Environmental Challenges 5 (2021) 100273

Contents lists available at ScienceDirect

Environmental Challenges

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

Impacts of climate variability and changing land use/land cover on River Mpanga flows in Uganda, East Africa

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A R T I C L E I N F O

Keywords:
SWAT
Land use/land cover (LULC) changes
Hydrological modeling
River Mpanga catchment
partitioning river flow drivers
Uganda

A B S T R A C T

We analyzed River Mpanga Catchment (RMC) land use/land cover (LULC) types based on Landsat images for 2000, 2008 and 2014. Soil and Water Assessment Tool (SWAT) was driven by daily meteorological data from 2000 to 2011 to investigate impacts of LULC changes on river flow variation. In 2000, 2008, and 2014, cropland covered 33.0%, 69.1%, and 72.2% of RMC area, respectively. However, the fractions of the RMC area covered by grassland in 2000, 2008, and 2014 were 39.4%, 12.5%, and 10.4%, respectively. The portion of RMC area covered by human settlement increased from 0.2% in 2000 to 0.5% by 2014. RMC was characterized by increasing trends in annual rainfall and river flows. SWAT calibration and validation at daily scale over the periods 2000–2005 and 2006–2011 yielded Nash Sutcliffe Efficiency of 0.77 and 0.75, respectively. Contribution from transitions in LULC types to river flow changes over the period 2000–2008 was 7.65%. Generally, 70.46% of the total river flow variation was contributed by climate variability in terms of changes in climatic conditions. However, 21.89% of the total river flow variance remained unexplained and this could be attributed to other factors not considered in this study including extra impacts of human activities such water abstractions for agricultural, industrial and domestic needs. These findings are important for planning predictive land and water resources management amidst impacts of climate variability and human activities on water resources.

1. Introduction

Sustainable management of the Earth's surface including water resources and land remains a critical environmental challenge that society must address (Mustard et al., 2004). This challenge arises due to competing water demands for agriculture, mining, tourism, urbanization, and industries. Due to continuous population growth and other factors, there have been dramatic land use/land cover (LULC) changes across the various watersheds in the world thereby putting water resources and land under increasing stress (Global Water Partnership 2009). Climate variability and changes in LULC types affect quantity of river flow (Pirnia et al., 2019).

Several studies across the different regions of the world showed varying extents to which climate variability and human activities influenced changes in river flows (see e.g. (Pirnia et al., 2019, Kumar et al., 2018, Wang et al., 2016, Zhao et al., 2016, Tan et al., 2015, Xu et al., 2014, Zhang et al., 2011, Wang et al., 2009)). Contributions of climate variability and human activities to the decrease in the river flows of Guantai catchment over the period 1950–2005 were 26.1% and 73.9%, respectively (Bao et al., 2012). Over the two periods 1961–1966 and 1973–2001, 35% and 68% of the decrease in rainfall-runoff across the Chao River basin in China were attributed to climate variations and human activities, respectively (Wang et al., 2009). Changes in the water resources availability of the Weihe River Basin were more attributable to climate variability than land use change (Zhao et al., 2016). For Haihe basin, the impacts of climate variation and LULC changes were found to account for the runoff decrease by 26.9% and 73.1% on average, respectively (Xu et al., 2014). In the Hun–Tai River basin, the contributions of climate variability and human activities to the reduction of annual streamflow over the period 1961–2006 were 43% and 57%, respectively (Zhang et al., 2011). Climate variability and human activities contributed to the decrease in annual runoff of the Mian River basin by 23.9% and 76.1%, respectively (Fan et al., 2010). For the Johor River basin in Malaysia, climate and human activities were found to raise annual stream flow by 4.4% and 0.06%, respectively (Tan et al., 2015). Contributions of climatic variability and human activities to the decrease in the stream flow changes in the Haraz River basin, northern Iran was 34.78% and 65.21%, respectively (Pirnia et al., 2019). The above information shows that the extents to which climate variability and LULC changes impact on the changes in river flows vary from one catchment to another and across regions. This is because catchments are spatially different with respect to size, topography, soils, geology, space–time variability of climatic variables such as rainfall

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https://doi.org/10.1016/j.envc.2021.100273
Received 1 April 2021; Received in revised form 1 September 2021; Accepted 2 September 2021

and evapotranspiration and also the levels of human involvements in changing LULC types are not the same for various watersheds (Onyutha, 2016).

In East Africa or the region where the current study area is located, there were several researchers who investigated the influence of LULC changes on river flows of various watersheds some of which include the Blue Nile basin (Gebrehiwot et al., 2013, Rientjes et al., 2011, Bewket and Sterk, 2005), Lake Bunyonyi catchment (Kizza et al., 2017), Murchison Bay catchment Anaba et al., (2017), River Muzizi catchment (Bahati et al., 2021), Nyando catchment (Olang and Fürst, 2011), Mara catchment (Mwangi et al., 2016, Mango et al., 2011, Mati et al., 2008), Nzoia catchment (Odira et al., 2010), Malagarasi River catchment (Tanzania) (Kashaigili and Majaliwa, 2013), Njoro catchment Baker and Miller, (2013), and Wami River Basin (Nobert and Jeremiah, 2012). For instance, Baker and Miller, (2013) reported that LULC changes resulted into an increased surface runoff and decreased groundwater recharge for the Njoro watershed located in Kenya's Rift Valley. Mango et al. (2011) warned that any further conversion of forests to agriculture and grassland in the Upper Mara River Basin headwaters would reduce dry season flows and increase peak flows. Mati et al. (Mati et al., 2008) reported that changes in LULC types in Mara catchment increased the peak flow by 7%. Further information regarding impacts of LULC changes on the surface runoff of the various catchments across East Africa can be obtained in a review paper by Guzha et al., (2018). Despite the above information, there were no studies which could be found in literature to have been conducted on the impacts of LULC changes on river flow of River Mpanga catchment.

Available data shows that River Mpanga flows have been increasing since 2000. Attempts to explain such trend can be through answering some questions. For instance, is there evidence of LULC changes across the River Mpanga catchment (RMC)? What could be the causes of such LULC changes? What are the contributions of climate variability and LULC changes to the river flow variation in the RMC? There are several human activities, such as deforestation, sand mining, poor farming practices, wetland encroachment, and overgrazing which lead to LULC changes in the RMC. Impacts of LULC changes and climate variability on runoff across the RMC have never been investigated studied before our study. Furthermore, implementation of Integrated Water Resources Management (IWRM) in the study area remains thin coupled with limited exercise of IWRM in practice (Nicol and Odinga, 2016). This is because the embedding of catchment management institutions in local political and other processes with respect to the integration of land- and water-related aspects is still a big challenge in Uganda (Nicol and Odinga, 2016). One form of support for planning of proper watershed management is provision of information on historical LULC changes and its potential effects on water resources. A typical way to get such information is through analysis of high-quality aerial photos or satellite images of LULC types archived over a long period of time. However, archives of such data with high spatial and temporal resolutions are difficult to obtain for the study area. Besides, the use of aerial images alone cannot directly indicate how the changes in a particular land cover type are affecting river flows. Thus, the available LULC data from satellite images can be complimented with catchment hydrological modeling (Onyutha and Willems, 2018). For such modeling studies (see e.g. (Kumar et al., 2018), (Kumar et al., 2017), (Narsimlu et al., 2015)), semi-distributed macro-scale hydrological models such as, the Soil and Water Assessment Tool (SWAT) (Arnold et al., 1993), (Neitsch et al., 2002) and Variable Infiltration Capacity model (Liang et al., 1994) tend to be used.

At this time, only three studies Anaba et al., (2017), Bahati et al., (2021), Mutenyo et al., (2011) applied SWAT to some catchments in Uganda. Mutenyo et al., (2011) focused on assessing the effectiveness of SWAT in predicting the flows of River Manafwa in the eastern Uganda. Anaba et al. (Anaba et al., 2017) applied SWAT to simulate river flows for estimating sediment yield from the Murchison Bay catchment. Bahati et al. (Bahati et al., 2021) applied SWAT to investigate the effect of LULC changes on hydropower of Muzizi hydropower plant. The main reason why applications of physically-based or semi-distributed hydrological models to Ugandan watersheds remain limited is scarcity of quality data required by the models at fine temporal and spatial resolutions.

It is worth noting that impacts of LULC on hydrology can be analyzed in context of climate change or climate variability. The difference between climate variability and climate change lies in the time scales used for analysis. For climate change impact investigation, two long-term periods (say, at least 30 years) one under current and the other from future climatic conditions are considered. Furthermore, climate change tends to focus on the stationarity of the climate system. Under climate variability, wet and dry climatic conditions tend to occur in a clustered way in time (Onyutha and Willems, 2017). The epochs over which wet or dry conditions occur can vary from annual to decadal (or multi-decadal) time scales. Under climate variability we focus on the oscillation lows and highs of climatic conditions which are known to engender extreme events such as droughts and floods. The idea is that the extent of the damage from such hydrological extremes (like flooding events) can be exacerbated by how LULC types are modified through human activities. Whether to consider climate change or variability, hydrological changes can be linked to human activities in a number of ways as follows.

i) In the context of climate change, the use of predicted (of future) LULC information is combined with outputs from scenario outputs from general circulation models for hydrological analysis. An example of such analysis for a catchment within the same region where our study area is located was conducted by Bahati et al. (Bahati et al., 2021) in which scenarios from four climate models were combined with future LULC types in River Muzizi catchment for 2060 projected using the MOLUSCE (Module for Land Use Change Evaluation).
ii) In case there is a significant hydrological change (for instance, step jump in mean in river flow), analysis of LULC types and river flow before and after the change-point can be used for the hydrological attribution. Typical examples of such analysis (though not for the current study area) can be found in Pirnia et al., (2019) and Wang et al., (2016). A hydrological sensitivity elasticity-based method can also be applied such that the river flow sensitivity to precipitation and PET is computed with respect to dryness index and plant available water coefficient (see e.g. (Koster and Suarez, 1999, Zhang et al., 2001, Milly and Dunne, 2002, Sun et al., 2005)).
iii) We can use one LULC map under changing climatic conditions and this can be good for scenario analysis to investigate the sensitivity of a catchment to the changes in climatic conditions. This method can be used to answer, for instance, the question on the amount by which the maximum annual flows will change when precipitation intensities are maintained as they occurred over the given period while potential evapotranspiration (PET) rates are increased, say, by 5% compared to the historical values.
iv) A number of LULC maps can also be used under constant climatic condition over a particular period. Here, the differences in results of simulations based on various LULC maps characterize impacts of LULC changes on hydrology during the period under consideration. If there is only one LULC map, other LULC information can be generated for scenario analysis. Such an approach can be used to answer a question such as: To what extent will the river flow change if 5% of forest across a catchment is converted to cropland while areas for all the other LULC types remain constant or minimally affected?
v) A sub-period can be selected as the baseline such that a (semi)distributed model like SWAT is run to simulate hydrological conditions over various epochs especially before and after the baseline. Using this approach, Kumar et al., (2018) investigated impacts of LULC on water availability of Tons River Basin, Madhya Pradesh, India. The distributed model can also be run over

the various sub-periods but with most of the model parameters kept at their optimal values while a few of them with physical meanings such as the curve number (CN) are allowed to change. Details on CN can be found in Rawat and Singh, (2017). The idea would be to determine whether variation in the relevant parameters like CN can explain changes in simulated flow.

Therefore, this study aimed at undertaking SWAT-based quantitative investigation of the contributions from LULC changes, climate variability and other factors to the changing river flows of RMC. In this study, application of SWAT was based on a number of LULC maps under the assumption of constant climatic conditions over a particular period. LULC changes were deemed to impact on runoff through differential alteration in evaporation rate across the catchment. Due to limitation of observed data, the use of reanalysis or satellite rainfall products was explored prior to the hydrological modeling.

2. Materials and methods

2.1. Study area

River Mpanga in Uganda within East Africa originates from the foot of the Mountain Rwenzori. RMC is located in the southwestern part of Uganda (Fig. 1). River Mpanga is endorheic and flows through the districts of Kabarole, Kyenjojo and Kamwenge before discharging into Lake George. RMC has various sub-catchments including Upper Mpanga, Middle Mpanga, Lower Mpanga, and Rushango with drainage areas equal to 384, 1174, 477, and 3170 km^2, respectively. The RMC area up to Lake George is 5205 km^2. Sub-catchment areas upstream of hydrological stations at Kampala-Fort Portal and Fort Portal-Ibanda roads are 401 and 1484 km^2, respectively (Fig. 1). Elevation from the source of the river to the gauge station considered in this study ranges from 1153 m to nearly 3000 m above sea level.

The River Mpanga is the source of domestic piped water supplied to a number of urban areas in the Southwestern part of Uganda including Fort Portal city, Kamwenge and Ibanda towns. Furthermore, the river is important for the Mpanga Falls hydroelectric power station. Mpanga hydropower plant was commissioned in 2011 in Kamwenge District with a capacity of 18 Megawatts to serve 20000 households (Daily Monitor 2011). The hydropower plant has not been able to generate power to its full capacity throughout the year (M. Ministry of Water and Environment 2014) due to reduced volumes of water flowing in the river especially in dry seasons.

At the foot of Rwenzori Mountain where River Mpanga emanates, the climate is wet year-round with annual rainfall up to about 3000 mm in some years. Annually, the study area receives rainfall of about 2500 mm on average (Ministry for Water and Environment 2020). On a monthly scale, average temperature varies over the range 27–31°C and due to high evaporation rates, average monthly humidity varies from 60 to 80% (National Environment Management Authority 2009).

2.2. Data

2.2.1. Hydro-meteorological data

Hydro-meteorological data required for hydrological modeling using SWAT included precipitation, wind, relative humidity, solar radiation, and river discharge. These datasets were obtained from various sources.

i) Daily river flows observed at gauge stations numbered 84215 (Fort Portal-Ibanda Road) and 84212 (Kampala-Fort Portal Road) with series over the periods 2000–2011 and 1999–2018, respectively, were obtained from Ministry of Water and Environment in Uganda.
ii) Daily rainfall data at four weather stations including Kiburara Prison Farm, Isunga Estate, Kyehara, and Kilembe Mines (see Fig. 1 for their locations) were obtained from Uganda National Meteorological Authority. Reliable data from these stations used in this study were between 1999 and 2012.
iii) Due to few stations at which observed rainfall series were obtained, meteorological datasets were required at many other locations within the catchment. One option would have been to interpolate observed rainfall data to fine spatial resolution or grid points. However, the interpolation would be characterized by uncertainty due to the few weather stations available for this study. Eventually, meteorological series were obtained from other sources. Daily rainfall (mm/day) series were obtained from the Japanese 55-year Reanalysis (JRA-55) (Kobayashi et al., 2015), Climate Hazards group InfraRed Precipitation with Stations (CHIRPS) version 2.0 (or CHIRPS v2.0) (Funk et al., 2015) and National Centers for Environmental Prediction's (NCEP's) Climate Forecast System Reanalysis (CFSR) (Saha et al., 2014). The data for JRA-55 ($1^\circ \times 1^\circ$ grid), CHIRPS v2.0 ($0.25^\circ \times 0.25^\circ$ grid), and CFSR ($0.25^\circ \times 0.25^\circ$) were over periods 1958–2017, 1981–2019, 1979–2013, respectively. The JRA-55, CHIRPS v2.0 and CFSR were downloaded via ftp://ftp.climserv.ipsl.polytechnique.fr/FROGs (accessed: 15th December 2020), https://climexp.knmi.nl/selectdailyfield2.cgi?id=someone@somewhere (accessed: 27th May 2021), and https://globalweather.tamu.edu/ (accessed: 27th January 2021), respectively. Other CFSR series downloaded were daily, wind (m/s), minimum and maximum temperature (°C), relative humidity, and solar radiation (MJ/m^2). These additional CFSR datasets also covered the period 1979–2013.

2.2.1. Topographical data and soil map

Some of the spatial data required to run SWAT included the Digital Elevation Model (DEM), and soil map. These datasets were obtained from different sources.

i) The hole-filled DEM of 30 m × 30 m (Jarvis et al., 2008) was downloaded online via https://lta.cr.usgs.gov (accessed: 4th June 2019).
ii) The soil map was acquired from the soil database of the United States' Food Agricultural Organization (FAO-UNESCO 2003). The soil map was at a scale of 1:5,000,000 (FAO-UNESCO 1977).

2.2.2. LULC map

Another spatial data required to run SWAT comprised LULC map. Remotely sensed LULC data can be downloaded from the United States Geological Survey website https://earthexplorer.usgs.gov (accessed: 12 July 2021). In this case, one needs to classify LULC types either using supervised or unsupervised classification tool. However, in this study, the classified 2000, 2008 and 2014 National Land Cover maps at scale of 1:250,000 were obtained from the National Forestry Authority (NFA) of Uganda. In the next step, each LULC map was reclassified into a number of important classes in the SWAT LULC classification table including agriculture/cropland, pasture/grasslands, human settlements (built-up areas), forested areas, water bodies, wetlands and other lands. Reclassification involved modifying values from the obtained raster into classes that characterized LULC types corresponding to those of SWAT LULC database. The reclassified LULC maps 2000, 2008 and 2014 were hereinafter denoted as LuM2000, LuM2008, and LuM2014, respectively.

2.3. Hydrological modeling using SWAT

2.3.1. Selection of the rainfall series

As mentioned before, sufficient number of observed rainfall series was lacking for the study area. Furthermore, it was deemed that the quality of the data from the various sources (JRA-55, CFSR, and CHIRPS v2.0) was not the same. Another series coined from JRA-55, CFSR, and CHIRPS v2.0 (and hereinafter denoted as JCC) was used. Consider that u, v and w denote values of JRA-55, CFSR, and CHIRPS v2.0, respectively.

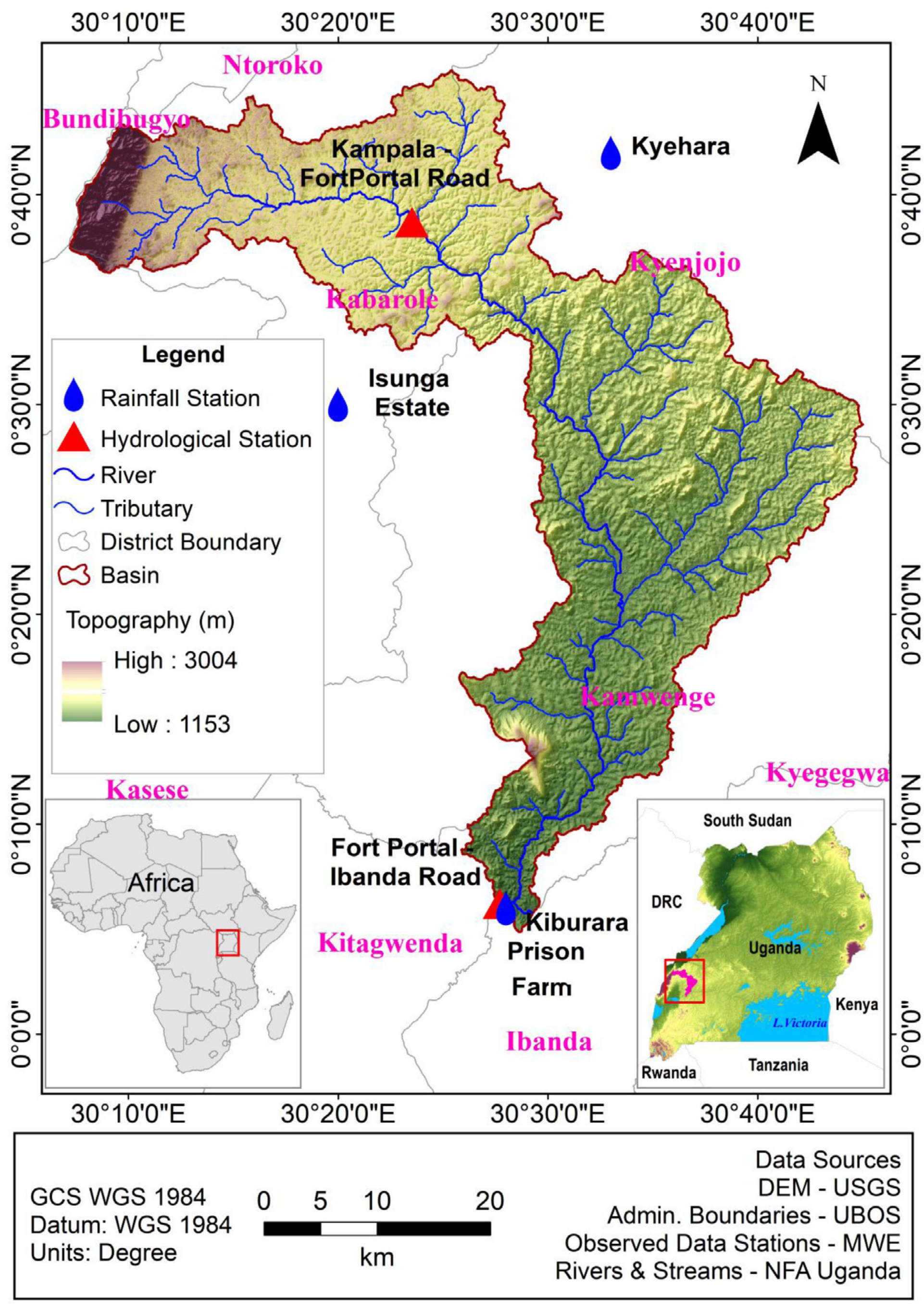

Fig. 1. Location of River Mpanga as well as rainfall and streamflow measuring stations.

Furthermore, let qrepresent observed daily river flow while n denotes the sample size of u, v or w. Since reanalysis datasets tend to underestimate observed extreme rainfall, a threshold of $q_{75}m^3/s$ (representing the 75th percentile of observed river flow) was selected to compute JCC. Finally, the i^{th} value of JCC was computed using

$$JCC_i = \begin{cases} 3^{-1} \times (u_i + v_i + w_i) \text{if} q_i < q_{75} \\ max(u_i, v_i, w_i) \text{if} q_i \geq q_{75} \end{cases} \quad \text{for} 1 \leq i \leq n \tag{1}$$

where max denotes the maximum of the three i^{th} values of u, v or w. To obtain the most suitable reanalysis to use along with the observed rainfall, analysis of correlation was performed between river flow and rainfall series of (i) JRA-55, (ii) CFSR, (iii) CHIRPS v2.0, and (iv) JCC. Other SWAT meteorological inputs apart from rainfall series were based on the CFSR data.

2.3.2. Model build-up

SWAT 2012 version was used for the hydrological modeling. The first step in the model setup was to delineate the catchment using DEM. Catchment delineation was done to determine the area of land drained by a river and its tributaries. To identify drainage patterns, the catchment was divided into sub-basins. The sub-basins were further divided into smaller parts called hydrologic response units (HRUs). HRUs can be taken to mean unique combinations of LULC types, soil attributes, and/or slope classes distributed over a sub-basin (Neitsch et al., 2011). After creation of HRUs, the next step was to import weather data into the model. Lastly, the model was run on daily time step with data from 2000 to 2005. SWAT requires warm up period at the beginning of the input series. Since the data record period was short in this study, we created and transferred copies of input series for three years (from 2002 to 2004) to the beginning of the datasets. This procedure lengthened

Table 1
Conditions for differences among sets of model outputs.

Combination	Assumed simulation condition			Cause(s) of the differences in sets of model outputs
	(1)	(2)	(3)	
i)	True	True	False	Changes in LUCL types
ii)	True	False	True	Changes in climatic conditions
iii)	False	True	True	Equifinality of model parameters
iv)	False	False	True	a) Equifinality of model parameters b) Changes in climatic conditions
v)	False	True	False	a) Equifinality of model parameters b) Changes in LUCL types
vi)	True	False	False	a) Changes in climatic conditions b) Changes in LUCL types
vii)	False	False	False	a)Equifinality of model parameters b) Changes in climatic conditions c) Changes in LULC types

Assumed simulation conditions:
(1) Optimal set of parameters is kept constant during each simulation.
(2) The same hydrometeorological inputs are used in each simulation.
(3) The various LULC maps are totally identical.

the input series by 3 years. Thus, data of 3-years was used for the model warm up. The methods available in SWAT to simulate excess rainfall include CN and Green-Ampt approach. In this study, CN was used due to its relevance for the study objectives. Assessment of inputs and outputs from SWAT was made based on the information provided by Arnold et al., (2012). Before calibration, sensitivity analysis was performed using the global approach in semi-automated Sequential Uncertainty Fitting (SUFI2) algorithm (Abbaspour, 2015).

2.3.3. Calibration and validation

SWAT was driven by daily hydro-meteorological data from 2000 to 2005 with the spatial data comprising soil map and LuM2000. For calibration, SUFI-2 method within the SWAT Calibration and Uncertainty Procedures (SWAT-CUP) (Abbaspour et al., 2007) was used to calibrate SWAT against observed daily flow. SUFI-2 method tends to be commonly applied due to its suitability for calibrating SWAT (see e.g. (Kumar et al., 2017), (Narsimlu et al., 2015)).

Since this study considered variability of river flow (a phenomenon which comprises both high and low flows), model performance was assessed in terms of the Nash-Sutcliffe Efficiency (NSE) (Nash and Sutcliffe, 1970), percentage bias (PBias), root mean squared error (RMSE) and coefficient of determination (R^2) such that

$$NSE = 1 - \frac{\sum_{i=1}^{n} \left(q_i - s_i\right)^2}{\sum_{i=1}^{n} \left(q_i - \bar{q}\right)^2} \tag{2}$$

$$PBias = \frac{\sum_{i=1}^{n} \left(q_i - s_i\right)}{\sum_{i=1}^{n} q_i} \times 100 \tag{3}$$

$$RMSE = \sqrt{n^{-1} \times \sum_{i=1}^{n} \left(q_i - s_i\right)^2} \tag{4}$$

$$R^2 = \frac{\left(\sum_{i=1}^{n} \left(q_i - \bar{q}\right)\left(s_i - \bar{s}\right)\right)^2}{\sum_{i=1}^{n} \left(q_i - \bar{q}\right)^2 \sum_{i=1}^{n} \left(s_i - \bar{s}\right)^2} \tag{5}$$

where q denotes observed data, s represents modeled series, while$\bar{q}$and $\bar{s}$are the mean values of the q_i's and s_i's, respectively. NSE varies from negative infinity to one while the values of R^2 exist over the range 0 –1. Application of R^2 is based on the assumption that observed modelled series are linearly related (Onyutha, 2020).

Validation requires driving a model using independent data (or series not used for calibration). In this study, SWAT was validated using daily hydro-meteorological data over the period 2006–2011. Like for calibration, performance of the model during validation was assessed using NSE and R^2.

2.3.4. Simulations

Optimal parameter values obtained during calibration were used to parameterize SWAT. In the next step, there were three SWAT simulations. In other words, SWAT was driven by daily series over the period 2006–2011 but separately run using LuM2000, LuM2008 and LuM2014 maps. During each simulation, parameters were fixed at their optimal values and the soil data remained the same as those used during calibration.

2.3.5. Contribution from changes in LULC types to river flow variation

In attribution of hydrological changes, it is expected that the simulated river flow series obtained based on LuM2000, LuM2008, and LuM2014 would be the same so long as (1) the optimal set of parameters is kept constant during each simulation, (2) the same hydrometeorological inputs (such as precipitation and PET series) are used as model inputs, and (3) there are no differences among the LULC maps (in other words, the spatial information from LuM2000, LuM2008, and LuM2014 are totally the same). However, sets of simulated results can vary based on whether any of the conditions (1)–(3) are true as detailed in Table 1.

If a model is calibrated several times, the various sets of model parameters (when assumed conditions 2 and 3 are true) can be used to quantify uncertainties on simulated flows. This can be done, for instance, through the generalized likelihood uncertainty estimation strategy (Beven and Binley, 1992). It becomes complex to unravel the synergistic contributions of many conditions, like combinations (iv)–(vi), when considered at the same time. Thus, combinations (i)–(ii) were considered in this study. For combination (i) in Table 1, there were two simulations, one based on LuM2008 and the other using LuM2014. The absolute difference between the mean of model outputs based on LuM2000 and the mean of simulated series obtained using LuM2008 (as a percentage of the mean of modeled series based on LuM2000) was considered to be due to the changes in LULC types over the period 2000–2008. Similarly, the ratio of the absolute difference between the mean of model outputs based on LuM2000 and the mean of simulated series obtained using LuM2014 to the mean of modeled series based on LuM2000 (expressed in percentage) was considered to be due to the changes in LULC types over the period 2000–2014.

2.3.6. Contribution from changes in climatic conditions to river flow variation

The null hypothesis H_0 (no correlation) between river flow and catchment-wide averaged rainfall was tested. This was on the assumption that river flow changes can largely be attributed to rainfall variation if the overall rainfall-runoff generation processes of the catchments are not significantly impacted upon, for instance through the human activities like changes in LULC types (Onyutha and Willems, 2018). The

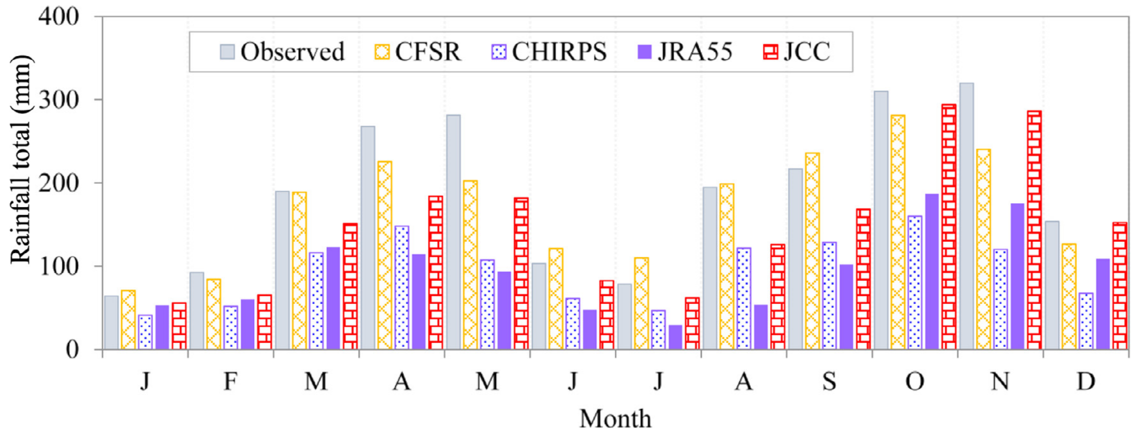

Fig. 2. Mean of long-term (2000-2011) monthly rainfall total in RMC.

second assumption was that the relationship between rainfall and river flow is linear. It turns out that there are several factors which influence rainfall-runoff generation such as rates of infiltration, evaporation, percolation, river water abstraction, and volume of industrial effluents discharged into the river. Thus, the relationships among these factors and river flow are complex and may not necessarily be linear in nature. Furthermore, variation of rainfall alone cannot explain the total river flow variance. Therefore, to characterize the influence of the variation in climatic conditions on river flow changes, variables such as precipitation, humidity, temperature or PET should be considered. In this way, if we ignore the limitation of the model to accurately capture rainfall-runoff generation processes (due to imperfections in model structure, parameter uncertainty, and observation errors on inputs) and assume that the changes in LULC types or river flow is minimal, the simulated series can be considered to be indicative of the contribution from the variation in meteorological conditions on river flow changes. In other words, if the catchment remains in its natural form without impacts of human activities, and assuming climatic variables such as precipitation and PET have no observational error, the river flow would naturally be accurate if a perfect model is used. Here, we consider model outputs to characterize the various rainfall-runoff generation processes and changes in climatic conditions to be captured by the model structure. The assumption of minimal impacts of LULC changes on river flow changes means that we can use one LULC map for the hydrological modeling. Thus, model outputs over validation period 2006–2011 based on LuM2000 were used to test the H_0 (no correlation) between daily simulated and observed river flow.

Consider that the contributions due to climate variability, changes in LULC types, and other factors are A, B and C%, respectively. Let the amount of the total variance in observed flow explained by modeled series to be D%. After quantifying the term B, the value of C can be given by C =(100–B%). Finally, the term A can be obtained using $A = D \times C/100$. It is vital to check that $A+B+C\% \leq 100\%$, otherwise the values should be rescaled to be within the range 0–100%. For instance, rescaling can be done using $A_r = A/(A+B+C) \times 100$, $B_r = B/(A+B+C) \times 100$, and $C_r = C/(A+B+C) \times 100$ where A_r, B_r and C_r% are rescaled values of A, B and C%, respectively.

3. Results and discussion

3.1. Rainfall and river flow properties

Fig. 2 shows monthly rainfall pattern based on catchment-wide averaged series. The rainfall across the study area is of bimodal pattern. In other words, there exist two rainy seasons (Fig. 2). The "long" and "short" rains occur over the months of March-April-May (MAM) and September-October-November (SON), respectively. December-January-February (DJF) and June-July-August (JJA) seasons are characterized by "short" and "long" dry conditions, respectively. The bimodal pattern of monthly rainfall was well reproduced by series from the various sources. However, observed monthly totals were more comparable (in magnitude) to CFSR series than those of JRA-55 and CHIRPS v2.0.

Fig. 3 shows variation in annual rainfall and river flows over time. Considering data the station at Fort Portal-Ibanda Road, annual river flows increased steadily from 2000 to 2011 (Fig. 3a). River flow data recording at this station stopped before the end of 2012 because of the destruction during construction of Fort Portal-Ibanda road. The rate of increase in the river flow at this station was 0.47 cumecs/year. Both observed and JCC-based annual rainfall series averaged over the RMC were characterized by increasing trends like for the river flows (Fig. 3c-d). The rates of increase in observed and JCC annual rainfall series were 52.08 and 56.93 mm/year, respectively. However, river flow data observed at Fort Portal-Kampala road station (Fig. 3b) showed that the mean values of the sub-series over the periods 2000–2010 and 2011–2018 were different. River flows at this hydrological station (Fig. 3b) were found to be unusually high in 2011 and 2012 (and 2013 to some extent). Whereas such unusual flow data could indicate the effect of human intervention on hydrology, both observed and JCC annual rainfall across the RMC did not show step jump in mean in 2011 (Fig. 3c, d). Thus, the inhomogeneity in the river flow observed at the Fort Portal-Kampala road station required application of correction factors before its use for analysis. Given that a bigger catchment area was required for modeling and due to the questionable river flow data at Kampala-Fort Portal Road hydrological station especially over the period 2011-2013, the station at Fort Portal-Ibanda Road was adopted as the outlet of the catchment considered for this study.

3.2. Soil and LULC maps

Fig. 4 shows spatial information required as SWAT inputs and for assessment of the changes in LULC types. Geo-referenced and clipped catchment soil map (Fig. 4a) produced three (5) original soil groups which fell under three FAO soil categories including Gleyic Aerosols, Nitisols and Lixic Ferrasols and they covered 7.6%, 34.6% and 57.8% of the catchment area, respectively. The SWAT database names of FAO soil categorized as Gleyic Aerosols, Nitisols and Lixic Ferrasols were Benson, Swanton, and Weider, respectively.

Some of the common LULC types included bushland, cropland, and spaces taken up for human settlement (Fig. 4b–d). To simplify analysis, some of the LULC types were grouped. For instance, closed bushland and open bushland were grouped as bushland. Similarly, open grassland and closed grassland were combined to become grassland. Finally, moderate natural forest, dense natural forest, plantation forest, and sparse natural forest were combined into one class called forest.

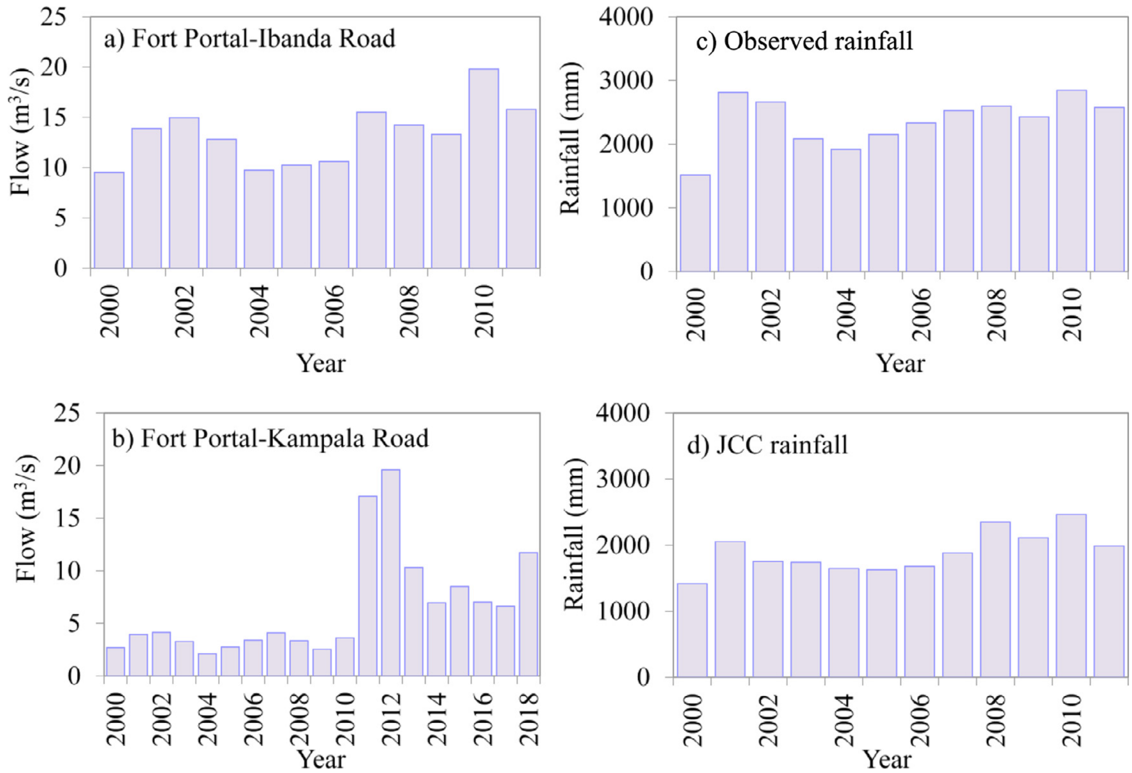

Fig. 3. Time series plots of annual (a-b) river flows, and (c-d) rainfall of RMC.

Fig. 5 shows distribution of the various LULC types. In 2000 (Fig. 5a), the catchment area mainly comprised grassland (39.5%), cropland or farmland (33.0%), and forest (22.0%). Bushland was taken to mean land that supports remnant vegetation or covered with a few short trees, shrubs, or natural vegetation. In cropland areas, the main crops grown in the study area comprise bananas, and cereals (maize, millet, sorghum) as well as a few perennial cash crops, such as coffee, tea and fruit trees. Based on LuM2008 (Fig. 5b), much area was covered by cropland/farmland (69.2%) followed by grassland (12.5%), and forest (11.8%). In 2014 (Fig. 5c), dominant LULC types were cropland/farmland (72.2%), forest (10.7%), and grassland (10.4%). Fig. 5d shows summary of the LULC changes in the study area. LULC types which increased in area were cropland, built-up areas, and woodland. Other LULC types including forest, grassland, and wetland reduced in their areas of coverage.

We think that the temporal alterations in LULC types in RMC and other parts of Uganda can generally be thought of in terms of laws and institutional policies or transition in land tenure. The key land laws after Uganda got independence included the 1969 Public Land Act and the 1975 land Reform Decree. According to the 1969 Public Land Act, all public lands were brought under the Uganda Lands Commission. However, the 1975 Land Reform Decree declared all land in Uganda to be public thereby abolishing the *mailo* tenure. Article 237 (1) of the Constitution of Uganda 1995 as well as Article 3 of the Land Act 1998 declared that "land in Uganda belonged to the citizens of Uganda" (Republic of Uganda 1995), (Republic of Uganda 1998). This declaration meant that radical titles of land were given to the citizens something which had been abolished by the 1975 Land Reform Decree. The 1998 Land Act (Republic of Uganda 1998) was aimed at reforming the land tenure relations in Uganda by recognizing land tenure systems including the customary (communal), *mailo*, freehold and leasehold. *Mailo* tenure comprised allotments of land to the Kabaka (the King of Buganda) and his chiefs following the 1900 agreement. Therefore, there were increased opportunities for citizens in the early 2000s in utilizing their land. However, after 2000 there were escalating conflicts, land grabbing and forceful evictions of tenants by land owners. To address issues of widespread evictions, the Land (Amendment) Act 2010 was instituted with the objective of enhancing security of occupancy of the lawful *bona fide* occupants (or tenants on registered land plus people on customary land) (Republic of Uganda 2010). In February 2013, the final document of the National Land Policy of Uganda Republic of Uganda, (2013) was ratified. One of the principles underpinning the National Land Policy of Uganda 2013 was that "Land must be productively used and sustainably managed for increased contribution to economic productivity and commercial competitiveness" Republic of Uganda, (2013). Another principle was that "Management of land resources must mitigate environmental effects, reverse decline in soil quality and land quality" Republic of Uganda, (2013). Therefore, changes in land laws could have contributed to the LULC changes.

Table 2
Population changes in some districts which share RMC.

SNo	District	Year		
		1991	2002	2014
1	Kabarole	299,573	356,914	469,236
2	Kamwenge	201,654	263,730	414,454
3	Kyenjojo	182,026	266,246	422,204

Another important reason for the changes in LULC across RMC was the population increase. To show that population of the RMC has been increasing, we can considered a few districts into which RMC extends including Kabarole, Kyenjoyo, Kamwenge districts among others (Table 2) based on information from the Uganda Bureau of Statistics (Uganda Bureau of Statistics 2016). Population increase could partly be ascribed to the massive influx of refugees (particularly the Congolese) into the western Uganda especially over the last two decades. Pursuant to Uganda 2006 Refugees Act (Republic of Uganda, 2006) and 2010 Refugees Regulations (Republic of Uganda, 2006), each refugee family was given a piece of land for their own exclusive use in terms of agriculture. Increase

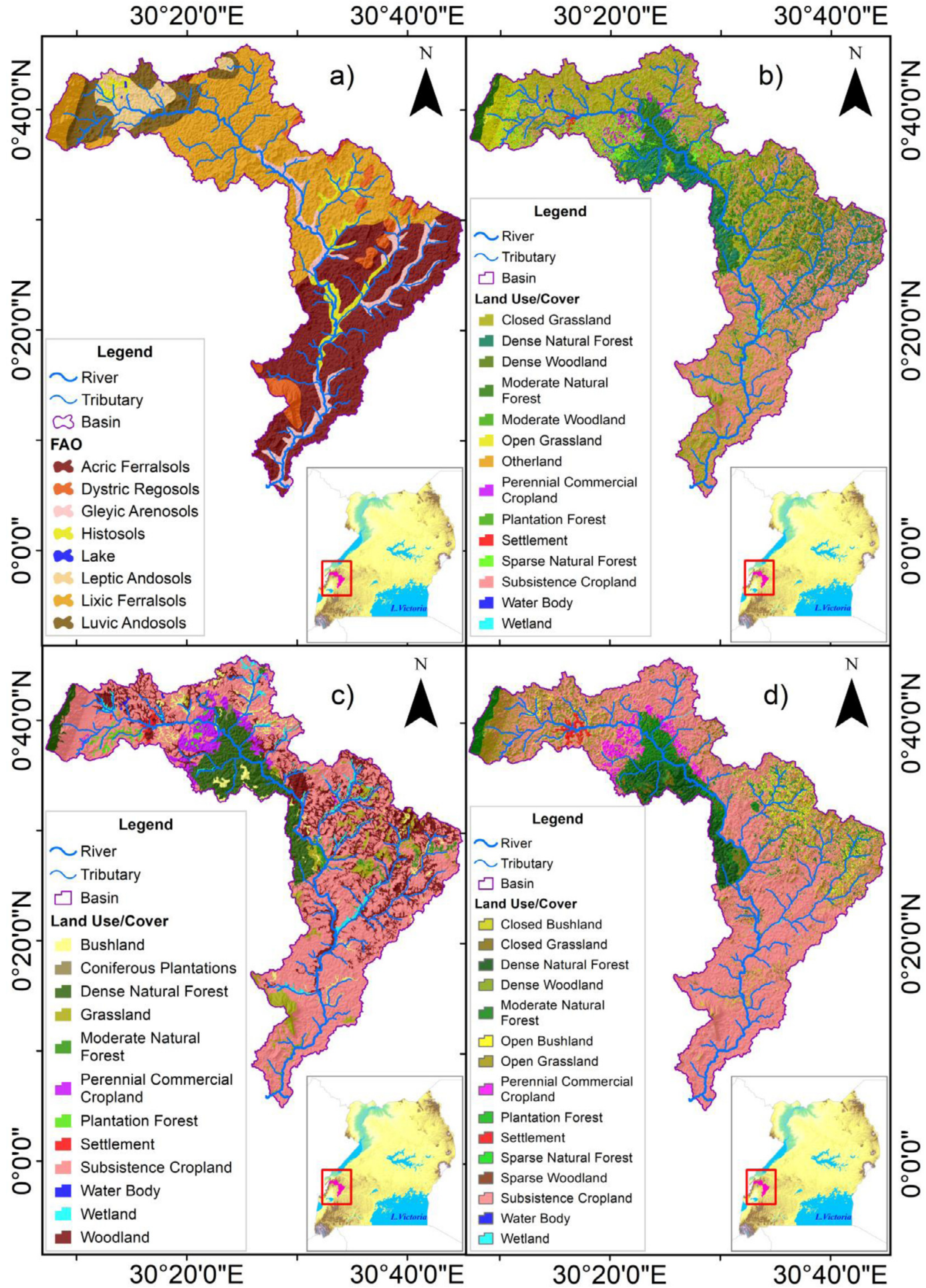

Fig. 4. Spatial data of a) soil map, and b) LuM2000, c) LuM2008, and d) LuM2014.

in population prompted deforestation and the clearing of grasses along river banks within the RMC mainly for cultivation and settlement (BRLi 2015).

The translation of pressure from population increase into changes in LULC types across East Africa as a region where the present study area is located has been well documented; see for instance (Rientjes et al., 2011, Bewket and Sterk, 2005, Kizza et al., 2017), (Mwangi et al., 2016), (Kashaigili and Majaliwa, 2013), (Enku et al., 2014, Wagesho, 2014, Barasa et al., 2011). For the Gilgel Abbay catchment of Ethiopia, Rientjes et al. (Rientjes et al., 2011) showed that in the period 1986–2001 forest land decreased from 32.9% to 16.7% while agricultural land increased from 40.2% to 62.7 %. Furthermore, forest cover area in Gilgel Abay was 51% in 1973 but decreased to 17% of the catchment area in 2001 (Enku et al., 2014). Bilate catchment in Ethiopia exhibited 68% forest cover loss over the period 1976–2000 (Wagesho, 2014). Nyangores catchment in Kenya registered 50% forest cover loss from 1976 to 2006 (Mwangi et al., 2016). In Chemoga watershed within the Blue Nile basin, there was agricultural conversion of 79% of the Riverine

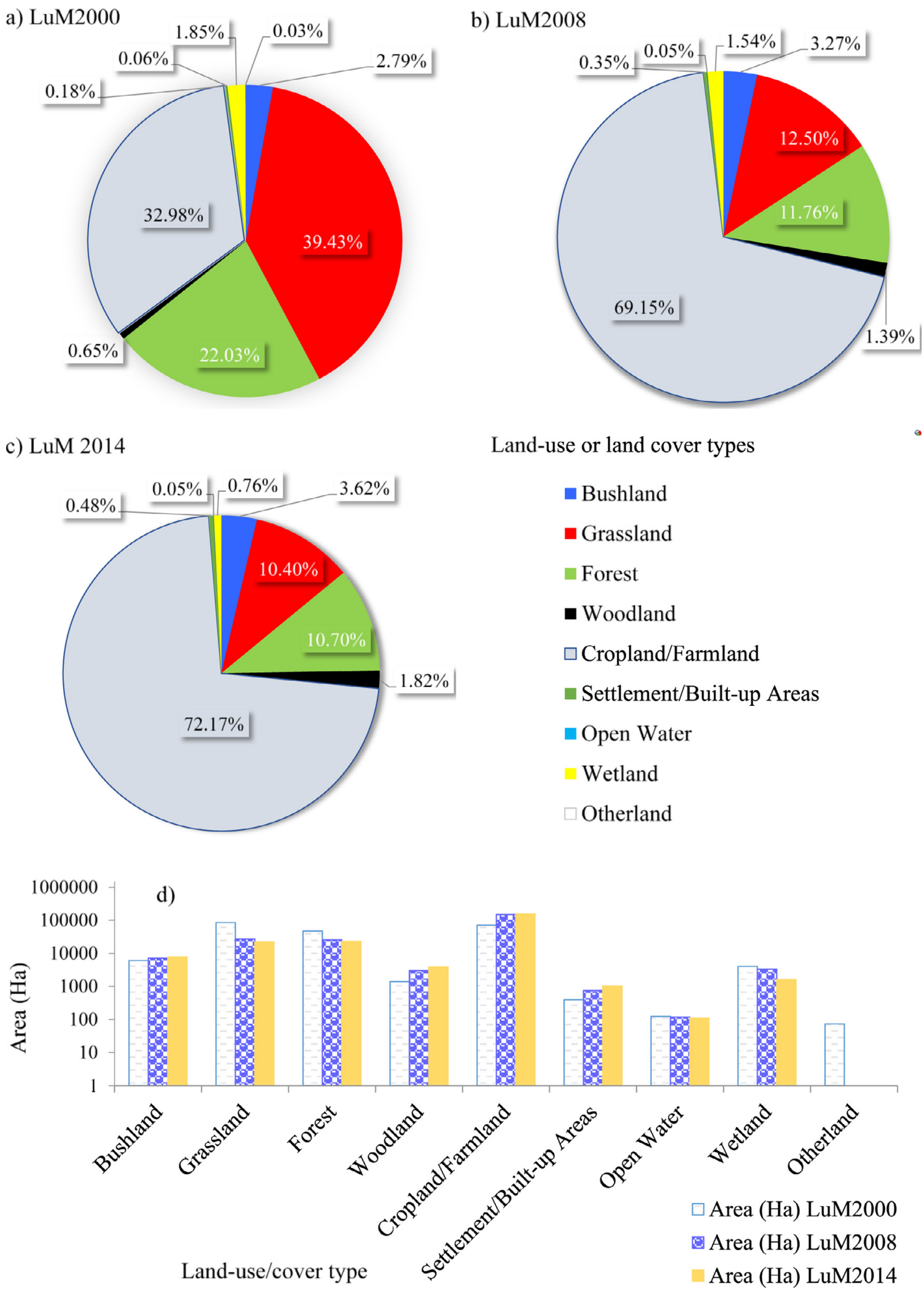

Fig. 5. LULC types based on a) LuM2000, b) LuM2008, c) LuM2014, and associated d) LULC changes. The vertical axis of the chart (d) was plotted in logarithmic scale for clarity.

forests in about 40 years (1957–1998) (Bewket and Sterk, 2005). In Malagarasi catchment of Tanzania, forest cover increased in area by 0.4% over the period 1984–2001 (Kashaigili and Majaliwa, 2013). In Weru-Weru catchment of Tanzania, there was a forest cover loss by 12% from 1990 to 2008 (Chiwa, 2008). Small-scale farmland gained variably from all the LULC types across the Lake Bunyonyi catchment in Uganda between 1999 and 2005 (Kizza et al., 2017). In the Murchison Bay catchment, 26.7% increase in runoff over over the period 1997-2008 could be ascribed to the rapidly changing LULC types (Anaba et al., 2017). In Kanungu District of the southwestern Uganda, areas covered by Tropical high forest decreased by 16% between 1975 and 1987 while the magnitude of small scale farming increased by 5% from 1975 to 1999

Table 3
LULC change summary for RMC.

ReclassifiedLULC	Total area (ha)			Fractionof catchment (%)			Change (%)	
	2000	2008	2014	2000	2008	2014	2000–2008	2008–2014
Bushland	6047	7087	7843	2.8	3.3	3.6	0.5	0.3
Grassland	85401	27068	22536	39.4	12.5	10.4	-26.9	-2.1
Forest	47710	25474	23181	22.0	11.8	10.7	-10.3	-1.1
Woodland	1404	3000	3946	0.6	1.4	1.8	0.7	0.4
Cropland/Farmland	71435	149778	156312	33.0	69.1	72.2	36.2	3.0
Settlement	395	750	1036	0.2	0.3	0.5	0.2	0.1
Open Water	125	118	110	0.1	0.1	0.1	<0.1	<0.1
Wetland	4012	3328	1639	1.9	1.5	0.8	-0.3	-0.8

Table 4
List of sensitive parameters.

No.	Parameter name	Description	*t*-Stat	*p*-value
1	CN2	Soil moisture condition II curve number	-6.323	<0.001
2	SURLAG	Surface runoff lag coefficient	-2.567	0.018
3	GW REVAP	Groundwater evapotranspiration coefficient	-2.232	0.037
4	OV_N	Manning's "*n*" value for overland flow	-1.678	0.109
5	GW DELAY	Ground delay (days)	1.445	0.164
6	ALPHA BF	Base flow alpha factor (days)	-1.223	0.236
7	SOL AWC	Available water capacity of the soil layer (mm H_2O /mm soil)	-0.898	0.380

(Barasa et al., 2011). Forested area (cropland as a percentage of the River Muzizi catchment within the same region where our study area decreased (increased) from 41.48% (40.16%) in 2000 to 31.12% (50.02%) by 2014 (Bahati et al., 2021).

Percentage changes in LULC types can be found in (Table 3). Between 2000 and 2008, areas covered by cropland, settlement, woodland and bushland increased. The largest increment (36.2%) was in the area under farmland/cropland. Areas of grassland, forest areas, open water and wetlands decreased. The outstanding decline (26.9%) was for grassland. This was followed by forests (10.3%). Between 2008 and 2014, the area under cropland/farmland increased by 3.0%. However, grassland, forest, and wetland areas reduced by 2.1%, 1.1%, and 0.78%, respectively. The decline in forest cover was due to increased cutting down of trees for various uses such as firewood and timber (Ministry of Water and Environment, 2013). Percentage of the catchment area covered by wetland (open water) in 2000, 2008 and 2014 was 1.85% (0.058%), 1.54% (0.054%), and 0.76% (0.051%), respectively. The decrease in the areas covered by open water and wetland decreased over time in the RMC reflects the increasing level of encroachment on wetlands over the study period. Wetland encroachments are due to failure by the citizens to adhere to the relevant policies or regulations for conservation or management of wetlands, riverbanks and lakeshores in the country. Thus, the National Environment Management Authority in liaison with the Ministry of Water and Environment should devise and implement measures that can impede further increasing trend in the levels of wetland encroachments.

3.3. Hydrological modeling

3.3.1. Selection of the rainfall series to use for modeling

The coefficients of correlation between daily river flow and rainfall from CFSR, CHIRPS, and JRA55 were 0.199, 0.098 and 0.204, respectively. This indicated that performances of CFSR and JRA-55 were comparable and better than that of CHIRPS v2.0. However, correlation between river flow and JCC was 0.439. This showed that series obtained by combining various rainfall products could be better correlated with observed rainfall than in the case when reanalysis or satellite rainfall product is used individually. Eventually, JCC-based rainfall was used at other locations where there were observed data were lacking.

3.3.2. Sensitivity analysis

Table 4 shows results of sensitivity analysis in terms of Student's *t*-test statistic and probability or *p*-values. The most sensitive parameter was CN2 followed by SURLAG, and GW REVAP. CN2 was also found to be the most sensitive in previous studies (see e.g. (Anaba et al., 2017), Mutenyo et al., (2011)) that applied SWAT to two catchments in Uganda. CN2 tends to be a function of soil permeability, LULC and the antecedent soil moisture thereby influencing runoff generation. An increase in CN2 leads to large volumes of stream flow.

3.3.3. Calibration and validation

Fig. 6 and Table 5 show results of model performance. It is noticeable that the model captured well the variation in observed river flow (Fig. 6). Results in Fig. 6 and Table 5 indicated that:

i) the model performed well and could therefore be applied to quantitatively investigate the contributions of changes in climatic conditions and LULC types to the temporal variation in river flow of the RMC, and
ii) the use of reanalysis or satellite products to drive SWAT for RMC comprises a partial solution to the problem of data limitation that hampers hydrological modeling studies on investigating changes in water resources especially in Uganda (and perhaps other developing countries). We remark that apart from CFSR, JRA-55 and CHIRPS v2.0 there are several other reanalysis or satellite datasets which can be applied for hydrological modeling in data scarce regions. For instance, Mubialiwo et al. (2021) applied daily precipitation, minimum and maximum temperature data from the Princeton Global Forcing (Sheffield et al., 2006) (after bias correction) to River Malaba sub-catchment and obtained NSE of up to 0.8. Capacity to reproduce observed climatology (for instance, with respect to extreme climatic events) varies among existing reanalysis or satellite products. For instance, CHIRPS was found to perform better than CFSR in reproducing observed rainfall across the River Muzizi catchment Bahati et al. (2021). Differences among reanalysis or satellite products can be large when (i) fine (e.g. hourly or daily) scale is used, and (ii) focus is on extreme climatic events. A part from random errors, reanalysis or satellite products can also be characterized by bias. The bias, for instance in satellite products, could stem from a number of

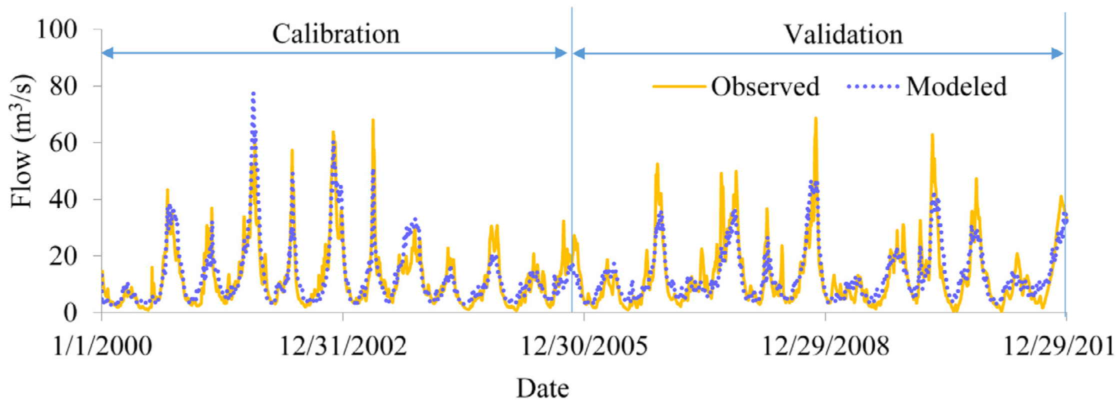

Fig. 6. Time series plot of observed versus simulated daily flow.

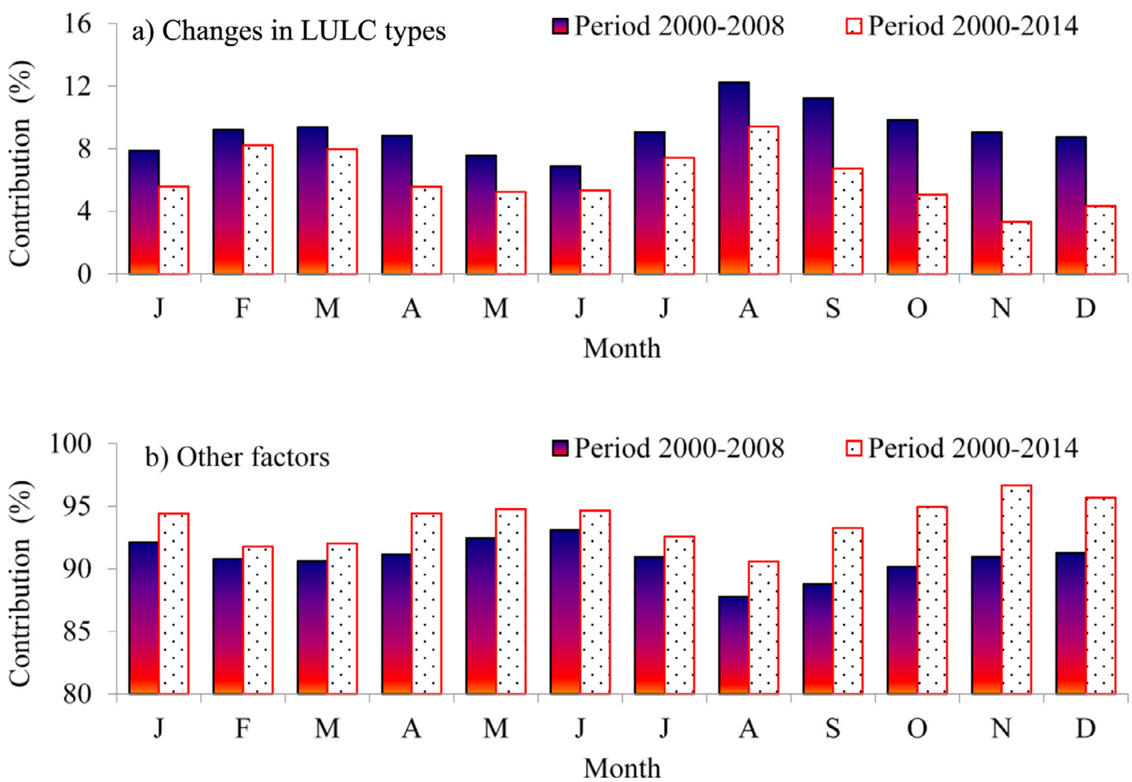

Fig. 7. Attributes of river flow changes in terms of average daily flow in each month and contributions from a) LULC changes and b) other factors such as climate variability.

Table 5
Statistical "goodness-of-fit" measures.

Metric	Period		
	Calibration(2000-2005)	Validation(2006-2011)	Full data record (2000-2011)
NSE	0.769	0.751	0.761
PBias	-0.018	-0.002	-0.010
R^2	0.779	0.777	0.763
RMSE (m^3/s)	5.451	5.632	5.542

sources such as imperfections in rainfall retrieval algorithms, and poor distribution of sensors. This means that bias correction may be required in reanalysis or satellite products. Finally, careful selection of which reanalysis or satellite product should be used can be made on a case by case basis with respect to the purpose of the study.

3.3.4. Contribution from changes in LULC types to river flow variation

Fig. 7 shows attributes of mean monthly flow. Contributions by LULC changes to the variation in river flow over the entire period 2000–2014 ranged from 3.3% (November) to 9.4% (August) (Fig. 7a). However, from 2000 to 2008 the contributions varied from 8.6% (April) to 13.5% (August). On average, the amount of contribution from LULC changes was 9.1%% and 6.2% over the periods 2000–2008 and 2000–2014, respectively. Thus, 7.65% of the changes in river flow over the period 2000–2014 was due to changes in LULC types on average. The remaining percentage in each month was due to other factors. These other factors collectively contributed close to 90% considering the period 2002–2014 (Fig. 7b).

3.3.5. Contribution from changes in climatic conditions to river flow variation

The percentage of the total variance in observed daily flow which was explained by the variation in catchment-wide average rainfall over the period 2000–2011 was 43.9%. The R^2 value for the relationship between observed and simulated series over the entire data period 2000–2011 was 0.763 or 76.3% (Table 5). This showed that variation in river flow did not result from changes in rainfall only. Other climatic variables which determine rates of evapotranspiration (including temperature, solar radiation, wind speed, and relative humidity) are also important for explaining variation in flow. Therefore, the mismatch between observed flow and output of a distributed hydrological model like SWAT (which considers the various factors or climatic conditions) is expected to be smaller (and thus, high R^2 value) than that in the case when individual climatic variable is used in the regression analysis

By taking into account results regarding the changes in LULC types over the period 2000–2014 (9.1% and 6.2% with average of 7.65%), contributions from other factors were 92.35% (i.e. 100-7.65%). Contribution from changes in climatic conditions or inter-annual climate variability was 70.46% ($\approx$ 76.3% of 92.35$\approx$0.763$\times$92.35$\approx$70.46%). Thus, changes in runoff were dominantly driven by climate variability. The remaining or unexplained 21.89% (i.e. 100-70.46-7.65) of the total variability in river flow can be thought of in terms of (i) additional impacts of human activities apart from changes in LULC types, and (ii) limited capacity of the hydrological model to capture complexities in rainfall-runoff generation processes. Two examples of additional human factors include a) possible flow returns into the river through discharge of effluents from industries, and b) abstraction of water at various locations in the RMC for irrigation, industrial and domestic supplies. Limited capacity of the hydrological model arises because of a) measurement errors on model inputs, b) observation errors on the data against which calibration is to be made, c) inaccuracies in model parameters, and d) imperfection of model structure.

4. Conclusions

The aim of this study was to quantitatively assess contributions of climate variability and LULC changes to the increasing runoff in the RMC. This was done while also testing the suitability of reanalysis or satellite products in driving SWAT as a semi-distributed hydrological model when applied under data-scarcity.

In 2000, most of the RMC area comprised grassland (39.5%), cropland/farmland (33.0%), and forest (22.0%). Due to changes in land tenure and increased pressure from rapidly growing population on natural resources, the fractions of the catchment area covered by grassland, cropland/farmland, and forest became 10.4%, 72.2%, and 10.7%, respectively. In 2000, 2008 and 2014, wetland covered 1.85%, 1.54%, and 0.76% of the catchment area, respectively. Furthermore, LULC changes were possibly driven by the policy-institutional factors such as shifts in land laws.

SWAT calibration (2000–2005) and validation (2006–2011) at daily scale yielded NSE of 0.77 and 0.75, respectively. This indicated that outputs from SWAT were suitable for investigating attributes of river flow variation in the RMC. Furthermore, availability of the reanalysis or satellite meteorological products can offer partial solution to the data scarcity which hampers physically-based hydrological modeling for watersheds in developing countries like Uganda.

Analysis showed that from 2000 to 2011, annual runoff increased at a rate of 0.47 cumecs/year. This increase was mainly due to the positive trend in rainfall which was at a rate of 52.08 mm/year. Positive trend in rainfall implies increasing surface runoff. Given the increasing rate of deforestation across the catchment, increasing rainfall-runoff can lead to erosion and sedimentation and these can (i) be detrimental to the turbine in the hydropower plant, and (ii) lower the quality of water from River Mpanga to be supplied to the nearby towns thereby increasing water treatment cost. Physical and chemical water qualities of River Mpanga were already confirmed to be largely influenced by (i) the river sediment extraction and (ii) transportation of suspended solids and nutrients from upstream due to erosion of river bed and bank erosions (Van Butsel et al., 2017). Enforcing regulations that prevent deforestation and the implementation of tree planting programmes or projects should be considered in the River Mpanga catchment management plan. Creation of riparian buffer zones along the river can also be good management practice to deal with possible soil erosion and sedimentation. Measures to control rampart LULC changes should be implemented in the framework of the IWRM.

Over the period 2000–2008 (2000–2014), contribution from transition in LULC types to changes in river flow was 9.1% (6.2%). In other words, human factors influenced this runoff increase more from 2000 to 2008 than over the period 2008 to 2014. At least 43.9% of the total variance in river flow could be explained by the variation in rainfall. When various changes in climatic variables (such as temperature or evapotranspiration) were considered to collectively characterize climate variability, up to 70.46% of the total variance in river flow was explained. Of the total variance in river flow changes, 21.89% remained unexplained. This could be due to other factors not considered in this study including (i) abstraction of water for irrigation, industrial use, and domestic consumption or by population in the urban centers within the catchment, and (ii) possible flow returns into the river from industries within the catchment. It was recently found that abstraction of water within the River Mpanga catchment affect river flow variation to the extents which lead to losses of hydropower (Onyutha et al., 2021).

These findings can support planning of predictive environmental management amidst impacts of climate variability and human activities on water resources. We recommended other related studies (on hydrological quantification of LULC changes and human activities on water resources) to be conducted for the different catchments in Uganda. This would be important to support developments of management plans for the various catchments in the country.

Funding

This research received no external funding.

Author contributions

Charles Onyutha: Conceptualization, data curation, formal analysis, investigation, methodology, validation, supervision, writing-review & editing; *Catherine Turyahabwe*: Conceptualization, data acquisition, data curation, formal analysis, investigation, methodology, validation, and writing draft manuscript; *Paul Kaweesa*: Conceptualization, formal analysis, proofreading draft manuscript, and assistantship in supervision.

Declaration of Competing Interest

The authors declare that there are no conflicts of interest.

Acknowledgments

The authors acknowledge that this study made use of the Japanese 55-year Reanalysis (JRA-55) (Kobayashi et al., 2015), Climate Hazards group InfraRed Precipitation with Stations (CHIRPS) version 2.0 (or CHIRPS v2.0) (Funk et al., 2015), and National Centers for Environmental Prediction's (NCEP's) Climate Forecast System Reanalysis (CFSR) (Saha et al., 2014). The authors recognize that this paper was partially

based on a Master of Science study by Turyahabwe (Turyahabwe, 2019) under the supervision of Charles Onyutha (Ph.D.) assisted by Eng. Paul Kaweesa.

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