Research article

Impacts of climate and land use/cover changes on streamflow at Kibungo sub-catchment, Tanzania

Lusajo Henry Mfwango\textsuperscript{a,b,*}, Tenalem Ayenew\textsuperscript{c}, Henry F. Mahoo\textsuperscript{d}

\textsuperscript{a} Africa Centre of Excellence for Water Management (ACEWM), College of Natural and Computational Sciences, Addis Ababa University, P.O. Box 1176, Ethiopia
\textsuperscript{b} Water Institute (W.I.), P. O. Box 35059, Dar es Salaam, Tanzania
\textsuperscript{c} School of Earth Sciences, Addis Ababa University, P.O. Box 1176, Ethiopia
\textsuperscript{d} Department of Agriculture Engineering and Land Planning, Sokoine University of Agriculture, Tanzania

\textbf{A R T I C L E   I N F O}

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\textbf{A B S T R A C T}

The impacts of changing climate and land use/cover on streamflow in the Kibungo sub-catchment were evaluated using the Soil and Water Assessment Tool (SWAT). Rainfall, minimum, and maximum temperature data for six stations from the ensemble mean of the RCMs (RCA4, RACMO22T, CCLM4-8-17) were used under RCP 4.5 and RCP 8.5. The homogeneity and trend test were used to detect the change point and identify the pattern in the annual time series, respectively. Land Change Modeler (LCM) was used to predict land use maps of 2040 and 2070 from historical maps. Streamflow was simulated for 2021–2040 and 2041–2070 based on the homogeneity test results. The model calibration (2009–2016) and validation (2009–2016) for streamflow were successful. The homogeneity test detects a change point in 2040. A significant decrease in annual rainfall by 22.9 mm/yr (RCP 4.5) and 57 mm/yr (RCP 8.5) for 2021–2040 and an insignificant decrease was obtained during 2041–2070 under both emission scenarios. The annual temperature increased insignificantly by 0.004 °C/yr under RCP 4.5 while a significant increase of 0.21 °C/yr under RCP 8.5 was observed for 2021–2040. For 2041–2070, a significant increase of 0.016 °C/yr (RCP 4.5) and 0.045 °C/yr (RCP 8.5) was observed. The change in land use/cover resulted in increasing the build-up area (84%), agricultural fields (55.6%), and a decrease in the forest area (10.5%) during 2021–2040. During 2041–2070, the build-up area increased by 32.1%, the agricultural field by 36%, and the forest area decreased by 11%. Streamflow decreased significantly by 65.4 m\(^3\)/yr (RCP 4.5) and 195.9 m\(^3\)/yr (RCP 8.5) from 2021 to 2040. An insignificant decrease of 13.7 m\(^3\)/s (RCP 4.5) and 7.63 m\(^3\)/s (RCP 8.5) was observed during 2041–2070. This study provides an insight to the managers, planners, and policymakers on environmental protection/conservation for sustainable utilization of water resources at the Kibungo sub-catchment.

\textsuperscript{*} Corresponding author.
E-mail address: lusajo.henry@aau.edu.et (L.H. Mfwango).

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warming will reach 1.5 °C (Guliyardi et al., 2018). East Africa is expected to see temperature increases between 1 °C and 5 °C by the 2090s, while rainfall may increase by as much as 48% (Ddamulira, 2016). In Tanzania, temperatures have increased in most highland areas, late-onset and early withdrawal (cessation) of rain, decreasing rain amounts, and seasonal shifting of rainfall patterns. Despite the uncertainties surrounding projected precipitation changes, temperatures are likely to increase (Kangalawe and Lyimo, 2013; Luhunga et al., 2018), projected an increase in maximum temperature for 2011–2040 by 0.9 °C and 1.0 under RCP 4.5 and 8.5, respectively, while during 2041–2070, the maximum temperature is projected to increase by 1.6 °C under RCP 4.5 and 2.2 °C under RCP 8.5. The increment of 0.7 °C under RCP 4.5 and 0.8 °C under RCP 8.5 in minimum temperature is expected during 2011–2040, while during 2041–2070 the minimum temperature is projected to increase by 1.4 °C and 2.1 °C under RCP 4.5 and 8.5 respectively. A mixed trend in rainfall is expected by 2100, while some parts will experience an increase of 5–45%, other parts will witness a decrease of 10–15% (Mwandosya et al., 1998). According to URT (2003), as cited in Mujule et al. (2015), land use change and deforestation contribute 87% of Greenhouse gas (GHG) emissions to the country. The current rate of deforestation is approximated to be 400,000 ha/year, mainly caused by agricultural activities (URT, 2013a, as cited in Mujule et al., 2015).

The Kibungo sub-catchment of the Upper Ruvu catchment is among Tanzania’s most potential agricultural areas due to its favorable climate conditions and fertile soils. It is the source of the main tributary of the Ruvu river, which supplies water to the highly populated (approximately 6 million) industrialized city of Dar es Salaam (Andreasen, 2017). Analysis of the change in land use/cover in the Ruvu basin by Yanda and Munishi (2007) indicated that natural forest and woodland decreased by 2% and 20%, respectively, while cultivated land increased by 25% from 1995 to 2000. In the Uluguru mountains, the forest cover declined from 260 km² in 1977 to 230 km² in 2000, with an annual loss rate of 0.6% per annum (Burgess et al., 2002). Unsustainable agricultural practices with limited soil conservation methods are standard in the Kibungo sub-catchment (Yanda and Munishi, 2007). Streamflow analysis at 1HS_Ruvu Kibungo for the period of 54 years from 1952 to 2005 indicated a decrease in annual flow of 8.5 m³/s, a decrease in wet season flow of 16 m³/s, and a decrease in the dry season of 5 m³/s, which could be attributed to the factors mentioned above. Water security and sustainable water management strategies can only be enhanced if reliable assessment of the impact of climate change and land use change on hydrology can be developed.

Climate change and land use/cover change alter hydrological processes such as surface runoff, base flow, evapotranspiration, and streamflow and impact the variability of these processes over time and space (Mango et al., 2010; Rahman et al., 2015). With the advancement in hydrological modeling, researchers globally have been able to investigate the impact of climate change and land use/cover change on hydrology at different scales (Mahe, 2006; Lafontaine et al., 2015; Pervez and Henchey, 2015; Zhang et al., 2016; Thi et al., 2017; Yang et al., 2019; Osei et al., 2019; Nyatuame et al., 2020; Ragab, 2020; Chim et al., 2021; Hu et al., 2021; Teklay et al., 2021). Märhaento et al. (2018) found that the combined impact of land use change and climate change in a tropical catchment will significantly affect the water balance component more than when drivers operate independently. Guo et al. (2008) found that climate change is a dominant factor in annual streamflow, whereas land cover change is critical in seasonal streamflow in the Poyang Lake basin, China. Based on the reviewed literature, the studies conducted in Tanzania focused mainly on a single factor, either climate (Yanda and Melese, 2013; Kassian et al., 2017; Mutayoba et al., 2018; Nyembo et al., 2022) or change in land use/cover change (Nobert, 2012; Näsching et al., 2019; Chilagwe et al., 2021; Said et al., 2021). Few studies evaluated the combined impact of climate change and land use/cover changes on the hydrological process. Natkhin et al. (2013) evaluated the impact of climate change and land use change on the discharge regime of the Ngerengere River between 1970 and 2010. The results indicated an increase in low flow duration (LFD) and base flow index (BFI) due to the combined impact of the two factors. The study of the impact of land use/land cover change on water resources in a tropical catchment under different climate change scenarios (Näschen et al., 2019) found that due to the combined effect, the high flow increased by 84% in the Kilombero catchment.

Despite the potential benefits to socio-economic development, the effects of future climate change and land use change on the hydrology of the Ruvu river in the Kibungo sub-catchment are rarely evaluated. This study evaluated the combined impact of future climate change and land use/cover change on streamflow in the Kibungo sub-catchment using the SWAT model. The specific objectives were (i) To characterize the pattern of the future rainfall and temperature of the sub-catchment, (ii) To predict the future land use/cover and generate the map for 2040 and 2070, and (iii) To simulate the streamflow under changing climate and land use/cover under RCP 4.5 and RCP 8.5 for 2021–2040 and 2041–2070.

The remaining parts of this article are structured as follows: Section 2, provide a detailed description of the study area; Section 3, describes the type of data used and the methods; Section 4, provides details of the finding from the trend analysis of climate data, the land use/cover change analysis, and SWAT model simulations; Section 5, provide a detailed discussion of our results, and finally conclusions and recommendations is given in section six.

### 2. Study area

The Kibungo sub-catchment occupies an area of 466.5 km² of the Upper Ruvu Catchment, which also comprises the Ngerengere and Mgeta sub-catchments. It is located between latitudes 6° 50’–7° 10’ S and longitudes 37° 00’–37° 50’ E (Figure 1) on the eastern slope of the Uluguru ranges, part of the eastern arc mountains (Mfwango et al., 2022). The Kibungo Sub-catchment is the source of the main tributary of the Ruvu River, which supplies fresh water to some parts of the Morogoro region, the Coast Region, and Dar es Salaam for domestic, agricultural, and industrial purposes (Burgess et al., 2002). The study area experiences a bimodal rainfall pattern, with short rains (Vuli) from October to December and long rains (Masika) from March to May (Shemanga et al., 2010). Orographic features influence spatial-temporal variation in rainfall within the sub-catchment, with the highest rainfall observed at higher altitudes. An analysis of historical rainfall data for the 38 years between 1982 and 2019 showed that the Kibungo sub-catchment averaged 1358.7 mm of annual rainfall, equivalent to 113.2 mm every month (Mfwango et al., 2022). The minimum temperature is around (18 °C) in August, while the maximum is (32 °C) in February. The annual average temperature is 26 °C (IUCN, 2010).

According to Ngoye and Machiwa (2004), the catchment’s vegetation cover consists of mountain forests, thickets, woodlands, tropical evergreens, and semideciduous forests along the river and tributaries. Chromic Cambisols (BC) is the dominant soil type within the catchment area (FAO, 2005). The community living within the catchment depends on agriculture, mining, and forest products (Charcoal production and timber harvesting) for their livelihood. The catchment is enriched with fertile soil, and suitable climate conditions that favour the growth of crops such as maize, beans, cocoyam, bananas, and oranges at lower elevations, and the higher altitude crops such as cabbage, potatoes, and peas are cultivated (Msuya et al., 2010). However, agriculture is poorly practiced with limited use of soil conservation measures. The unsustainable utilization of land and water resources has resulted in environmental degradation that consequently affects ecosystem services provided by the catchment.

### 3. Methodology

#### 3.1. SWAT model and input data

Soil and Water Assessment Tool (SWAT), developed by the United States Department of Agriculture-Agricultural Research Service (USDA-ARS), is a semi-distributed, continuous-time, process-based model used to evaluate the effect of alternative management decisions on water...
resources and non-point source pollution from small catchment to large scale river basins (Arnold et al., 1998; Gassman et al., 2007). SWAT divides a watershed into multiple subbasins and hydrological response units (HRUs) based on land use, slope, and soil characteristics. The HRU is the smallest unit of a watershed in which evapotranspiration, surface runoff and peak runoff rates, groundwater flow, and sediment yield are calculated. The land phase and the routing phase simulate hydrological processes within the SWAT model. The equation of water balance (Arnold et al., 2012) drives all SWAT processes.

\[ SW_t = SW_0 + \sum_{i=1}^{t} \left( R_{\text{day}} - Q_{\text{surf}} - E_a - W_{\text{seep}} - Q_{\text{gw}} \right) \]

where, \( SW_t \) is the final soil water content (mm), \( SW_0 \) is the initial soil water content (mm), \( t \) is the time (days), \( R_{\text{day}} \) is the amount of precipitation (mm), \( Q_{\text{surf}} \) is the amount of surface runoff (mm), \( E_a \) is the amount of evapotranspiration (mm), \( W_{\text{seep}} \) is the amount of water entering the vadose zone from the soil profile (mm), and \( Q_{\text{gw}} \) is the amount of return flow (mm).

Surface runoff is calculated using the soil conservation service curve-number (SCS-CN) method or the Green–Ampt infiltration method. Gassman et al. (2007) provide a detailed description of the SWAT model. The input data required to run the SWAT model categories into; spatial, weather, and hydrological data. These data were obtained from various sources as follows;

(i) Spatial Data

Digital elevation model (DEM): These data were downloaded from Shuttle Radar Topography Mission (SRTM) 1 Arc-Second Global at a resolution of 30 m (https://earthexplorer.usgs.gov/) (Figure 1). DEM was used to determine subbasin parameters, including slope gradient, slope length of the terrain, and the stream network.

Land use/cover (LULC) map: describes the spatial distribution of various land use/cover types found within the catchment. This study utilizes LULC maps for the years 1991, 2008, and 2020 (Mfwango et al., 2022). The following classes were found within the sub-catchment: forest, agricultural field, build-up, grassland, barren land, river basin/river, and shrub/bushlands. This information is essential for a periodic assessment of the impact of LULC changes on streamflow.

Soil data: Physical properties of the soil determine the hydrological response of the catchment to the impact of climate and land use/cover change. This information was extracted from the Digital Soil Map of the World (DSMW) of the Food and Agriculture Organisation (FAO) (https://www.fao.org/soils-portal/en/) by using ArcGIS. The main soil found within the catchment is Chromic Cambisols (BC) with the following
properties: loam textural properties, bulk density (1.2 g/cm³), available water content (0.097 mmH₂O/mmSoil), and saturated hydraulic conductivity (17.7 mm/h) at the topsoil while the subsoil comprises with bulk density (1.3 g/cm³), available water content (0.097 mm H₂O/mm Soil), and saturated hydraulic conductivity (8.55 mm/h).

(ii) Meteorological data

These include observed/recorded rainfall data, minimum and maximum temperatures, and the Regional Climatic Model (RCM).

Observed daily data: Rainfall, minimum and maximum temperature spanning from 1980 to 2020 for six stations (Figure 1) found within the catchment were collected from Tanzania Meteorological Authority (TMA). These data from each station were subjected to quality control by plotting a time series graph to detect missing records and outliers caused by instrumental or human errors. The missing records were filled using Inverse Distance Weighting (IDW) method (Moseleti et al., 2016; Sam-hitha and Srikanth, 2017), which is based on filling unknown points with known points.

Regional Climate Models data: Daily minimum and maximum temperature and rainfall data from three RCMs for the historical (1980–2004) and the future period (2021–2070) under two Representative Concentration Pathways (RCP 4.5 and 8.5) were derived from the Coordinated Regional Climate Downscaling Experiment (CORDEX) under the Africa Domain (https://esgf-data.dkrz.de/projects/esgf-dkrz/). RCP 4.5 is a medium stabilization scenario that peaks at 4.5 W/m², while RCP 8.5 is the high emission scenario with rising radiative forcing of 8.5 W/m² (Van Vuuren et al., 2011). The selected RCMs have the same resolution (0.4° by 0.4°), initial conditions (r1), initialization method (i1), and underlying perturbation physics (p1). To obtain point climate data for each station, the RCM for the historical period, RCP 4.5, and RCP 8.5 scenarios were bias corrected to observed data using CMhyd software (Rathjens et al., 2016) (https://swat.tamu.edu/software/cmhyd). Power transformation and Distribution mapping methods for rainfall and temperature were used for bias correction (Teutschbein and Seibert, 2010; M’Po et al., 2016). The list of RCMs and their corresponding driving General Circulation Models (GCM) are presented in Table 1. Since climate models are subject to uncertainties due to boundary conditions, natural variability within the climate models, and differences in model formulations (Nikulin et al., 2012), therefore, an ensemble average of three RCMs was obtained by using the simple arithmetic mean method as it has been applied by Bhatta et al. (2019) and Gunathilake et al. (2020). This article does not cover the details of bias correction.

(iii) Hydrological data:

Hydrological data describe the state and dynamics of ground and surface water. A long-term data series is essential to understanding various hydrological processes, modeling, forecasting water resources and hazards (drought and flooding), and monitoring water quality and quantity (McMillan et al., 2018). Daily observed streamflow data (m³/s) recorded at the Kibungo gauge station (1H5) from 1995 to 2019 was obtained from the Wami/Ruvu Basin Water Board (WRBWB), Tanzania. It was characterized by missing values that ranged from days to months. The data were subjected to quality control, which involves filling missing records by the Markov chain Monte Carlo (MCMC) method, which uses Multiple Imputation Algorithms in XLSTAT available on an Excel spreadsheet.

3.2. Model set up, calibration, and validation

The SWAT model set-up and data preparation were performed using the ArcSWAT2012 tool in the QGIS environment. Using DEM and stream network data, drainage areas covering 466.5 km² were discretized into seven subbasins, further subdivided into 207 hydrological units based on soil, land use, and slope. A default streamflow simulation followed the model set-up in the Kibungo sub-catchment. Sensitivity analysis, model calibration, and validation were conducted using R-SWAT (https://github.com/tamnva/SWATshiny). R-SWAT is a web-based interface for analyzing parameters’ sensitivity, calibration, and uncertainty inside the Soil and Water Assessment Tool (SWAT) model set-up in the Kibungo sub-catchment. Sensitivity analysis, model calibration, and validation were conducted using R-SWAT (https://github.com/tamnva/SWATshiny). R-SWAT is a web-based interface for analyzing parameters’ sensitivity, calibration, and uncertainty inside the Soil and Water Assessment Tool (SWAT). R-SWAT uses the Latin Hypercube One-factor-at-a-Time (LIH-OAT) approach (Morris, 1991) and the Sequential Uncertainty Fitting (SUFi-2) algorithm to do the sensitivity analysis and model calibration. Sensitivity analysis measures the rate of change in the output of a model in response to changes in its inputs (parameters). Seventeen hydrological parameters (Table 2) with default lower and upper bound values derived from the SWAT model database and other literature (Xidomba et al., 2008; Nobert and Jeremiah, 2012; Abbaspour et al., 2015) were selected for Global Sensitivity Analysis. The model was run for 3000 simulations. Parameter sensitivity was determined using t-statistics and the p-value. Sensitivity analysis measures the rate of change in the output of a model in response to changes in its inputs (parameters). Seventeen hydrological parameters (Table 2) with default lower and upper bound values derived from the SWAT model database and other literature (Xidomba et al., 2008; Nobert and Jeremiah, 2012; Abbaspour et al., 2015) were selected for Global Sensitivity Analysis. The model was run for 3000 simulations. Parameter sensitivity was determined using t-statistics and the p-value.

The observed daily weather data (rainfall, minimum, and maximum temperature) and streamflow data from 2006 to 2019 were separated into three phases to calibrate and validate the models: warm-up (2006–2008), calibration (2009–2016), and validation (2017–2019). We used a long enough calibration period to capture different meteorological and hydrological conditions (e.g., wet and dry years) to get the correct model response in all other periods. Following Arnold et al. (2012) and Abbaspour et al. (2015) guidelines, five iterations were executed with 600 simulations for each run until reasonable minimum

| Parameter | Description | Initial range |
|-----------|-------------|---------------|
| e_CN2.mgt | SCS runoff curve number for moisture condition II | -0.1–0.1 |
| e_SURLAG.hru | Surface runoff lag time | 0.05–24 |
| e_ALPHA_BF.gw | Baseflow alpha factor (days) | 0–1 |
| e_REVAPMN.gw | Threshold depth of water in the shallow aquifer for 'revap' to occur (mm) | 0–500 |
| e_GW_DELAY.gw | Groundwater delay (days) | 0–500 |
| e_GW_REVAP.gw | Groundwater ‘revap’ coefficient | 0.02–0.2 |
| e_RCHRG_DP.gw | Deep aquifer percolation fraction | 0–1 |
| e_GWQMNN.gw | Threshold depth of water in the shallow aquifer required for return flow to occur (mm) | 0–5000 |
| e_EPCO.hru | Plant uptake compensation factor | 0–1 |
| e_ESCO.hru | Soil evaporation compensation factor | 0–1 |
| e_SLSUBBSN.hru | Average slope length | 10–150 |
| e_CH_K2.rte | Effective hydraulic conductivity in main channel | 0.01–500 |
| e_CH_N2.rte | Manning’s ‘n’ value for the main channel | 0.01–0.3 |
| e_SOL_ABC.soil | Available water capacity of the soil layer | 0–1 |
| e_SOL_K.soil | Saturated hydraulic conductivity | 0–500 |
| e_OV_N.hru | Manning’s ‘n’ value for overland flow | 0.1–30 |
| e_HRU_SLP.hru | Average slope steepness (fraction) | 0–1 |

Table 2. SWAT model parameters with their initial values.

Table 1. Selected RCMs and their respective GCMs.

| Variable | RCM | Driving GCM |
|----------|-----|-------------|
| Rainfall (Historical data, RCP 4.5 & RCP 8.5) | RCA4 | NorESM1-M |
| | RACMO22T | HadGEM2-ES |
| | CCLM4-8-17 | HadGEM2-ES |
| Temperature (Minimum & Maximum (Historical data, RCP 4.5 & RCP 8.5) | RCA4 | NorESM1-M |
| | RACMO22T | HadGEM2-ES |
| | CCLM4-8-17 | HadGEM2-ES |
| | RCA4 | NorESM1-M |
disparities between the observed and simulated streamflow were obtained. Model performance was qualitatively assessed using visual time-series graphs and quantitatively using Nash–Sutcliffe efficiency (NSE) (Nash and Sutcliffe, 1970), coefficient of determination (R²), and Kling Gupta Efficiency (KGE) (Gupta et al., 2009). Kouchi et al. (2017) categorized the model performance as unsatisfactory, satisfactory, good, and very good depending on the value of NSE, R², and KGE.

3.3. Homogeneity test and trend analysis

Rainfall and temperature are critical physical factors that influence the climate of a region (Chinchorkar et al., 2015). Therefore, a thorough understanding of its characteristics is a prerequisite for an impact assessment on hydrological processes (Machiwal and Jha, 2008). The homogeneity test and trend analysis are commonly employed to detect breaks/change points and trends in meteorological variables (Chaney et al., 2014; Yadav et al., 2014; Mahajan and Dodamani, 2015; Mehta and Yadav, 2021). Change points are sudden changes in time series data that divide an observation into two or more sub-periods, each with its characteristics (Krajevski et al., 2021). The RCMs ensemble mean of daily rainfall, and minimum and maximum temperature were aggregated for all stations to prepare the annual time series. The Buishand range test (Buishand, 1982), Pettitt’s test (Pettitt, 1979), and the standard normal homogeneity test (SNHT) (Alexandersson, 1986) were used to determine when a break in an annual time series data is most likely to occur. The homogeneity was tested at a 5% significance level under the null hypothesis; data are homogeneous and alternative hypothesis; there is a date at which the change occurs. Since each approach can detect distinct change points in the same time series data, decisions on the occurrence of change points were based on the criteria described by Ilori and Ajayi (2020). First, at a 5% significance level, the data are considered homogeneous if one or none of the test methods reject the null hypothesis. Secondly, the data are heterogeneous when two or three test methods reject the null hypothesis at a 5% significance level. Third, the time-series data are considered doubtful and need further evaluation when all three test methods disagree on the change point.

Detection of breakpoints led to splitting the data into two periods, and then trend analysis was performed. Mann-Kendall (Mann, 1945), a non-parametric test, was used to determine the direction changes in time series. This method is better suited to data that are not normally distributed because it is less susceptible to outliers (Birsan et al., 2005). We formulated two hypotheses: the null hypothesis (there is no trend in the time series) and the alternative hypothesis (there is a trend in the time series). The null hypothesis was tested using the statistical value (p-value) at a confidence level of 15%. If the p-value is less than the significant level (α = 0.05), the null hypothesis is rejected, and the alternative hypothesis is accepted, showing that the test is statistically significant. The null hypothesis cannot be rejected when the p-value is greater than the significant level (α = 0.05), suggesting that the test is statistically insignificant. Sen’s slope estimator (Sen, 1968) was used to determine the magnitude of the trend. A positive score implies an upward trend, while a negative value suggests a downward trend. A detailed description of the Mann–Kendall and Sen’s slope estimator is found in Yadav et al. (2014) and Kumar et al. (2017).

3.4. Future land use/cover prediction

Based on the classified historical satellite images of 2008 and 2020, the prediction of the LULC maps for 2040 and 2070 was made using a Land Change Model (LCM) in TerrSet Geospatial Monitoring and Modeling System (TGMMMS) software ver. 18.31 (Eastman, 2016). We followed three steps:

(i) Change analysis; this involved analyzing LULC maps of 2008 and 2020 to understand the extent of land-use changes and generating change maps.

(ii) Transition Potential; This tab allows the creation of potential transitional maps. The potential of pixels to change into a different class is determined by drivers of change (Mas et al., 2014). The transition sub-model, forest to build-up, and forest to the agricultural field were grouped to anthropogenic disturbance. Our objective was to forecast how human activities might affect LULC. Distance from roads, distance from rivers, distance from towns, slope, and elevation have been utilized as variables that affect land use/cover change. These variables were prepared in ArcGIS 10.4.1 environment, imported, and converted to the proper format required by TGMMMS for transformation and modeling. The variables were selected based on their availability, anticipated relative importance, and the corresponding impact on the change in LULC.

(iii) Change Prediction; Cellular Automata-Markov Chain (CA-MC) module was used to determine the change that will occur in the future. The process involves analyzing a pair of land cover images and generating a transition matrix, a transition area matrix, and conditional probability images (Eastman, 2016). During this stage, land use maps for 2040 and 2070 were produced. The reader can refer to Mishra et al. (2014), Eastman (2016), and Reza et al. (2019) for details of the prediction of LULC using LCM in Terrset software.

3.5. Evaluation of the impact of climate change and land use/cover change on streamflow

The combined impact of Climate change and LULC change was assessed by running the SWAT model using future climate data (2021–2040 and 2041–2070) and LULC (2040 and 2070) under two emission scenarios (RCP 4.5 and RCP 8.5). LULC maps of 2040 and 2070 were used to run the SWAT model for the near future (2021–2040) and the far future (2041–2070). The decision to separate simulation periods was based on the results of the homogeneity test on the future climate variable. An ensemble mean of rainfall and minimum and maximum temperatures from three RCMs (Table 1) was used as input to run the SWAT model.

To understand the characteristics of future simulated streamflow, the trend analysis and the statistical results of monthly, seasonal, and interannual for both study periods under two emission scenarios were analyzed using the Mann–Kendall trend analysis. Two hypotheses were tested; null hypothesis: there is no significant trend in streamflow data, and alternative hypothesis: There is a significant increase or decrease trend in streamflow data. The significance of increasing or decreasing trend was tested at a 5% (α = 0.05) level. The null hypothesis was rejected when the calculated p-value was less than the alpha value (0.05). The value of Sen’s slope provides the direction and magnitude of the trend in the streamflow data.

Additionally, the simulated streamflow for both periods under RCP 4.5 and RCP 8.5 was compared with historical observations (1995–2019) on a monthly and seasonal basis, and the statistical results were presented. The analysis was made in consideration of the availability of historical streamflow data. For our case, historical streamflow data at the Kibungo gauge station (1H5) were available for 25 years from 1995 to 2019.
4. Results

4.1. Sensitivity analysis, model calibration, and validation

In the global sensitivity analysis of 17 flow parameters (Table 2), only ten parameters were sensitive to flow. Table 3 presents the calibrated parameters with their fitted values. The most sensitive parameter was CH_K2, which controls the routing in the main channel. ALPHA_BF was the second sensitive parameter, followed by SURLAG, SLSUBBSN, CH_N2, OV_N, CN2, SOL_AWC, SOL_K, HRU_SLP, and two-parameter control groundwater movement (ALPHA_BF, RCHRG_DP).

Table 3. List of calibrated parameters and their value.

| Parameter          | Minimum       | Maximum       | Fitted Value |
|--------------------|---------------|---------------|--------------|
| v_CH_K2.rte        | 71.721        | 435.941       | 265.8987     |
| v_ALPHA_BF.gw      | 0.1043        | 0.5545        | 0.1846       |
| v_SURLAG.hru       | 0.319         | 22.2363       | 19.2143      |
| v_SLSUBBSN.hru     | 76.8876       | 148.3899      | 109.5575     |
| v_CH_N2.rte        | 0.0547        | 0.2845        | 0.0716       |
| r_OV_N.hru         | 17.1397       | 29.5489       | 24.0184      |
| r_CN2.mgt          | -0.152        | -0.0103       | -0.028       |
| r_SOL_AWC.sol      | 0.0664        | 0.9333        | 0.578        |
| r_HRU_SLP.hru      | 0.0068        | 0.176         | 0.0841       |
| r_RCHRG_DP.gw      | 0.4118        | 0.932         | 0.7925       |

Graphical comparisons of the measured streamflow at the outlet of the Kibungo sub-catchment and its simulated discharge values are shown in Figure 2 for the calibration and validation processes. The P-factor and the R-factor during calibration were 0.54 and 0.62, respectively. Although the P-factor and the R-factor were below the standard (Abbaspour et al., 2015), the performance indices during the calibration and validation period indicated satisfactory results (Kouchi et al., 2017). The value of NSE, R², and KGE for the calibration period was 0.63, 0.64, and 0.69, respectively. For the validation period, NSE was 0.64, R² was 0.65, and KGE was 0.74.

4.2. Homogeneity test and trend analysis of future climate variables

4.2.1. Homogeneity test

Homogeneity tests were conducted on rainfall and minimum and maximum temperature under RCP 4.5 and RCP 8.5 at all stations. Generally, our results indicated inhomogeneity in rainfall and temperature data between 2021 and 2070 under the RCP 4.5 and RCP 8.5 emission scenarios. The Buishand’s range test and Pettitt’s test detect the change point in the annual rainfall series at 2040 for both RCP scenarios for all the stations except Mtamba (2036) in the Buishand’s range test. SNHT detects a change point at 2040 for RCP 4.5, while different change points under RCP 8.5 were detected for different stations (Tegerero mission, Tawa Health Centre, and Kinole Primary School at 2033, Mtamba and Mkuyuni Primary School at 2036, Nyingwa at 2040).

Regarding the minimum temperature, under RCP 4.5, Buishand’s test and Pettitt detect a change point in 2042, while SNHT detects a change in 2040 for all stations. Buishand’s Range test and SNHT detect change points in 2041, while Pettitt’s test detects different change points for the different stations ((Tegerero mission (2041), Tawa Health Centre (2053), Kinole Primary School (2041), Nyingwa (2053), Mtamba (2053) and Mkuyuni Primary School (2041)) for maximum temperature under RCP 4.5.

For minimum temperature under RCP 8.5, the Buishand’s range test and SNHT detect a change point at 2045, while Pettitt’s test detects a change point at 2046. Buishand’s Range test and Pettitt’s test detected change points at 2046, while SNHT detects change points at 2056 for maximum temperature under RCP 8.5. The rainfall data indicated a break at 2040 under both emission scenarios. Minimum and maximum temperature indicated breakpoints at 2042 and 2041 respectively under RCP 4.5. The break point at 2045 for minimum temperature and 2046 for maximum temperature was found under RCP 8.5.

4.2.2. Trend analysis

Rainfall data was evaluated monthly, seasonal, and interannually, while temperature analysis was conducted monthly and interannually in a separate time interval (2021–2040 and 2041–2070) under both RCPs emission scenarios. Since the homogeneity test for rainfall time series found similar change years under both RCPs, the year 2040 was considered to separate time-series data. Figure 3(a-d) presents the annual time series...
Figure 3. Time-series of future Rainfall and Mean temperature at Kibungo Sub-catchment.

Figure 4. Predicted Land use/cover of the Kibungo Sub-catchment.
for rainfall and temperature for the near future (2021–2040) and the far future (2041–2070) under both emission scenarios.

4.2.2.1. Rainfall trend analysis. Figure 3 presents a time-series plot of monthly rainfall and mean monthly temperature from the ensemble mean at all the stations for 2021–2040 and 2041–2070 under both emission scenarios. From 2021 to 2040, the projection indicated a unimodal rainfall pattern from October to April in both emission scenarios. High rainfall will be observed in November and December, while June to September will receive little or no rainfall (Figure 3a and b). According to the literature, the catchment receives a bimodal rainfall pattern; heavy rain during Spring (March–May) and short rain (November to January). Our findings revealed a change in rainfall pattern for 2021–2040 from bimodal to unimodal. Both emission scenarios will observe a bimodal rainfall pattern during 2041–2070 (Figure 3c and d).

The Sen slope estimator indicated a significant decrease in rainfall between 12.2–22.9 mm/year and 17.8–57 mm/year between the stations under RCP 4.5 and RCP 8.5, respectively, for 2021–2040. Between 2041 and 2070, rainfall decrease is insignificant, ranging from 1.24 to 2.9 mm/year and 0.16–8.7 mm/year under RCP 4.5 and RCP 8.5, respectively. The sub-catchment will experience high annual rainfall between 2021 and 2040 compared to 2041–2070. Between 2021 and 2040, the expected mean annual rainfall will be 1844.7 mm/year, which will be reduced to 1383.7 mm/year between 2041 and 2070 for RCP 4.5. Under RCP 8.5, the annual rainfall will be 1894.5 mm for 2021–2040 and 1386.3 mm for 2041–2070.

Monthly rainfall data for 2021–2040 showed a significant upward trend in January, June to October, and December for all stations under the RCP 4.5 scenario. From February to April, there was a significant decrease trend. In all stations, the decreasing trend was insignificant in the same scenario in May and November. From 2041 to 2070, all stations found significantly increased trends from January through April. Furthermore, from June to December, a declining tendency was observed. There was no statistically significant increase trend in May among the stations under RCP 4.5. Under RCP 8.5, during 2021–2040, a rising trend was observed in July and August, while a decreasing trend was observed in February, March, and November. The increasing trend was not significant in January, May, June, September, October, and November, except for the Kinole Primary School station, which had a significant increasing trend in May and a decreasing trend in April and October. An insignificant trend of decrease was observed in April for all stations. During the period 2041–2070, from February to May, all stations showed a significant upward trend and a downward trend in June, July, and September to December. The decreasing trend was not significant in January and August under RCP 8.5.

For all RCP scenarios, the seasonal analysis revealed a significant decreasing trend in rainfall during Spring from 2021 to 2040 and a significant increasing trend from 2041 to 2070. Summer showed a significant increasing trend for 2021–2040 and a significant decrease for 2041–2070 for both scenarios. Under RCP 4.5, there was a significant increase trend in Autumn from 2021 to 2040, then a decline from 2041 to 2070. The autumn season for both study periods under RCP 8.5 indicated a significant decreasing trend. An insignificant decrease was observed under RCP 8.5 for 2041–2070, whereas an increasing trend was observed under RCP 4.5 for Winter. During 2021–2040, Winter showed no significant increasing trend under RCP 4.5. On the other hand, under RCPs 8.5, a decreasing trend was detected at Tegerero mission, Nyingwa, Mkuyuni Primary School, and Tawa Health Centre, whereas no significant decreasing trend was recorded at Kinole Primary School and Mtamba.

Analysis of annual rainfall revealed a significant downward trend during 2021–2040 under both RCPs scenarios. Except for the Kinole Primary School station, which shows a significant decreasing trend in

### Table 4. Streamflow trend analysis (2021–2040).

| Scenario | Test | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec | Annual |
|----------|------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|--------|
| RCP 4.5 | t    | 0.23| 0.06| -0.16| 0.53| -0.65| -0.37| -0.42| <0.01| -0.22| -0.21| -0.14| 0.17| 0.06  |
|          | p-value |      |     |     |     |     |     |     |     |     |     |     |     | <0.0* |
| RCP 8.5 | t    | 0.49| 0.14| -0.14| -0.12| -0.33| -0.25| -0.42| -0.22| -0.31| -0.14| -0.03| 0.17| 0.06  |
|          | p-value |      |     |     |     |     |     |     |     |     |     |     |     | <0.0* |

* Significant increasing or decreasing trend, ** Increasing trend.
annual rainfall under RCP 8.5, no significant decrease was observed over 2041–2070 for both emission scenarios.

4.2.2.2. Temperature trend analysis. Under the RCP 4.5 emission scenario, the study of mean monthly temperature for all stations from 2021 to 2040 revealed a significant increasing trend from May to November and a significant decreasing trend from January to March, April, and December except for the Tegerero mission and Mkuyuni Primary School which exhibited an insignificant declining trend in mean monthly temperature in April and December. During 2041–2070, all stations showed a significant rising trend from January through July and December, while significant decreasing trends were observed from September to November. August observed an insignificant increasing trend under the RCP 4.5 scenario. Under RCP 8.5, significant decreasing trends were detected for all months except April and December, where no significant decrease was observed from 2021 to 2040. All stations observed a significant increasing trend from January to July and November to December, while September and October indicated a significant decreasing trend for RCP 8.5 from 2041 to 2070. No significant decreasing trend was observed in August for all stations.

Under the RCP 4.5 scenario, the analysis of annual temperature indicated an insignificant increase trend from 2021 to 2040 but a significant increasing trend from 2041 to 2070. The RCP 8.5 scenario, indicated a significant increase in annual temperature for 2021–2040 and 2041–2070. Sen’s slope estimator indicated an insignificant increase in annual temperature by 0.004 °C/year under RCP 4.5 and a significant increase of 0.021 °C/year under RCP 8.5 from 2021 to 2040. Between 2041 and 2070, the annual temperature increased significantly by 0.016 °C/year and 0.045 °C/year under RCP 4.5 and RCP 8.5, respectively. From Figure 3, the statistical results for 2021–2040 indicated a mean annual temperature of 26.1 °C, a maximum temperature of 29.4 (November), and a minimum temperature of 21.9 °C (June) under RCP 8.5. Between 2041 and 2070, the annual temperature was 27.1 °C, the maximum temperature was 29.2 °C (November), and the minimum temperature was 24.6 °C (June).

4.3. Land use/cover prediction

The multi-layer perceptron neural network (MLPNN) approach was used to run the transitional sub-model (Anthropogenic disturbance). A total of 9069 samples (50% training/50% training) per class were used. The accuracy rate of 74.6% and the skill of measure 0.66 were obtained. Statistical results of land use/cover maps prediction indicated an increase in build-up area from 14 to 22.4 km² (84%), agricultural field from 45.9 to 71.4 km² (55.6%), and a decrease in forest area from 322.3 to 288.4 km² (10.5%) for 2021–2040. During 2041–2070, the build-up area increased from 22.4 to 29.6 km² (32.1%), the agricultural field increased from 71.4 to 97.7 km² (36%), and the forest area decreased from 288.4 to 256.6 km² (11%). Insignificant changes were observed in other land use/cover classes. The overall prediction results indicated that by the 2070s, the build-up increased by 111.4% (14–29.6 km²), the agricultural field increased by 112.9% (45.9–97.7 km²) and the forest area decreased from 322.3 to 256.6 km² equivalent to 20.4%. The predicted land use/cover maps are presented in Figure 4.

4.4. Impact of climate change and land use/cover change on streamflow

The results of streamflow trend analysis on a monthly, seasonal and interannual basis for 2021–2040 and 2041–2070 and statistical comparison of streamflow between historical (1995–2019) and future periods (2021–2040 & 2041–2070) under emission scenarios (RCP 4.5 & 8.5) are presented in the following subsections.

4.4.1. Streamflow trend analysis for 2021–2040

The trend analysis results for 2021–2040 are presented in Table 4. Monthly findings showed a significant increase in flow in January, with a declining trend in April, May, June, and July under RCP 4.5. An insignificant increase trend was found in February and December, while August to November indicated an insignificant decreasing trend under the same scenario. Under the RCP 8.5 emission scenario, streamflow decreased significantly from March to August, November, and December, while the other months showed an insignificant decreasing trend. A
seasonal analysis indicated decreasing trends for both RCPs, except RCP 4.5, which showed insignificant decreases in Autumn and Winter. There was a significant decrease in interannual streamflow in both RCPs.

Figure 5 presents the monthly and seasonal flow for the historical (1995–2019) and future (2021–2040) periods under RCP 4.5 and RCP 8.5. Analysis of the mean monthly streamflow for 2021–2040 indicated that the streamflow would reach the maximum peak in December (1327.9 m$^3$/s) and November (1463.9 m$^3$/s) for RCP 4.5 and RCP 8.5, respectively. The minimum mean monthly flow will be observed during September for RCP 4.5 (151.7 m$^3$/s) and RCP 8.5 (151.4 m$^3$/s). Figure 5(a) indicated a decline in streamflow from January to September and began to increase in October. The findings contrast with the long-term average of the historical period (1995–2019), which shows the maximum streamflow in April (1079.5 m$^3$/s) and the minimum streamflow in October (240.6 m$^3$/s). Seasonal analysis (Figure 5b) indicated that high streamflow would be observed during the Winter season (3231.8 m$^3$/s (RCP 4.5), 3250.3 m$^3$/s (RCP 8.5)), and minimum seasonal flow during Summer (753.8 m$^3$/s), while historical data indicated maximum streamflow during Spring (2425 m$^3$/s) and minimum during Autumn (873.1 m$^3$/s). Figure 5(c) presents the time series of the interannual streamflow from 2021 to 2040. During this period, the mean annual streamflow was found to be 7323.8 m$^3$/s and 7647.1 m$^3$/s for RCP 4.5 and RCP 8.5, respectively. The maximum annual streamflow was observed in 2023 (9261 m$^3$/s) under RCP 4.5 and in 2028 (11,395.7 m$^3$/s) under RCP 8.5. On the other hand, the minimum annual flow was observed in 2031 (5228.3 m$^3$/s) under RCP 4.5 and in 2039 (5130.3 m$^3$/s) under RCP 8.5. On average, a significant decrease in streamflow by 65.4 m$^3$/s under RCP 4.5 and 195.9 m$^3$/s under RCP 8.5 during 2021–2040 was observed.

4.4.2. Streamflow trend analysis for 2041–2070

Table 5 presents the results of trend analysis for the period of 2041–2070. Under RCP 4.5, there was a significant increasing trend from March to September, while a significant decrease was observed in January, November, and December. February and October indicated an insignificant increasing trend in streamflow. Significant increases in streamflow were observed under RCP 8.5 from April to September, while significant decreases were observed in January, October, November, and December. During February, the decreasing trend in streamflow was not significant. Under both RCPs, the seasonal analysis revealed a significant increase in the spring and summer seasons and a significant decrease in Autumn and Winter. Interannual streamflow indicated no significant increase for RCP 4.5 and an insignificant decrease for RCP 8.5.

Statistical results on monthly streamflow for the period of 2041–2070 indicated that streamflow peaks twice in a year (Figure 6a). The primary peak was observed in April (659.5 m$^3$/s), and the sondary peak in December (607.8 m$^3$/s) under RCP 4.5. Under RCP 8.5, the primary peak was observed in November (822.3 m$^3$/s) and the secondary peak in April (722.6 m$^3$/s). The minimum streamflow was observed during September for RCP 4.5 (128.2 m$^3$/s) and RCP 8.5 (14.9 m$^3$/s). Seasonal analysis (Figure 6b) showed that high streamflow would be observed during the spring season for RCP 4.5 (1564.7 m$^3$/s) and RCP 8.5 (1694.5 m$^3$/s). The lowest seasonal streamflow during this period was 905.9 m$^3$/s in Autumn for RCP 4.5 and 866.6 m$^3$/s in Summer for RCP 8.5. Figure 6(c) presents the interannual streamflow for the same study period. During this period, the average annual flow was 4852.3 m$^3$/s for RCP 4.5 and 4844.3 m$^3$/s for RCP 8.5. The minimum annual streamflow was observed in 2054 (2893.6 m$^3$/s) and 2041 (2377.8 m$^3$/s) under RCP 4.5 and RCP 8.5, respectively. On the other hand, the maximum annual streamflow was observed in 2070 (8320.5 m$^3$/s) and 2040 (10,479.6 m$^3$/s) under RCP 4.5 and RCP 8.5, respectively. Trend analysis on annual streamflow indicated an insignificant increase in streamflow by 13.7 m$^3$/s and an insignificant decrease by 7.63 m$^3$/s under RCP 4.5 and RCP 8.5, respectively, at a 5% significant level.

| Scenario Series | Test Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec | Annual | Spring | Summer | Autumn | Winter | p-value | Sen slope |
|-----------------|---------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|--------|--------|--------|--------|--------|---------|-----------|
| RCP 4.5         | 0.00   | 0.10 | 0.18 | 0.14 | 0.16 | 0.43 | 0.42 | 0.28 | 0.30 | 0.24 | 0.44 | 0.25 | -0.03 | 0.44   | 0.25   | 0.05   | 0.05    | 0.00     | -0.67    |
| RCP 8.5         | -0.46  | -0.17 | 0.16 | 0.43 | 0.42 | 0.28 | 0.30 | 0.24 | 0.24 | 0.24 | -0.10 | -0.65 | -0.67 | -0.03 | 0.44   | 0.25   | 0.05   | 0.00     | -0.67    |

* Significant increase or decreasing trend, - decreasing trend, - increasing trend.
5. Discussion

Rainfall and temperature are significant climatic variables affecting a watershed’s hydrological processes. As the number of climate model data grows, it becomes easier to assess its future impact on hydrology. However, a detailed understanding of homogeneity in climatic time-series data is required (Alexandersson and Moberg, 1997; Caloiero et al., 2020). Our results revealed inhomogeneity in time series data of rainfall and temperature under both emission scenarios (RCP 4.5 and RCP 8.5). Homogeneity in time-series data is mainly caused by changing observation methods, instrument reliability, station relocation, and the condition around the station (Wijngaard et al., 2003; Firat et al., 2012). Inhomogeneity in future climate data might be caused by drawbacks in the bias correction procedures. According to Teutschbein and Seibert (2013), most bias correction methods assume the stationarity of model error, which means the correction algorithm and its parameterization at the present climate condition will remain the same for future climate conditions.

Detection of change points was more stable in rainfall data than in temperature time series. Three techniques (Buishand’s Range test, SNHT, and Pettitt’s test) applied were able to detect the breakpoint in time-series data; however, the results of the Buishand’s Range test and the Pettitt test showed agreement many times compared to the Buishand and Pettitt’s Range test, SNHT, and Pettitt’s Test’s test. This agreed with the fact that Buishand’s range test and Pettitt’s test detect breaks in the middle of a series, but SNHT detects breaks around the beginning and at the end of a series quite effectively (Hawkins, 1977; Alexandersson, 1986; Wijngaard et al., 2003).

Trend analysis of rainfall and temperature indicated a mixed trend on a monthly and seasonal basis. From 2021 to 2040, a significant decreasing trend in rainfall was observed in the spring season and increased in summer and autumn, indicating the shifting of the rainy season compared to the historical period. The observation contradicts the current condition of the study area. Usually, the catchment receives a bimodal rainfall: the long rainy season (March–May) and short rainy (September–November) (Luhunga et al., 2018; Borhara et al., 2020). A unimodal rainfall pattern was observed from October to April in both emission scenarios for 2021–2040. The high rainfall is expected in November and December, while June to September will receive little rainfall (<100 mm).

Between 2041 and 2070, Seasonal trend analysis observed an increasing trend in the spring season and decreasing in summer and autumn. The winter season shows no significant increase and decreases under RCP 4.5 and RCP 8.5, respectively. The rainfall pattern during this period will result in bimodal patterns resembling current climatic conditions (Borhara et al., 2020). The shifting in rainfall season is evidence of climate change. The warming of the Earth’s atmosphere and the increasing sea surface temperature in the Indian Ocean as a result of global warming affect the movement of the Intertropical Convergence Zone (ITCZ) and control the rainfall pattern within the country (Borhara et al., 2020). The increasing trend in temperature has been observed in earlier studies (Mwandosya et al., 1998; Hulme et al., 2001; Omumbo et al., 2011; Ddamulira, 2016; Borhara et al., 2020). However, these studies showed uncertainties in rainfall projection at the country level.

The results indicated the land use/cover change during the study period. Agricultural fields and settlement areas have increased at the expense of forest land. Similar observations were made by Ngondo et al. (2022). According to the UN (2015), the country’s population is projected to reach 137 million by 2050 and 299 million by 2100. The increasing population coupled with climate change will affect the hydrological processes of the catchment. As climate change may influence change in land use and vice versa (Pielke, 2005), the suitability of climatic conditions and fertile soil (Paavola, 2004; Muthui and Mariki, 2018) in the Kibungo sub-catchment attracts many migrants, consequently degradation of the catchment.

Streamflow analysis indicated a decreasing trend at the Kibungo gauge station (1H5). The negative impact of climate change and land use change on streamflow has been observed in the Samin catchment on the Loess Plateau, China (Zhang et al., 2008), Java, Indonesia (Marhaento et al., 2018), the Owabi catchment, Ghana (Osei et al., 2019) and Finchaa Catchment, Ethiopia (Dibaba et al., 2020). Our findings revealed a significant decrease in annual streamflow for the near future (2021–2041) under both RCPs. A similar observation was made by Marhaento et al.(2018) in the tropical catchment for 2030–2050. An insignificant increasing and decreasing trend were observed under RCP 4.5 and RCP 8.5.
8.5, respectively, for the far future (2041–2070). Monthly and seasonal analysis indicated mixed streamflow in both RCPs. Streamflow decreased during the dry season and increased during the rainy season compared to the historical period, indicating poor catchment storage resulted from land use cover change (Mango et al., 2011).

Furthermore, we found that simulated streamflow and future rainfall follow a similar pattern on a monthly and seasonal basis, implying that decreasing/increasing and pattern shifting in streamflow could be attributed to climate change. Ma et al. (2009), Setegen et al. (2011) and Erler et al. (2019) found similar results on the influence of climate change on streamflow.

6. Conclusions and recommendations

The impact of future climate change and land use/cover change on streamflow was evaluated in the Kibungo sub-catchment between 2021–2040 and 2041–2070 under RCP 4.5 and RCP 8.5. The SWAT model was calibrated and validated successfully for 2009–2016 and 2017–2019, respectively. Before the simulation processes, a homogeneity test and trend analysis of the climate variables were performed to understand the climate characteristics of the study area.

Our findings revealed a decrease in annual rainfall and an increase in annual temperature. Annual rainfall decreases significantly by 22.9 mm/year and 57 mm/year under RCP 4.5 and RCP 8.5, respectively, from 2021 to 2040.

The annual temperature increased insignificantly by 0.004 °C/yr under RCP 4.5 while a significant increase of 0.21 °C/yr under RCP 8.5 was observed for 2021–2040. During 2041–2070, a significant increase of 0.016 °C/yr and 0.045 °C/yr was observed under RCP 4.5 and RCP 8.5 respectively.

Land use/cover indicates an increase in build-up area from 14 to 22.4 km², agricultural field increased from 45.9 to 71.4 km² while forest area decreased from 322.3 to 288.4 km² from 2021 to 2040. A similar trend was observed during 2041–2070 where the build-up area increased from 22.4 to 29.6 km², the agricultural field increased from 71.4 to 97.7 km², and the forest area decreased from 288.4 to 256.6 km². The change in climate and land use/cover led to a significant decrease in annual streamflow during 2021–2040, by 65.4 m³/s (RCP 4.5) and 195.9 m³/year (RCP 8.5). During 2041–2070 insignificant decrease of 13.7 m³/s and 7.63 m³/s under RCP 4.5 and RCP 8.5 respectively.

The evaluation of the impacts of climate change and land use/cover on hydrological processes is of great importance for managing and planning water resources. The findings from this study imply that climate change and land use/cover change will have a negative impact on various socio-economic sectors, e.g., agricultural, domestic water supply, and transportation. The impact will be more significant during 2021–2040 than in 2041–2070. Therefore, appropriate interventions to achieve water security and sustainability are essential. A regular awareness campaign with the participation of the community at the village level is essential since they are the key player in the implementation of the policy. At the Government level, future water resource management plans/policies should prioritize developing effective and reliable strategies for dealing with climate change and variability. Although the impacts of climate change and land use/cover change on streamflow have been successfully evaluated at the Kibungo sub-catchment, for the priority on mitigation and adaptation measures, future studies should focus on identifying which factor has more influence on the change of streamflow.

Declarations

Author contribution statement

Lusajo Henry Mfwango: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Wrote the paper.

Tenalem Ayeneew; Henry F. Mahoo: Conceived and designed the experiments; Contributed reagents, materials, analysis tools or data; Wrote the paper.

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Data availability statement

Data will be made available on request.

Declaration of interest’s statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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