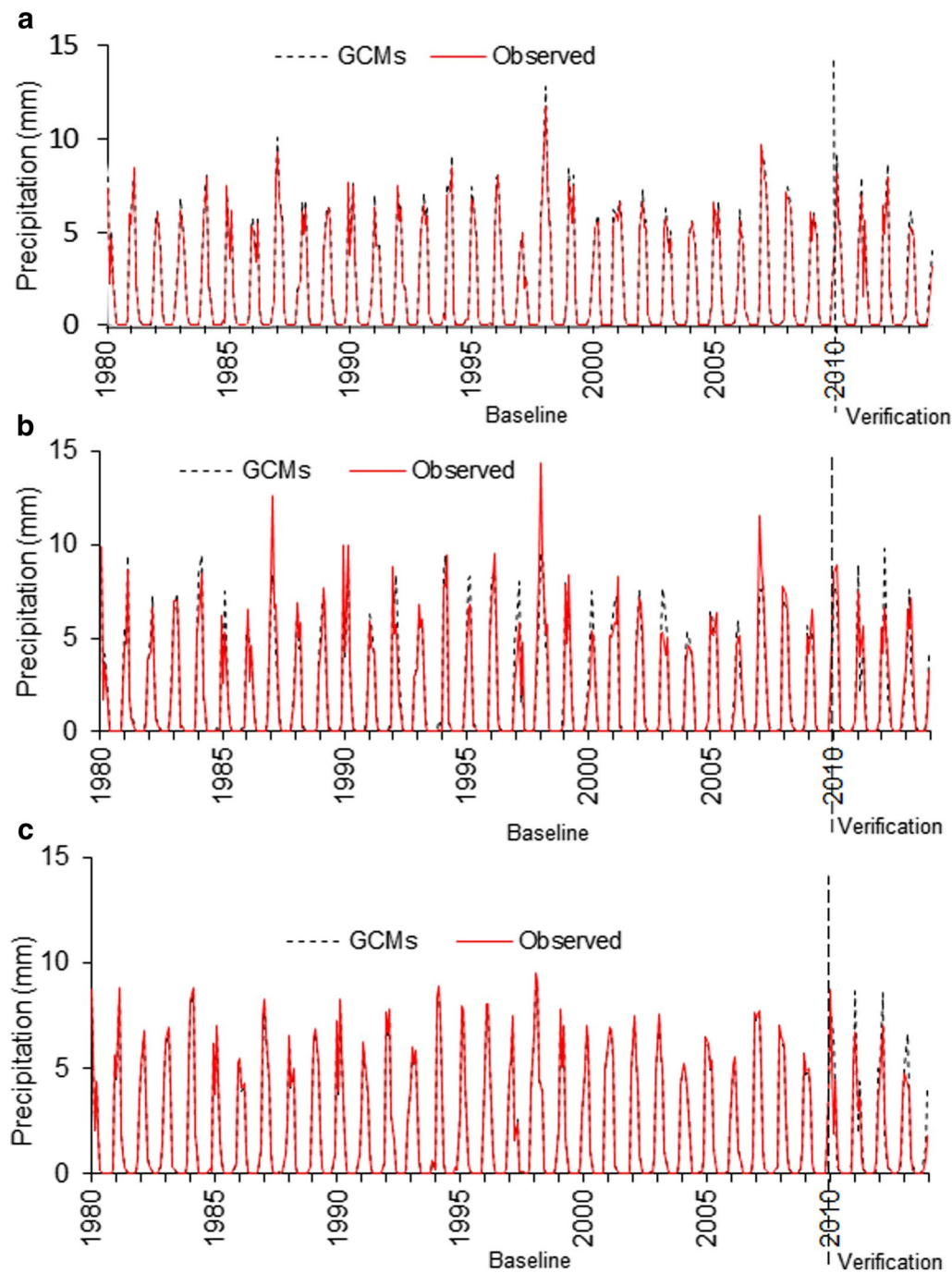
Fig. 12 Observed and GCMs-derived mean monthly precipitation for the three weather stations (**a** Kihanga, **b** Ikweha and **c** Kinyanambo) during baseline and verification periods

of about 0.8 °C over the past 30 years. The temperature of the period between 2010 and 2039 are expected to increase by 1.1 °C (from 18.1 °C in 2010 to 19.2 °C) (Fig. 15b).

A comparison of the amount of precipitation for each month averaged over a 30 years period, both in the

baseline and near-term periods, showed higher amounts of precipitation in the wet months of January–April in the near-term than in the baseline period (Fig. 16). The change in the amount of precipitation in these months for the two periods ranged from 2 to 6 mm/month (~2–7%). In the early months of the wet season (November and

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Fig. 13 Observed and GCMs-derived mean monthly temperature for the three weather stations (**a** Kihanga, **b** Ikweha and **c** Kinyanambo) during baseline and verification periods

December), the near-term showed less amounts of precipitation than the baseline period. The precipitation decrease was 6 mm/month (~20%) in November and 4 mm/month (~3%) in December (Fig. 16). The minimum and maximum monthly mean temperature for the watershed were higher in the near-term than in the

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Table 6 Statistical analysis results of the monthly precipitation and temperature for the baseline and verification periods

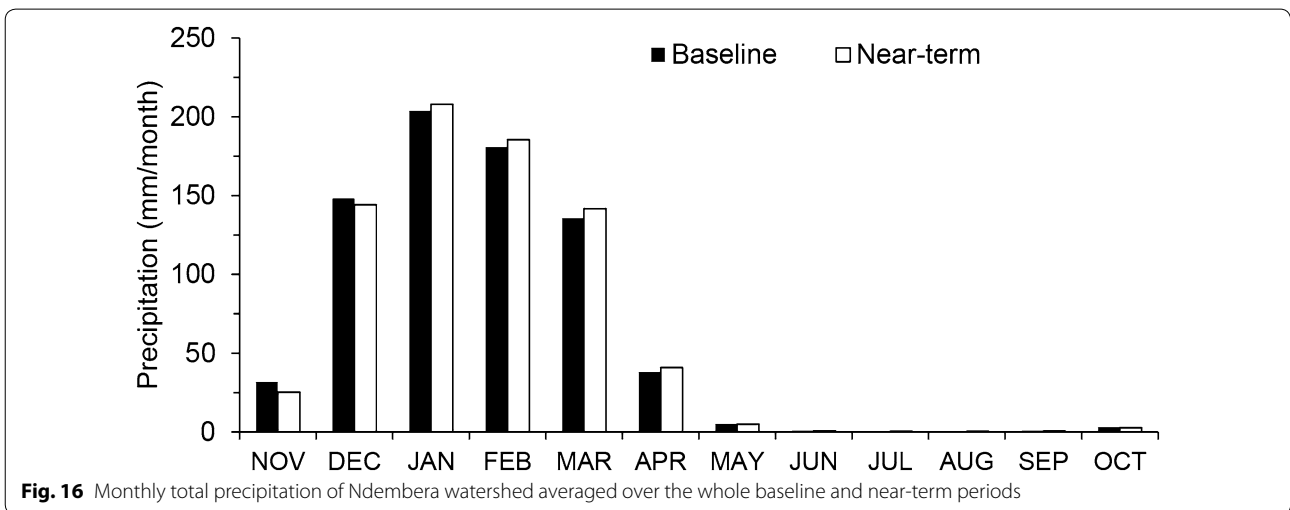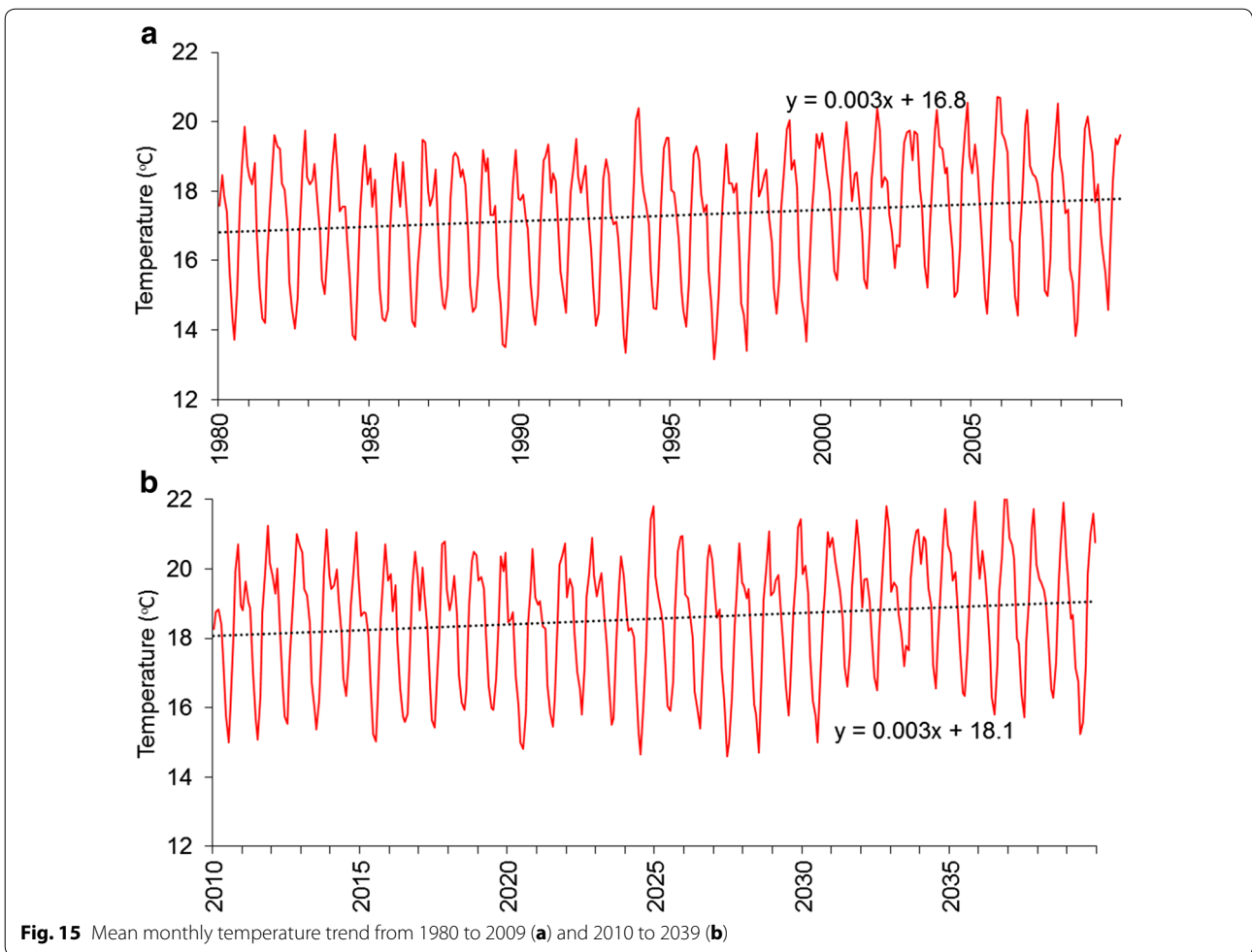| Station	Parameter	Period	ME	R	Mean		SD		Median	
					GCM	Observed	GCMs	Observed	GCMs	Observed
Kihanga (80353)	Precipitation	Baseline	− 00.09	0.99	2.12	2.03	2.80	2.69	0.29	0.28
		Verification	− 0.19	0.98	2.00	1.81	2.66	2.48	0.30	0.37
Ikweha (83350)	Temperature	Baseline	− 0.79	0.96	17.30	18.10	1.82	1.60	17.65	18.10
		Verification	0.81	0.77	18.32	17.52	1.83	1.71	18.73	17.45
	Precipitation	Baseline	0.05	0.96	2.08	2.02	2.80	2.93	0.27	0.11
		Verification	− 0.15	0.92	1.95	2.10	2.72	2.75	0.35	0.28
	Temperature	Baseline	− 1.19	0.95	17.95	19.14	2.03	1.99	18.43	19.23
		Verification	− 0.91	0.92	19.31	20.22	1.17	1.40	19.36	20.16
Kinyanambo (83353)	Precipitation	Baseline	− 0.05	0.99	2.00	2.05	2.67	2.74	0.29	0.30
		Verification	− 0.19	0.92	1.86	1.66	2.55	2.22	0.39	0.31
	Temperature	Baseline	0.95	0.99	17.29	16.35	1.82	1.79	17.66	16.70
		Verification	1.24	0.91	18.33	17.09	1.83	1.57	18.72	17.21
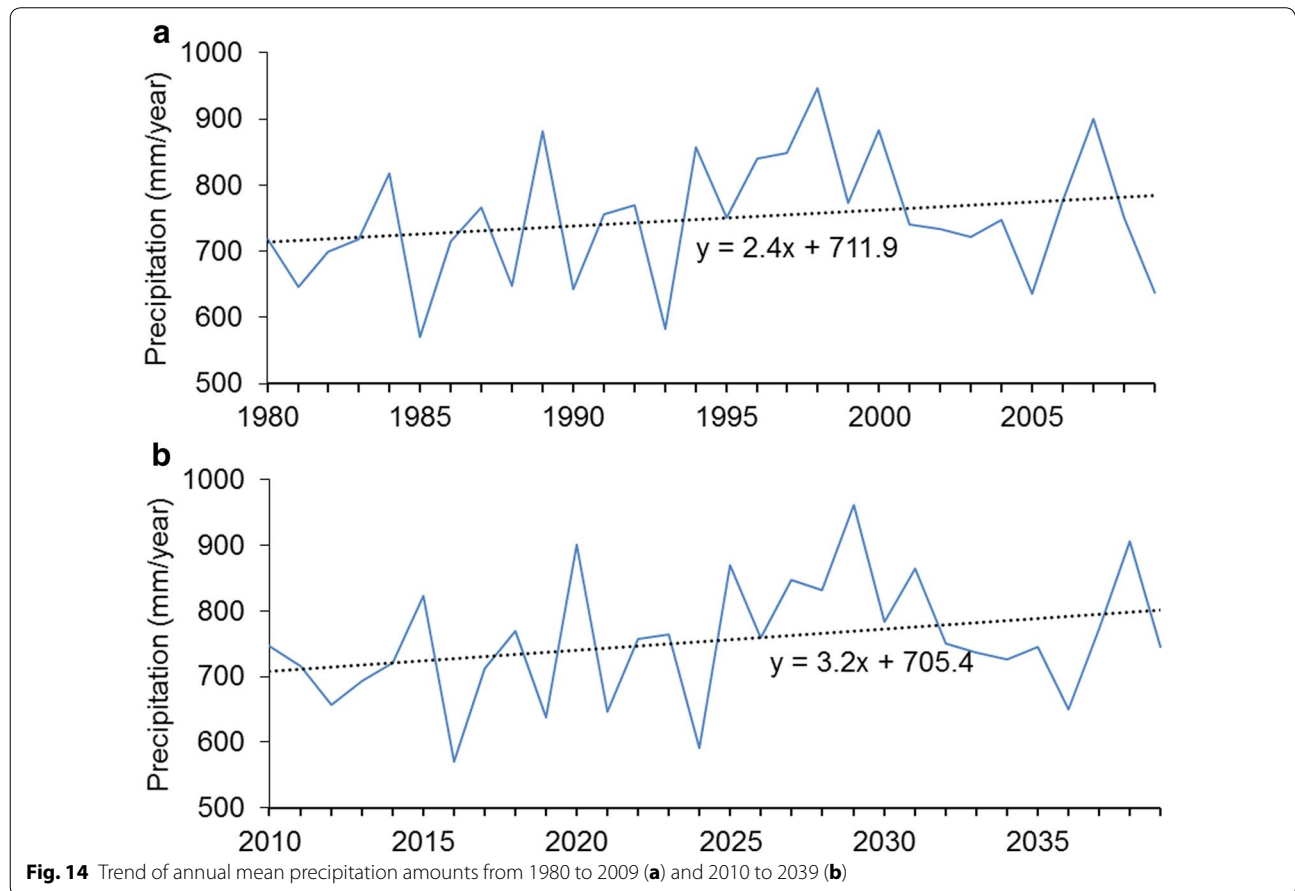
Fig. 14 Trend of annual mean precipitation amounts from 1980 to 2009 (**a**) and 2010 to 2039 (**b**)

baseline period throughout the year (Fig. 17). The highest temperature change between the two periods was 1.5 °C in November for maximum temperature and 1.4 °C in June and July for the minimum temperature.
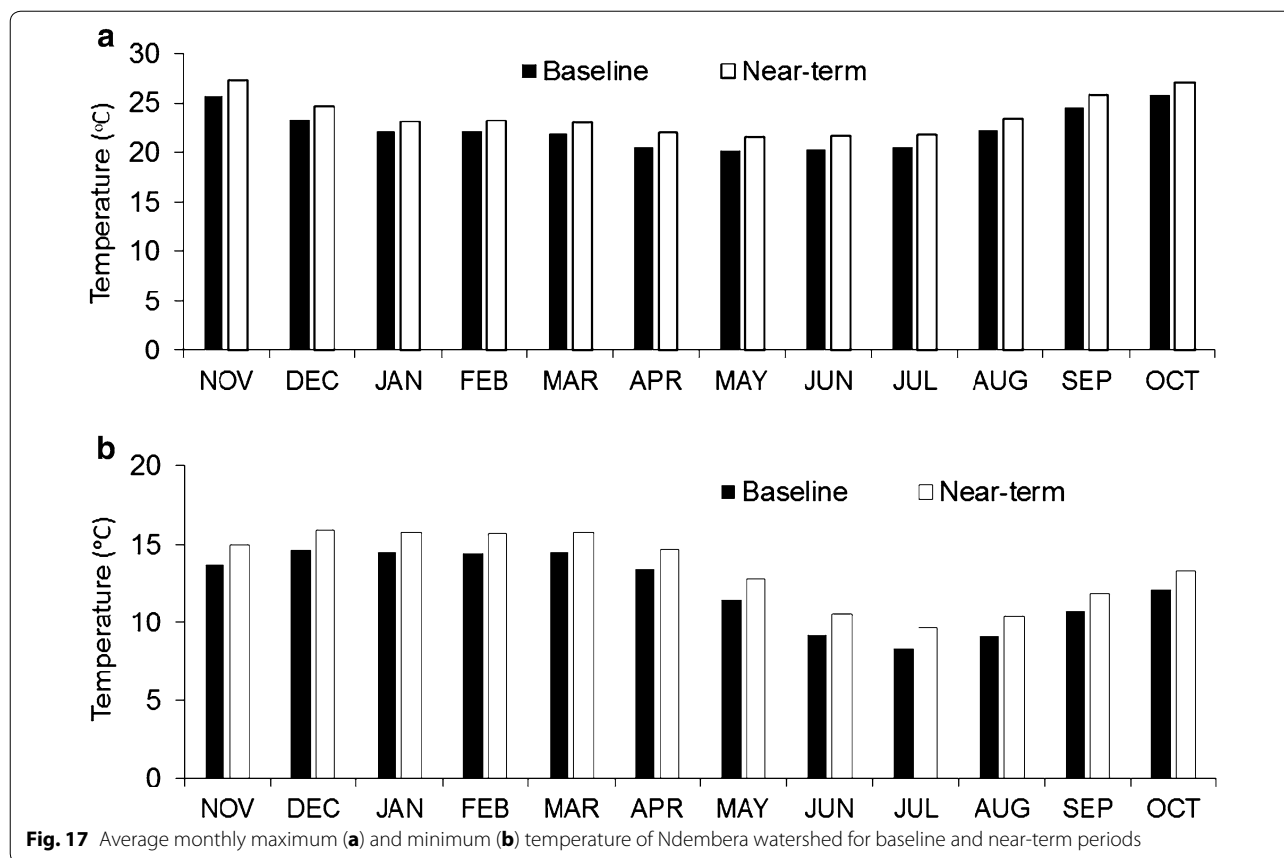
Land use/cover change and its impact on the catchment water balance

The largest future land use/cover change between 2013 and 2020 were observed in the mixed forest lands (Fig. 18). The mixed forest land decreased by 12%.

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Fig. 15 Mean monthly temperature trend from 1980 to 2009 (**a**) and 2010 to 2039 (**b**)

Fig. 16 Monthly total precipitation of Ndembera watershed averaged over the whole baseline and near-term periods

The areas under agricultural land were projected to increase by 10%, while evergreen forests increased by 7%. The shrub lands (Range-Brush) and grasslands (Range-Grasses) showed a decrease of 6 and 1%, respectively. Very small changes were observed for urban land and wetlands.

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Fig. 17 Average monthly maximum (**a**) and minimum (**b**) temperature of Ndembera watershed for baseline and near-term periods

The observed land use/cover changes from 2013 to 2020 scenario affected the water balance of the watershed in a number of ways. These include a decrease of the total water yield and the lateral flow components by 32 mm/year (~ 13%) and 34 mm/year (~ 49%) (Fig. 19). On the contrary, the evapotranspiration and surface runoff increased by 30 mm/year (~ 8%) and 5 mm/year (16%), respectively. The amount of water loss from the channels during downstream flow (transmission losses) increased by 20 mm/year (88%). Some very minor changes were noted for the rest of the components such as total aquifer recharge, shallow and deep groundwater flow and water percolating out of the soil.

Water balance ratios, the Streamflow/Precipitation and baseflow/total flow indicated negative changes of − 0.05 and − 0.14, respectively (Table 7). On one hand, the baseflow contribution in the watershed total flow under 2013 and 2020 land use/cover scenarios were 0.78 and 0.64, respectively. On the other hand, the surface runoff contributed only 0.22 to 0.36, respectively. The ET/precipitation and Surface Runoff/Total flow ratios showed positive changes of 0.04 and 0.14, respectively. Furthermore, land use changes had no effect on the amount of precipitation that was partitioned into percolation and deep recharge.

A comparison of the average monthly river discharge at 1ka33 for the baseline and future land use/cover scenarios showed small differences, both in the mean discharge values and the timing of ascent and recession of the hydrograph (Fig. 20). During the ascent of the hydrographs in December and January, the simulated mean monthly discharge under the 2020 land use/cover was above the baseline discharge, that is, 5 and 14 m³/s compared with 4.5 and 13 m³/s, respectively. On the contrary, during the recession of the hydrograph, from March to April (wet season) through June and October (dry season), the simulated discharge under the 2020 land use/cover was lower than the baseline discharge. In addition, there was a horizontal shift of the discharge hydrograph to the left, showing some early ascending and recession of the hydrograph in the wet months (Fig. 20).

Impact of future climate change on the catchment water balance

Near-term climate change affected water balance components by decreasing the lateral water flow from 70 to 35 mm/year (~ 100% change) and the total water yield from 260 mm/year to 240 mm/year, a decrease of ~ 8% (Fig. 21). The evapotranspiration increased from
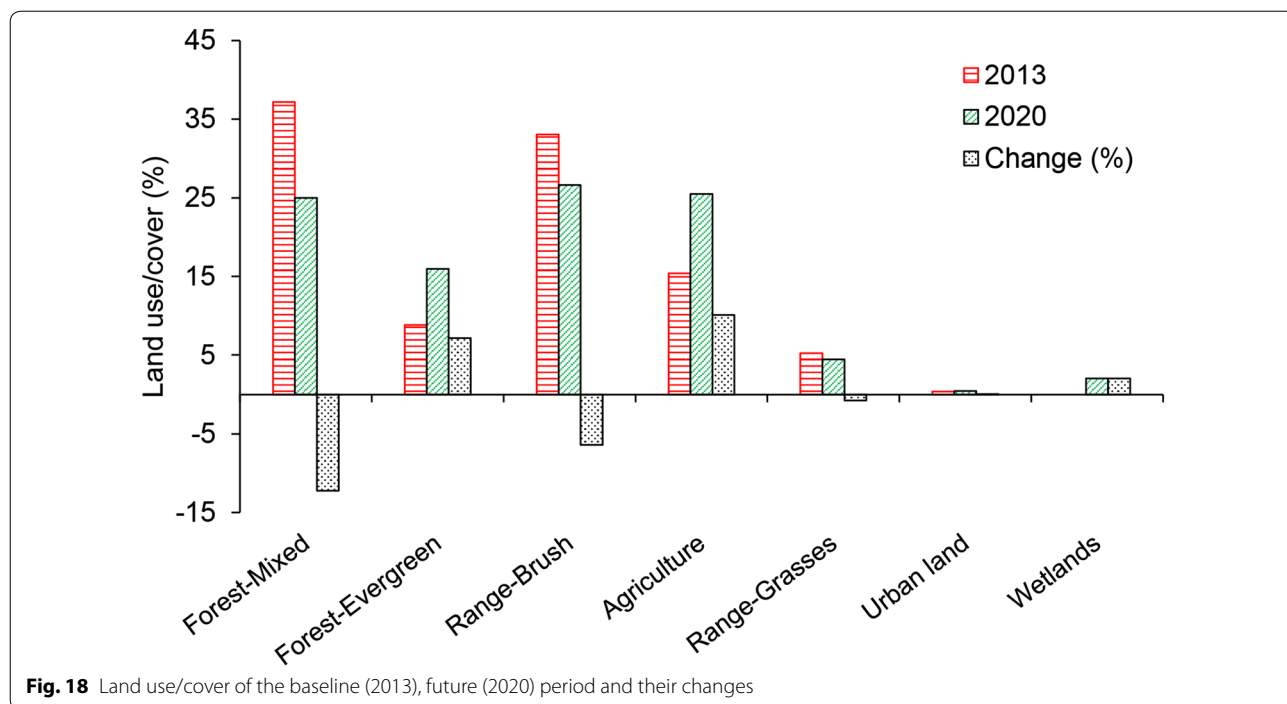
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Fig. 18 Land use/cover of the baseline (2013), future (2020) period and their changes
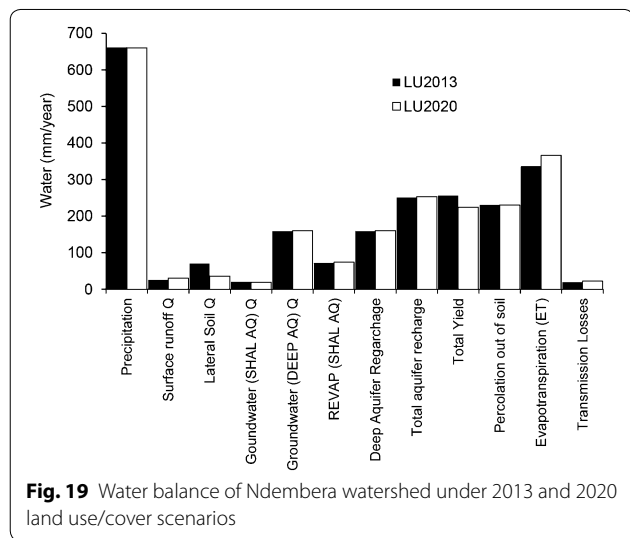

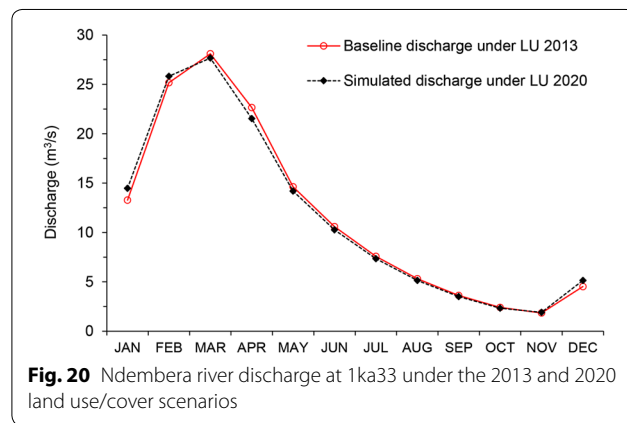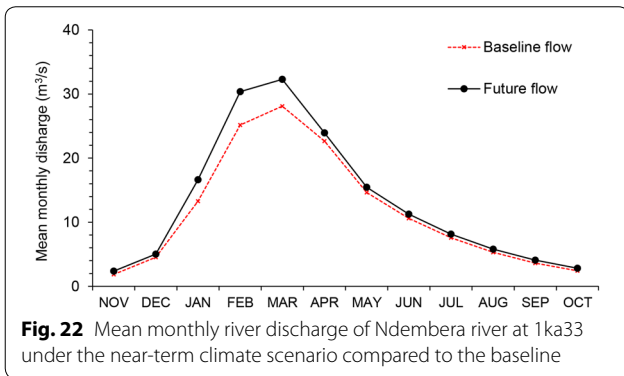**Fig. 19** Water balance of Ndembera watershed under 2013 and 2020 land use/cover scenarios

Fig. 20 Ndembera river discharge at 1ka33 under the 2013 and 2020 land use/cover scenarios

336 mm/year in the baseline to 453 mm/year (about 35% change). Compared with the baseline climate scenario, the surface runoff, total losses of water in channels during downstream flow and the Revap from shallow aquifer showed a relatively small decrease under the future climate change scenario. The shallow aquifer flow, deep aquifer recharge, groundwater recharge and percolation increased by a relatively small amount under the future climate scenario.
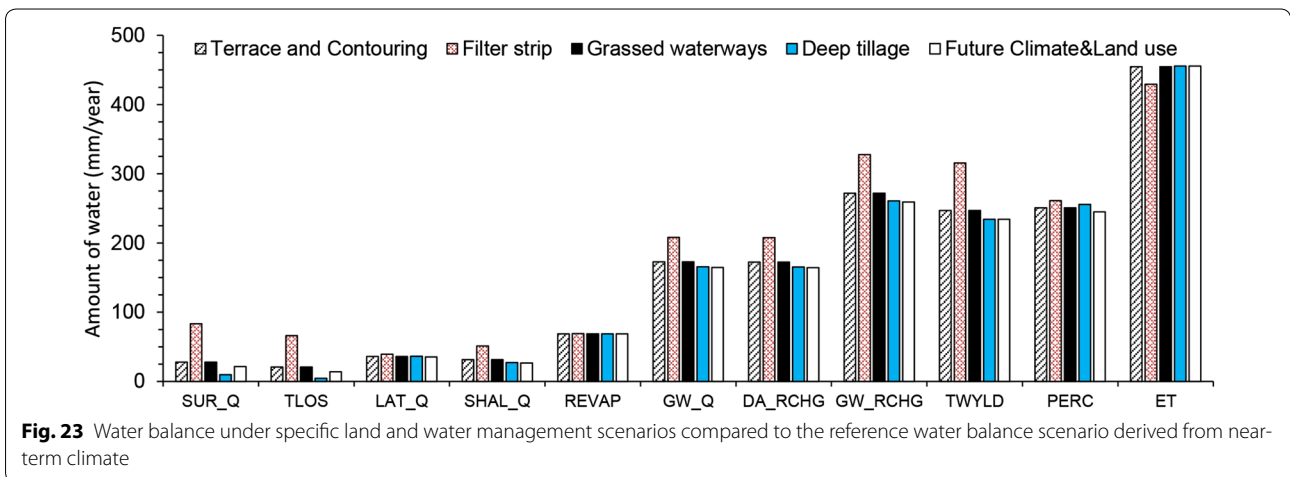
The near-term climate change scenario will increase the mean monthly river discharge for the near-term period relative to the baseline period (Fig. 22). Large differences between the baseline and future period flows were noted

Table 7 Changes in the water balance ratios under 2013 and 2020 land use scenarios

Water balance ratios	LU2013	LU2020	Change
Streamflow/precipitation	0.18	0.13	− 0.05
Baseflow/total flow	0.78	0.64	− 0.14
Surface runoff/total flow	0.22	0.36	0.14
Percolation/precipitation	0.38	0.38	0
Deep recharge/precipitation	0.24	0.24	0
ET/precipitation	0.51	0.55	0.04

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Fig. 21 Near-term water balance simulated under the GCMs ensemble mean climate data compared to the baseline water balance

Fig. 22 Mean monthly river discharge of Ndembera river at 1ka33 under the near-term climate scenario compared to the baseline

during the wet season, especially in the months of January–March. The February river discharge will increase from 25 m³/s in the baseline period to 30 m³/s in the future period (~21% increase). Similarly, in the month of March, the discharge will increase from 28 to 32 m³/s (~15% change).

Impacts of land and water management practices on water balance and river discharge

The simulation of water balance of the watershed under the four land and water management practices increased the amount of water in almost all water balance components (Fig. 23). The amount of evapotranspiration of water under filter strips decreased by almost 26 mm/year (~6%). Furthermore, filter strips decreased the surface runoff by 12 mm/year (~54%) while the deep ripper tillage decreased the transmission losses in streams by 10 mm/year (~66%). Unexpectedly, the grassed waterways and terrace and contouring management practices increased the surface runoff by equal intensity of 31% (~21–28 mm/year). In general, the filter strips showed relatively greater changes in the annual water balance in most of the components compared with other land and water management practices. Such changes included increase in the surface runoff from 21 to 83 mm/year, total water yield from 234 to 315 mm/year and the

Fig. 23 Water balance under specific land and water management scenarios compared to the reference water balance scenario derived from near-term climate

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percolation from 234 to 261 mm/year. The deep aquifer recharge and total groundwater recharge an increased by 43 and 68 mm/year, respectively.

The river discharge increased for almost all management practices compared with the discharge under the near-term climate and 2020 land use discharge scenario except for the deep ripper tillage (Fig. 24). The simulated flow under the filter strip practices scenario showed higher discharge than other management scenarios throughout the year. The river discharge under the filter strips were as higher as 42 m³/s in February and March compared with 26 and 30 m³/s of the reference discharge (discharge under the effect of near-term climate change and 2020 land use/cover) during the same months. These changes represent a change of about 62 and 40%, respectively. The hydrographs of the terracing and contouring as well as grassed waterways were slightly lower than the one under filter strips throughout the year but higher than the reference discharge during the wet season (January–April).

Discussion

Model parameterization and sensitivity analysis

The sensitivity analysis from other watersheds in the East African region had, among the top six sensitive parameters, few parameters similar to the one found in the Ndembera watershed. For example, in Murchison Bay Catchment, Uganda, the CN_2, GW_DELAY and GW_REVAP were among the top six sensitive parameters to river discharge (Anaba et al. 2017). The CN_2 and SOL_AWC were also among the most sensitive parameters reported in the Simiyu river Catchment in Tanzania (Mulungu and Munishi 2007).

The parameters presented in Table 2 and their sensitivity information in Fig. 10 are significant to the body of scientific knowledge in two ways. Firstly, allow a more stringent evaluation of the reality of the parameters used in the model parameterization and calibration as well as the models itself as suggested by van Griensven et al. (2012). Secondly, the results serve as a starting point of SWAT model parameterization in the subsequent studies within or in the nearby watershed which may need SWAT as a tool for hydrological processes related analysis. However, the parameter values may need some minor customizations because the catchments differ in their physical characteristics (Schmalz and Fohrer 2009).

Adequacy of the SWAT model and GCMs-derived data for hydrological processes simulation

The NSE values in Table 5 are far greater than the acceptable values; NSE > 0.5 (Moriasi et al. 2007). The PBIAS values −4.6 and 3.8 are within PBIAS < |25%|, can be said to describe a satisfactory model performance for monthly data of the stream flow (Dourte 2011; Moriasi et al. 2007). Small PBIAS values in this study indicate a good mass balance in terms of volume between the observed and simulated discharge. Although the *p*-factor and *r*-factor should be > 0.8 and < 1, respectively (Abbaspour 2007), the *p*-factor value of 0.48 (~ 0.5) in Table 5 is also sufficient under less stringent model quality requirements (Schuol et al. 2008).

The satisfactory model calibration and validation results in Table 5 as well as a good match of the observed and simulated flows in Fig. 11 are interpreted as the outcomes of good model input data, notably rainfall and model parameterization. Rainfall is an important data input for hydrological models (Strauch et al. 2012). The distributed rainfall information increases the simulation accuracy and predictive capacity of the model (Dwarakish and Ganasri 2015).
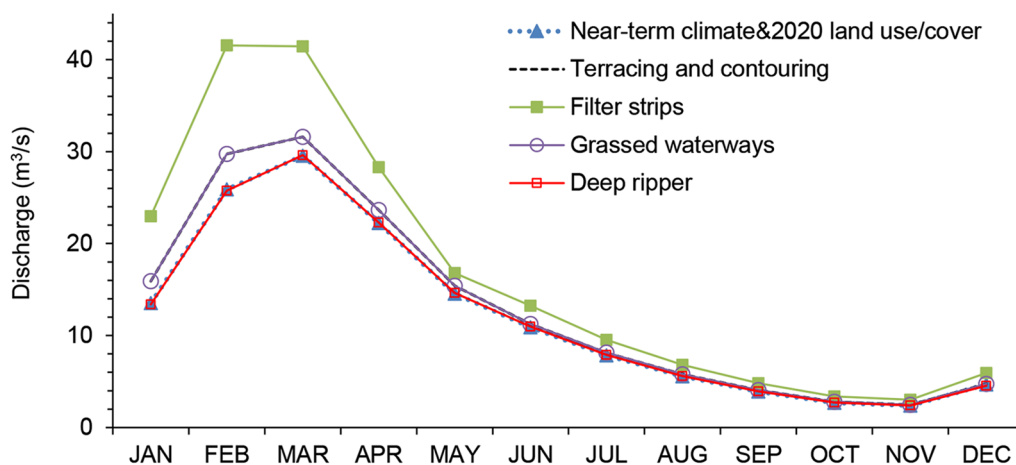
Fig. 24 Hydrographs of Ndembera River at 1ka33 under different land and water management practices compared the reference hydrograph

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A good match between the GCMs-derived and the observed climate data (Figs. 12 and 13), may be associated with the strength of the quadrant method for CMIP5-GCMs sub-selection which was also previously used by Subash et al. (2016). Indeed, this observation is evidenced by high correlation values, small mean error values and closely related distribution statistical parameters (Table 6). The mean error values in Table 6 are better than those reported by Mutayoba and Kashaigili (2017) who evaluated the performance of the CORDEX Regional Climate Models in simulating rainfall characteristics over Mbarali river, a river catchment very close to Ndembera within the same Usangu Catchment. The mean error values ranged from −19.2 to 35.4. Nevertheless, the magnitude of correlation values from the same study ranged from 0.77 to 0.99, similar to this study. These good validation results in this study could also be attributed to ready-made functions used for the CMIP5-GCMs statistical downscaling and climate projection (Hudson and Ruane 2013). Underestimated GCM climate in Fig. 13a, b could be partly attributed to the poor accuracy of the observed temperature data.

The trend of climate change in the Ndembera watershed

The increasing trend of the warmer conditions (1.1 °C) in the near future (Fig. 15b), is mainly attributed to the increased CO_2 concentration and other greenhouse gases in the atmosphere at a global level (Edenhofer et al. 2011). The trend and magnitude of temperature change in the near future period observed in this study does not differ much from 1.3 °C by 2030 observed in a previous study in Tanzania (Laderach and Eitzinger 2012). The same study reported an increasing trend of the annual precipitation as observed in the current study. In addition, the recent climate change projections study by Serdeczny et al. (2016) has also reported a warming trend in sub-Saharan Africa and increased precipitation in East Africa.

The impact of land use/cover change on water balance and river discharge

The decrease in the total water yield and lateral water flow and the increase in evapotranspiration and surface runoff depicted in Fig. 19 could be explained by the observed 2013–2020 land use/cover changes (Fig. 18). For example, the increase in evapotranspiration by 30 mm/year in Fig. 19 could be attributed to the 10% increase in agricultural land (Fig. 18), mainly the irrigated onion and rice farms. It is worth noting that the irrigated rice in small river watersheds in Usangu basin has higher water demand than most crops because of the pre-saturation of the soil profile and the need for a standing water layer (Lankford and Franks 2000). The large surface standing water in agricultural fields creates high

possibility of water loss through evaporation. Another argument accounting for the increased evapotranspiration is the increase in evergreen forest (7%, Fig. 18) mainly the eucalyptus and pine commercial trees in Mufindi District. This implies the increase of more plant biomass and high leaf area index due to increased canopy. Usually, the canopy stores more water when the precipitation is intercepted and, therefore, making more amount of water available for evaporation (Wang and Kalin 2011). The increase in evaporation from canopy and irrigated farms can also explain for the observed decrease in total water yield (Fig. 19).

The increase of surface runoff/total flow ratio (Table 7) is translated as the result of the increased agricultural area, urban land and a decrease of tree and grass cover in forests and rangelands (Fig. 18). The removal of forest trees and grass cover tends to increase storm runoff and decrease infiltration to groundwater and baseflow of streams (Kiersch 2006). The removal of forests reduces the infiltration opportunities which, in turn increases the amounts of water leaving the area as storm runoff and reduces the gain in baseflow. This usually diminishes the dry season flow (Kashaigili 2008). According to Dagar et al. (2016), the use of machinery for various tillage practices causes the compaction of the soils. This scenario may account for the decrease in infiltration to groundwater, increased surface runoff and decline in baseflow observed in the current study. The increased surface runoff leads to an increased amount of water flowing to the streams in wet season and it can ultimately be lost through evaporation (Arnold et al. 2009).

The decrease in the baseflow component from 0.78 to 0.64 under the 2013 and 2020 land use/cover scenarios in Table 7 complements the findings of continuous declining trend of baseflow across the Usangu catchment in the period between 1960 and 2009 (Shu and Villholth 2012). The authors reported deforestation, irrigation and groundwater abstraction as the main factors causing the baseflow decline. Land use/cover change has been associated with the declining the baseflow in other studies conducted within the Usangu catchment (Kashaigili 2008) and in other countries such as Botswana and South Africa (Palamuleni et al. 2011).

The decrease in total water yield observed in Fig. 19 as a result of land use/cover change is mainly attributed to the decrease in forest cover. According to Palamuleni et al. (2011), the destructive land cover change may disrupt the hydrological cycle either through increasing or diminishing the water yield. In the current study, water yield decreased with decreasing forest cover contrary to the previous studies where water yield increased with forest reduction (DeFries and Eshleman 2004; Feng et al. 2012). The contradicting findings suggest that water yield

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is a function of factors other than the forest cover which in this case appear to have had greater influence on water yield. Such factors may include the increased evapotranspiration from increased agricultural areas (Fig. 18) or increased evapotranspiration due to the unaccounted recent decade-long temperature increase.

The horizontal shift of the river discharge pattern depicted in Fig. 20 is an indication of increased surface runoff due to the removal of vegetation cover as a result of expanding agricultural area and decrease of mixed forests (Fig. 18). The Great Ruaha river showed similar discharge pattern as a result of land use/cover change in the areas around the Ihefu Wetland (Kashaigili 2008). The observed low flows in the dry season under the 2020 land use/cover scenario (Fig. 20) signify reduced agricultural production especially irrigated rice at the Madibira and Mkunywa irrigation schemes. As reported earlier, the shortage of water downstream will have negative consequences on wildlife in the Ruaha National Park (Kashaigili et al. 2006b).

The impact of near-term climate change on water balance and river discharge

The continued increase in evapotranspiration from 336 to 453 mm/year under the influence of the near-future climate change scenario (Fig. 21) is mainly attributed to the observed change of mean watershed temperature of 1.1 °C (Fig. 15b) and the increase of both the mean monthly minimum and maximum temperatures (Fig. 17). The results imply that the evapotranspiration was underestimated when the impacts of land use/cover change were evaluated in isolation. The increased evapotranspiration is known to increase the water demand of plants and increase water stress which may reduce crop yields (Jensen 1968). The possibility of a decrease in crop yields in the watershed due to the effects of global warming and the increase in temperature is supported by the findings from a previous study in Tanzania (Laderach and Eitzinger 2012). In this study, it was found out that a change of temperature by $+1.3$ °C will decrease areas suitable for coffee cultivation by 20–50% in 2050. Globally, 1 °C increase in temperature in the developing countries will lower the growth in agricultural output by 2.66% (Dell et al. 2012). One of the reasons for this is the increased evaporative loss (Beck and Bernauer 2011). Nevertheless, increased evaporative loss may lead to increased yield of some crops. For example, a study by Jones et al. (2015) predicted that increased evapotranspiration by 6% coupled with increased CO_2 concentration fertilization will result in increased yield of irrigated sugarcane in South Africa during the 2070–2100 period. This implies that climate change brings with it potentials for crop production if appropriate adaptation measures are taken.

Despite the fact that the future climate scenario showed wetter and warmer conditions in the near-future than the baseline period (Figs. 16, 17), the impact of precipitation seemed not to counter the effect of temperature on evapotranspiration. This resulted in the decrease of total water yield shown in Fig. 21. The observed increase in percolation, groundwater recharge, groundwater flow, shallow aquifer flow and reduced revap from the shallow aquifer in Fig. 21 is most probably the result of higher precipitation amounts in the future compared to the baseline. The major reason being that the precipitation is a major component of water balance (Beeson et al. 2011). The change in the amount of precipitation has also some implications on other water balance components (Arnold et al. 2009).

The increase in the future river discharge in the wettest months of January to April (Fig. 22) corresponds well with the increase of the near-term mean monthly precipitations in the same months (Fig. 16). These results are in line with the observation by Taniguchi (2012) and Wambura (2014) that the increase in streamflow depends on the amount of precipitation. The future climate simulation also showed increased discharge of rivers during high flow in Bangladesh (Kirby et al. 2016) and the Sahelian regions (Amogu et al. 2010; Descroix et al. 2012). The increase in high flows in the Ndembera river observed in Fig. 22 may have resulted from the combined effect of future climate and the 2020 land use. This scenario has high and positive potential for boosting irrigated agriculture in the downstream. These irrigated crops could be the high-temperature tolerant type such as sugarcane (Jones et al. 2015).

The impact of land and water management practices as mitigation strategies

The observed changes in water balance such as decreased evapotranspiration and increased percolation, groundwater flow and recharge as well as total water yield (Fig. 23) are dependent on land and water management practices. Contours and terracing reduce the steep slope of the land and, therefore, reduce and delay the surface runoff and allows a long time for rainwater percolation (Dou et al. 2009). Deep ripper tillage increases soil depth and enhances percolation and ultimately reduces overland surface flow (Lacey 2008). Grassed waterways reduce runoff volumes due to their comparably high infiltration rates and the reduction in runoff velocity. The grassed waterways reduced runoff by 10 and 90%, respectively, in the two watersheds in Munich (Fiener and Auerswald 2003). This is contrary to the unexpected increased surface runoff in the current study of about 31% under both grassed waterways and terrace and contouring (Fig. 23). Nevertheless, in this study, the surface runoff under

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filter strips was higher than in other management interventions (Fig. 23). This is due to the fact that filter strips do not affect the surface runoff in SWAT (Arnold et al. 2013). Moreover, high increase in percolation, shallow aquifer and groundwater flow, groundwater recharge and ultimately total water yield under the filter strips compared to other management interventions is attributed to this increased infiltration rate (Arnold et al. 2013).

The increase in streamflow under most of the management interventions observed in Fig. 24 is linked to the increased groundwater recharge due to the decrease of evapotranspiration as shown in Fig. 23. The reduced evapotranspiration and increased streamflow brought about by management practices contributes greatly to reducing the dependency on the river for irrigation and reduce water competition between users (Lankford and Franks 2000). In addition, these management practices will potentially reduce the stress caused by the decline in available water resource due to climate change (Carpenter et al. 1992).

Conclusion

The land use/cover changes in Ndembera river watershed from 2013 to 2020 will interact with the projected near-term warmer temperatures (1.1 °C) and affect water balance by increasing evapotranspiration and surface runoff and decrease in water yield. Changes in these components decreased the baseflow and streamflow, which ultimately decreased the availability of water within the watershed. Major land use/cover of concern are the increase in the areas under agricultural lands, increase in evergreen forests and decrease in mixed forests.

The simulation of combined effects of land use/cover and climate change on water balance generated larger changes than when land use/cover effects are analyzed in isolation. The future warmer climate will exacerbate the water losses in Ndembera river watershed, in turn, will make the watershed unsuitable for producing high temperature sensitive crops. Nevertheless, planting of high temperature tolerant crops such as sugarcane in the watershed could be one of the adaptation strategies. The success of growing crops that are tolerant to elevated temperatures will be realized by adopting land and water management practices which reduce loss and make more water available for crops.

Land and water management practices evaluated in this study have proved to be effective mitigation and adaptation measures for the observed adverse hydrological impacts of future climate and land use/cover changes. Among the four management practices which were evaluated, three of them namely filter strips, terracing and contouring and grassed waterways were the most effective. These practices had great effect in increasing groundwater recharge, groundwater flow, percolation and total water yield. Notably, filter strips were the most effective measures in reducing the evapotranspiration.

Ndembera watershed experience the loss of tree cover especially in the mixed forest areas. This reduces the potentials of the watershed to perform carbon dioxide gas sequestration function as well as loss of water through increased evapotranspiration and surface runoff. The replacement of trees should be encouraged, especially those ones which are adapted to the soil and climate of the planting area. In addition, the trees should be those with the moderate to aggressive development to occupy the site quickly. These trees should be able help in improving water retention capacity in the catchment as well as providing the multi-benefits. Such trees could include fruit trees or fodder for animals. These multi-benefit trees could also be planted as filter strip trees and on the edges of contours and terraces in the farms.

Authors' contributions
LWM and ANM guided the whole research activities and writing of the manuscript. CH did data collection, processing and analysis as well as writing the manuscript. AW and CH calibrated the SWAT model. All authors read and approved the final manuscript.

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