Evaluation of integrated impacts of climate and land use change on the river flow regime in Wamkurumadzi River, Shire Basin in Malawi

Lusungu Nkhoma, Cosmo Ngongondo, Zuze Dulanya and Maurice Monjerezi

ABSTRACT

Climate and land use change (CC and LUC hereafter) are interlinked factors that can lead to river flow regime changes, as well as affecting hydrological extremes such as floods and drought. There is now considerable evidence of CC and LUC in many catchments in Malawi but without corresponding evaluations of their impacts on river flow regimes. Therefore, this study assessed how both factors affect the flow regime of Wamkurumadzi River, a key tributary of the major Shire River in southern Malawi. Land use and hydroclimatic data for the basin were first analyzed for spatial–temporal trends in the historical period between the years 1984 and 2015. The Soil and Water Assessment Tool (SWAT) model was then applied with different LUC and CC scenarios in order to assess their sole and combined impacts on the river flow regime. The model was calibrated and validated using the split sample method from the year 1984 to 1999 and from the year 2000 to 2015. Model performance was acceptable according to the selected evaluation criteria, with the Nash–Sutcliffe (NSE) coefficient of 0.78 and coefficient of determination ($R^2$) of 0.96 during calibration and NSE of 0.93 and $R^2$ of 0.98 during validation. Results of the integrated impacts of LUC and CC suggest a slight increase in river discharge of 0.05 m$^3$/s for the period between the 1980s and 2000s. During the 1980s–1990s, both CC through rainfall decreased and LUC resulted in decreases in the mean river discharges by 1.58 and 0.37 m$^3$/s, respectively. The study also found that CC through increased rainfall in the 1990s–2000s decades saw an overall increase of 1.39 m$^3$/s in mean river discharge, while LUC shows the increase of mean river discharge by 0.25 m$^3$/s. However, the study observed that reforestation efforts in the basin were greatly responsible for the alteration of the river flow regime in the later period.

Key words | Climate change, land use change, Malawi, SWAT, Wamkurumadzi river

HIGHLIGHTS

- This article is among few studies undertaken in data-scarce regions applying the SWAT model.
- The approaches applied in evaluating the integrated impacts of climate change and land use are very innovative.
- The approaches are applicable in other data-scarce regions.
- Sheds significant light on remedies to catchment degradation.
- Strong potential to influence policy in water assessments and catchment management.
INTRODUCTION

The quantity of fresh water resources at all scales can be affected by integration of climatic and non-climatic factors such as land use change, agriculture, construction, pollutants and management of reservoirs (IPCC 2007). Climate change (CC) has been associated with changes in critical components of the hydrological cycle and systems such as changing precipitation patterns, occurrence of extreme events, changes in soil moisture and runoff, increasing evapotranspiration and a general intensification of the global hydrological cycle (IPCC 2007; Pervez & Henebry 2015). On the other hand, land use changes (LUC) are known to impact the hydrological cycle through the alteration of interception, infiltration rate, albedo and evapotranspiration (Chawla & Mujumdar 2015 and references therein). Such LUC often arises from human settlements, agricultural activities and deforestation, among others. The extent to which the land use determines the hydrological response of a catchment depends on the degree of modification of the natural land cover by human influences, the intensity of the changes and the location of the land use within a catchment (Warburton et al. 2012). The impacts of climate change on river basin hydrology are also often interlinked with LUC, especially in river basins undergoing various human-related pressures such as urbanization, road construction, irrigation agriculture intensification, afforestation and deforestation, drainage of wetlands and rapid population growth and climate change (Roo et al. 2001; Mango et al. 2011). It is, therefore, critical to understand the combined and isolated impacts of CC and LUC on water resources in order to inform management and planning decision-making (Mango et al. 2011).

Numerous studies have, therefore, been undertaken in order to understand the impacts of CC and LUC on water availability in various catchments (Ahiablame et al. 2017; Dwarakish & Ganasri 2015). Chawla & Mujumdar (2015) provide a summary of four commonly used approaches for conducting LUC- and CC-related impacts on river flows, namely experimental paired catchment approach, (ii) statistical techniques such as the Mann–Kendall (MK) test, (iii) empirical or conceptual models and (iv) distributed physically based hydrologic models. Chawla & Mujumdar (2015) argued that the distributed physically based hydrologic models are considered very appealing for impact studies and they further highlighted some merits for applying semi- or fully distributed hydrologic models. One model that has been widely applied is the Soil and Water Assessment Tool (SWAT). For instance, Pan et al. (2017) applied the SWAT model in the Beijiang River basin in China and found that climate change was the main driver of river discharge changes as compared to LUC. In the Heihe Basin in Northwest China, Luo et al. (2016) in their application of the SWAT model found inter-decadal variations on CC and LUC impacts, with the LUC-related flow changes more dominant in the 1980s, whereas the flow changes in the 1990s were principally driven by CC. In the upper Rhone River in Switzerland, Rahman et al. (2015) also applied the SWAT model and found a reduction of peak flows mainly driven by LUC, while CC influenced the actual timing of the peak flows. In their SWAT model application in the Mara Basin in Kenya, Mango et al. (2011) found reduced dry season flows coupled with increased peak flows influenced by the conversion of forest to grassland, whereas climate change did not significantly impact the river flow regime. In the Tapacurá River basin of Brazil, Santos et al. (2015) applied the SWAT model and found that LUC impacts on river flow and sediment regimes were more dominant over CC during 1967–1995 while CC (mainly through reduced rainfall) dominated from 1995 to 2008. On the other hand, El-Khoury et al. (2015) found similar directions in the impacts of both LUC and CC on the river and sediment regime of the South Nation River in Canada. From the foregoing, it is apparent that the effects of LUC and CC on the catchment hydrology are also dependent on individual characteristics of the catchment such as topography, bare rock and type of soil (Moran-Tejeda et al. 2010).

Southern Africa is among the regions where the impacts of climate change are projected to be worse than in most other regions of the world due to a web of factors such as frequent occurrence of climate risks (floods and drought), low adaptive capacity, high rates of poverty and overdependence on rainfed agriculture. In addition, the region has a fast-growing population and urbanization rates which exerts
considerable pressures on the environment and natural resources including forest cover. In the region’s key river basins such as the Zambezi, studies have already established that air temperature and potential evaporation are projected to increase while rainfall is projected to decrease, potentially leading to decreases in river flows and increased reservoir evaporation losses (Hamududu & Killingtveit 2016). In the same basin, Gomo et al. (2018) found a 4.6% loss of forest cover, 16% increase in cropland and a doubling of the urban area between 1992 and 2015 which will have consequences for the water resources availability. In the Upper Shire River basin of Malawi, Palamuleni et al. (2011) reported on increased river peak flows and faster routing times that coincided with increased conversion of forested areas into agricultural land. The findings by Palamuleni et al. (2011) were echoed by studies of Calder et al. (1995) in the entire Lake Malawi catchment, Gwate et al. (2015) in the Modder basin in South Africa, Mathivha et al. (2016) in the Luvuhu Catchment in South Africa, Guzha et al. (2018) in East Africa and Kambombe et al. (2018) for the Lake Chilwa basin in Malawi. However, not many integrated studies on LUC and CC impacts on water resources have been conducted in the region.

In Malawi, evidence suggests that the climate regime made significant shifts in the early 1990s (Coulibaly et al. 2015) although others such as McSweeny et al. (2010) and Ngongondo et al. (2011, 2015) reported no significant trends in the rainfall. Nevertheless, Ngongondo et al. (2014) found significant changes in rainfall extremes based on the simple daily intensity index and the consecutive number of dry and wet days. In addition, Ngongondo et al. (2015) also reported significant increases in the mean air temperature. Apart from climate variability, Malawi as a country has a high dependence on cultivated agriculture which can be detrimental to water resources by either leading to an increase or decrease in river flow. In addition, deforestation in Malawi has been rampant due to agricultural activities, human settlement and charcoal making. Consequently, Malawi has experienced considerable changes in the forest cover from 50% in 1960 to 45% in 1972 and to 41% in 1990 (Environmental Affairs Department (EAD) 2011). The forest cover declined from 3.9 million ha in 1990 to 3.2 million ha in 2010 with an annual deforestation rate of almost 1% during the period 2005–2010 (Coulibaly et al. 2015). On the other hand, the area under agriculture increased between 1991 and 2008 and covered 70% of the country.

Studies have shown that most major rivers in Malawi are still perennial, while the smaller rivers and streams have become seasonal due to the marked increase in land use and deforestation (Burgess & Halle 2006; Chimtengo et al. 2014). The average flows in most of these rivers have, however, been noted to be decreasing in recent years. For instance, the mean flow in the Shire River measured dropped from daily mean of 480 m³/s down to close to 130 m³/s, which is much less than the required minimum flow for hydro-electric power generation (Burgess & Halle 2006). The decreases in the average flows have been mainly due to land clearing for agriculture, poor agricultural practices in the catchment and deforestation. Deforestation decreases soil water retention capacity and increases surface runoff by accelerating water movement due to low resistance to flow and low soil compaction, while reforestation increases water retention capacity and thereby decreases surface runoff by decelerating water movement due to high resistance to flow and longer flow paths (Luo et al. 2016). Although these may potentially be the roles of deforestation and reforestation in catchment hydrology, the flows may also vary due to occurrences of hydrological extremes such as floods or droughts. Such changes are also normally catchment specific.

Wamkurumadzi River is a major perennial tributary of the Shire River, Malawi’s major socio-economic asset. The river has the potential to supply water for irrigation and other domestic activities within the catchment, including potential sites for dam and irrigation schemes development. Currently, no dam has been constructed and only eight smallholder farmers operated mini-irrigation schemes of sizes ranging between 0.2 and 3.5 ha. According to MacDonald (2015), the use of Wamkurumadzi River for supplying water within the catchment is currently limited. Most of the people living within the catchment area depend on agriculture and charcoal production for survival which pose some threats to the river due to LUC. On average, Neno District in the catchment produces the largest quantity of charcoal which is supplied to other towns and cities such as Blantyre (Mutimba & Kamoto 2015). Consequently, the catchment has experienced considerable degradation due to deforestation and other human activities, coupled with
climate change which, in turn, is affecting river flows. However, there is no study that has been undertaken to validate the main or joint factors affecting the river flow. Such analysis is important especially in Wamkurumadzi River, as potential dam sites were already identified. Therefore, the general objective of the study is to evaluate the integrated impacts of climate change and land use change on the river flow regime of the Wamkurumadzi River in southern Malawi. Specifically, the study aimed to (1) investigate the nature of temporal changes in land use in the catchment; (2) examine trends in climate in the catchment and (3) analyze the integrated impacts of LUC and CC on river flows.

STUDY AREA AND METHODS

Description of the study area

Wamkurumadzi River is one of the major perennial tributaries of the Shire River, with its headwaters in the Kirk Ranges and drains parts of Ntcheu, Balaka, Neno and Mwanza Districts in Southern Malawi. The total catchment area of the Wamkurumadzi River at Mlongolola station (15°3′S, 34°35′30″E) just before inflowing into the Shire River is about 586 km² (Figure 1). The river has a steep sloping topography varying between 12° and 25° (Mutimba & Kamoto 2013). According to the National Statistical Office (NSO 2018), the river basin had estimated average population densities of 96 and 131 per km² in 2008 and 2018, respectively. As of 2018, the basin had an estimated total population of 76,766, representing an inter-censual population growth of about 36.3% as compared to the 2008 population. The catchment is rich in surface water resources with an extensive network of rivers and streams flowing from springs in the nearby Tsamba Forest Reserve and surrounding areas to Wamkurumadzi River, the largest watercourse in the catchment (MacDonald 2015). However, the headwater districts are among areas that have been heavily affected by deforestation (Mutimba & Kamoto 2013).

Figure 1 | Map of Wamkurumadzi Catchment in Malawi.
The area experiences a tropical wet and dry type of climate (Savanna) characterized by a rainy season between November and April and a dry season between May and October. Annual average rainfall ranges between 800 mm in the low lying Wamkurumadzi Valley to over 1,200 mm in the highlands of the Kirk Range (MacDonald 2015). The mean annual temperature in the basin ranges between 8 and 32°C (Mutimba & Kamoto 2018). Wamkurumadzi River has a gentle recession with the highest flows usually registered around the month of March and the lowest flows experienced just before the onset of the rainy season around the months of October and November (MacDonald 2015). The Wamkurumadzi River and its tributaries supply water for irrigation development and domestic activities within the catchment area. Most of the people in the district depend on agricultural activities and natural resources such as firewood and charcoal production for their socio-economic livelihoods. Neno District is ranked among the top charcoal producers in the country with about 6,404 charcoal producers. In the sub-catchments of Wamkurumadzi River, about 90% of the population practice agriculture and water for irrigation is abstracted without abstraction rights. According to MacDonald (2015), records and land cover images have shown that large parts of the forest land have been replaced with agricultural areas for crop production and trees have been cut for timber, firewood and charcoal production.

Hydroclimatic data sources and analysis

The study used daily climate (rainfall and temperature) and hydrological data for the stations and record lengths are shown in Table 1. The climatic data were sourced from the Malawi Department of Climate Change and Meteorological Services. The stations Mwanza and Neno represented the upper highland areas of the catchment, whereas Lisungwi represented the lower-lying areas close to the confluence with the Shire River. The hydrological data were sourced from the Malawi Department of Water Resources, Surface Water Section through the Scottish funded Climate Justice Project at the University of Strathclyde. All the datasets were of relatively good quality but were nevertheless checked for quality control such as outlier detection.

The direction and significance of temporal trends in the hydroclimatic variables (rainfall, temperature and river discharge; Table 1) were analyzed using the non-parametric MK statistic (Mann 1945; Kendall 1975). Under the null hypothesis of no trends in the data, a significance level of α = 0.05 was used. The MK is a rank-based statistic that is recommended by the World Meteorological Organization (WMO) for the detection of monotonic trends in hydro- meteorological variables (WMO 1988) and has been widely applied (Luo et al. 2016).

Hydrological model setup, calibration and validation

This study applied the SWAT, a catchment scale, physically based, semi-distributed agro-hydrological model that operates on the daily time step. The model is designed to predict the impact of management on water, sediments and agricultural chemical yield in the ungauged watershed (Gassman et al. 2007; Babur et al. 2016). The SWAT model is among the most widely applied models in studying the impacts of land use on catchment hydrology (Gassman et al. 2007; Golmohammadi et al. 2014; Krysanova & White 2015; Malagó et al. 2017). The model was selected as it is known to be computationally efficient and capable of continuous simulation over long time periods. The major model components include weather, hydrology, soil temperature and properties and land management.

The SWAT model divides the catchment into numerous sub-catchments and a total of 29 such sub-catchments were found for the Wamkurumadzi basin. These sub-catchments were further divided into elementary hydrologic response

<table>
<thead>
<tr>
<th>Serial</th>
<th>Station name</th>
<th>Latitudinal (°S)</th>
<th>Longitudinal (°E)</th>
<th>Elevation (M.a.s.l)</th>
<th>Period</th>
<th>Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Mwanza Agric</td>
<td>−15.617</td>
<td>34.5167</td>
<td>649</td>
<td>1981–2015</td>
<td>Meteorological</td>
</tr>
<tr>
<td>2</td>
<td>Lisungwi Met</td>
<td>−15.43</td>
<td>34.77</td>
<td>351</td>
<td>1981–2016</td>
<td>Meteorological</td>
</tr>
<tr>
<td>3</td>
<td>Neno Met</td>
<td>−15.4</td>
<td>34.65</td>
<td>899</td>
<td>1981–2017</td>
<td>Meteorological</td>
</tr>
<tr>
<td>4</td>
<td>Mulongolola</td>
<td>−15.65</td>
<td>34.59</td>
<td>355</td>
<td>1984–2015</td>
<td>Hydrological</td>
</tr>
</tbody>
</table>
units (HRU) with homogenous land use, vegetation and soil characteristics (Simi et al. 2009; Leta et al. 2016). The model has an interface with ArcView GIS (Arc SWAT) for the definition of watershed hydrologic features and storage, as well as the organization and manipulation of related spatial and tabular data (Mango et al. 2011; Winchell et al. 2010). The Arc SWAT module of the model was applied in catchment delineation using a 30 m by 30 m resolution Digital Elevation Model (DEM) in Arc Map 10.0 (Simi et al. 2009). Four soil classes were used for the study area based on the FAO international classification method (Figure 2).

For LUC, cloud-free Landsat images of 30 m by 30 m spatial resolution for 1989, 1999 and 2015 were downloaded from the USGS website (https://landsat.usgs.gov/landsat-data-access). These images were analyzed through a combination of different bands in ArcGIS. Supervised image classification (Butt et al. 2015) was applied where the various land use categories were user-defined from the training datasets. The classes that were identified as training sites in this study were generic agricultural land, forested area, range grass, built-up areas and water.

The simulation with the SWAT model can be separated into two major divisions. First is the land phase of the hydrologic cycle which controls the amount of water, sediment, nutrient and pesticide loadings to the main channel in each sub-basin. The hydrological components simulated in this phase of the hydrological cycle are canopy storage, infiltration, redistribution, evapotranspiration, lateral subsurface flow, surface runoff, ponds, tributary channels and return flow (Neitsch et al. 2005). SWAT simulates the water balance in this phase as follows:

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

where \( SW_i \) is the final soil water content (mm); \( SW_0 \) is the initial soil water content on day \( i \) (mm); \( t \) is the time (days); \( R_{day} \) is the amount of precipitation on day \( i \) (mm); \( Q_{surf} \) is the amount of surface runoff on day \( i \) (mm); \( E_a \) is the amount of evapotranspiration on day \( i \) (mm); \( W_{seep} \) is the amount of water entering the vadose zone from the soil profile on day \( i \) (mm) and \( Q_{gw} \) is the amount of the return flow on day \( i \) (mm). The second division is the water or routing phase of the hydrologic cycle which can be defined as the movement of water and sediments through the channel network of the watershed to the outlet (Neitsch et al. 2005).

The model inputs of climate data were daily rainfall and minimum and maximum temperature for the period 1981–2015. These were collected from the Malawi Department of Climate Change and Meteorological Services. In addition, daily river discharge data for Wamkurumadzi River at Mlongolola Station for the period between 1981 and 2008 were collected from the Ministry of Agriculture and Water Development. The data were used for model calibration from 1984 to 1999 and validation from 2000 to 2015, with the period 1981–1983 serving as the model warm-up period. Calibration in SWAT is undertaken using the SWAT-CUP (SUFI-2 algorithm; Abbaspour et al. 2007).

Sensitivity analysis was also conducted in order to identify the parameters that most influenced the river flow and how the model is responding to the LU and CC under certain scenarios. The sequential uncertainty fitting (SUFI-2) within SWAT calibration and uncertainty procedures (SWAT-CUP) was used to identify the most sensitive streamflow parameter. The sensitive parameters that were used in this study include: SCN runoff number for moisture condition (CN2), available water capacity of the soil layer (SOL_AWC), surface runoff lag time (SURLAG), base flow alpha factor (ALPHA_BF) and ground water ‘revap’ coefficient (GW_REVAP).

Various statistical approaches were used to evaluate the SWAT model performance according to Moriasi et al. (2007). These included the Percent Bias (PBIAS), Nash–Sutcliffe coefficient (NSE), the coefficient of determination \( R^2 \) and the ratio of root mean error squared (RMSE) to observations standard deviations (RSR) given as follows:

\[ PBIAS = \frac{\sum_{i=1}^{n} (O_i - S_i) \times 100}{\sum_{i=1}^{n} O_i} \]  

\[ NSE = 1 - \frac{\sum_{i=1}^{n} (O_i - S_i)^2}{\sum_{i=1}^{n} (O_i - \bar{O})^2} \]

\[ R^2 = \left\{ \frac{\sum_{i=1}^{n} (O_i - \bar{O})(S_i - \bar{S})}{\left[ \sum_{i=1}^{n} (O_i - \bar{O})^2 \right]^{0.5} \left[ \sum_{i=1}^{n} (S_i - \bar{S})^2 \right]^{0.5}} \right\}^2 \]

\[ RSR = \frac{RMSE}{STDEV_O} \sqrt{\frac{\sum_{i=1}^{n} (O_i - S_i)^2}{\sum_{i=1}^{n} (O_i - \bar{O})^2}} \]
Figure 2 | Soils classification in the Wamkurumadzi Catchment.
where $Q_i$ is the observed discharge at time step $i$; $S_i$ is the simulated discharge at time step $i$; $\bar{O}$ is the mean observed discharge; $\bar{S}$ is the mean simulated discharge and $n$ is the number of observations.

According to Moriasi et al. (2007), the PBIAS has an optimal value of 0 and large positive (negative) values of PBIAS normally indicates underestimation (overestimation) with acceptable values normally within $D_v \pm 25\%$. On the other hand, NSE value ranges between 1 for best model performance and $\sim \infty$ or poor model performance with NSE values $\geq 0.50$ normally considered satisfactory. Furthermore, values of $R^2 \geq 0.50$ (with an optimal value of 1) and RSR $\leq 0.70$ (with an optimal value of 0) are also acceptable.

The model was also evaluated using graphs of the monthly flow regime of observed and simulated discharge. In addition, the flow duration curve (FDC) was plotted using the Weibull plotting position formula (Vogel & Fennessey 1994; Kotei et al. 2016). Although SWAT model simulations were at daily timescale, the model outputs were converted to the monthly timescale for further analysis since the main was to evaluate water availability in the basin.

**Evaluation of the impact of LU and CC on streamflow**

The approach of one factor at a time was used in order to evaluate the impact of LU and CC on streamflow using the calibrated SWAT model (Table 2). Rainfall change was in this study used as an indicator of climate change. The method involves changing one factor at a time while holding the other constant (Li et al. 2009). In order to find the combined impact of both LU and CC, land use maps representing three decades, i.e. 1980s, 1990s and 2000s, and climatic data of the same decades were used by changing one factor at a time while holding the others constant representing streamflow affected by the changed factor.

To evaluate the differences in the simulated mean discharges under the various scenarios, the student’s $t$-test was used under the null hypothesis of equal sample means ($H_0: \bar{x}_1 = \bar{x}_2 = 0$) and alternate hypothesis of unequal sample means ($H_1: \bar{x}_1 \neq \bar{x}_2$) calculated as:

$$t = \frac{\bar{x}_2 - \bar{x}_1}{s_{\bar{x}}/\sqrt{n_1/n_1 + s_2^2/n_2}}$$

where $\bar{x}_1$ and $\bar{x}_2$ are the mean discharges in the baseline and scenario period, respectively, and $s_1$ and $s_2$ are the respective standard deviations in the baseline and scenario period. At 95% confidence level, the null hypothesis is accepted if $|t| < 1.96$ and rejected otherwise.

**RESULTS AND DISCUSSION**

**LUC between 1989 and 2015**

The results of supervised classification of Landsat images from the years 1989, 1999 and 2015 are shown in Figure 3(a)–3(c) and are further summarized in Table 3. The results show considerable LUC in the Wamkurumadzi catchment area. It can be seen from Figure 3 and Table 3 that agricultural land had covered 30.63% in 1989, but this had decreased to 7.62% in 1999 before increasing to 15.14% in 2015. In addition, the urbanized area increased rapidly between 1989 and 1999, followed by a slight decrease in 2015. Furthermore, the area covered by forest decreased from 24.88% in 1989 to 19.76% in 1999 before increasing slightly to 20.68% in 2015. Rapid population growth in the area is among the factors that have led to increased demand for agricultural land and residential area, as the area experienced a 36% population growth.

**Table 2 | Land use (LU) and CC experimental scenarios**

<table>
<thead>
<tr>
<th>Scenario #</th>
<th>Scenario description</th>
<th>Climate</th>
<th>Land use</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>LU and meteorological data from the 1980s</td>
<td>1980s</td>
<td>1980s</td>
</tr>
<tr>
<td>S2</td>
<td>Changing LU while holding climate constant</td>
<td>1980s</td>
<td>1990s</td>
</tr>
<tr>
<td>S3</td>
<td>Changing climate while holding LU constant</td>
<td>1990s</td>
<td>1980s</td>
</tr>
<tr>
<td>S4</td>
<td>LU and meteorological data from the 1990s</td>
<td>1990s</td>
<td>1990s</td>
</tr>
<tr>
<td>S5</td>
<td>Changing LU while holding climate constant</td>
<td>1990s</td>
<td>2000s</td>
</tr>
<tr>
<td>S6</td>
<td>Changing climate while holding LU constant</td>
<td>2000s</td>
<td>1990s</td>
</tr>
<tr>
<td>S7</td>
<td>LU and meteorological data from the 2000s</td>
<td>2000s</td>
<td>2000s</td>
</tr>
</tbody>
</table>
between the inter-censual years of 2008 and 2018 (NSO 2018). However, the reduction in the agricultural area between the years 1989 and 1990 and the forest cover increase between the years 1999 and 2015 coincides with the period when projects such as the Forestry Replanting and Tree Nursery Project (FOREP) and

Figure 3 | The spatial-temporal land use changes in the Wamkurumadzi Basin, Malawi: (a) 1989; (b) 1999 and (c) 2015 (FRS, forest; RNGE, range grass; AGRL, agriculture; WATR, water; URBN, urbanized). (continued.)
Sustainable Management of Indigenous Forests (SMIF) were implemented in the Wamkurumadzi River basin and the surrounding areas by various stakeholders (Mauambeta et al. 2010). These projects were mainly aimed at diversifying the socio-economic livelihoods base of the communities through non-farm and forest-based business activities while
promoting reforestation. In addition, the Wamkurumadzi catchment area is among the areas that adopted strict forestry by laws for enhancing management of endangered natural resources. According to Mauambeta et al. (2010), the results of the projects revealed that the forest cover indeed increased by over 30% between 1998 and 2006.
However, these projects also contributed to the loss of agricultural land by the communities. Consequently, part of the population migrated from the area and this may have led to slight reductions in the built-up area between 1999 and 2015.

**Temporal trends of the hydroclimatology**

Water resources availability in a catchment normally responds to climatic and other inputs. Any assessments, therefore, needed to consider such signals jointly and in isolation. To investigate evidence of climate change in the catchment, the rainfall and temperature data for Mwanza and Neno stations, and the areal mean over the catchment, were analyzed for trends using the MK test and linear regression at daily, monthly and annual timescales (Table 4 and Figure 4(a)–4(c)).

For the individual stations, Mwanza Station had a significant positive MK trend at $\alpha = 0.05$ for the daily rainfall level, whereas Neno Station had a significant negative trend at the same level. The daily areal mean rainfall over the catchment, however, suggests an overall significant positive trend at $\alpha = 0.05$ level. Localized trends are apparent at the daily scale in the catchment as shown by the individual stations, which is in agreement with Ngongondo

### Table 3 | Land use for the period between 1989 and 2015

<table>
<thead>
<tr>
<th>Land use class</th>
<th>1989 Area (ha)</th>
<th>1989 %</th>
<th>1999 Area (ha)</th>
<th>1999 %</th>
<th>2015 Area (ha)</th>
<th>2015 %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Residential</td>
<td>6,316.04</td>
<td>8.28</td>
<td>40,339.08</td>
<td>52.88</td>
<td>31,417.46</td>
<td>41.18</td>
</tr>
<tr>
<td>Forest-Mixed</td>
<td>18,977.71</td>
<td>24.88</td>
<td>15,077.54</td>
<td>19.76</td>
<td>15,776.12</td>
<td>20.68</td>
</tr>
<tr>
<td>Agricultural Land</td>
<td>23,369.41</td>
<td>30.63</td>
<td>5,813.93</td>
<td>7.62</td>
<td>11,547.99</td>
<td>15.14</td>
</tr>
<tr>
<td>Grass land</td>
<td>27,460.20</td>
<td>36</td>
<td>14,866.75</td>
<td>19.49</td>
<td>17,291.39</td>
<td>22.67</td>
</tr>
<tr>
<td>Water</td>
<td>161.00</td>
<td>0.21</td>
<td>187.05</td>
<td>0.25</td>
<td>251.3943</td>
<td>0.33</td>
</tr>
<tr>
<td>Total</td>
<td>76,284.36</td>
<td>100</td>
<td>76,284.36</td>
<td>100</td>
<td>76,284.36</td>
<td>100</td>
</tr>
</tbody>
</table>

### Table 4 | Mann–Kendall (MK) test for rainfall data (1981–2015)

<table>
<thead>
<tr>
<th>Timescale</th>
<th>$a^*$</th>
<th>Mwanza</th>
<th>Neno</th>
<th>Mean</th>
<th>$b^*$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Daily</td>
<td>–1.96</td>
<td>5.76</td>
<td>–3.14</td>
<td>3.93</td>
<td>1.96</td>
</tr>
<tr>
<td>Monthly</td>
<td>–1.96</td>
<td>–1.44</td>
<td>–2.38</td>
<td>–1.9</td>
<td>1.96</td>
</tr>
<tr>
<td>Annual</td>
<td>–1.96</td>
<td>0.40</td>
<td>0.17</td>
<td>0.19</td>
<td>1.96</td>
</tr>
</tbody>
</table>

$a$ and $b$ are the 95% confidence limits for the MK statistic. MK values outside these limits are statistically significant.

### Figure 4

et al. (2014) who found a localized intensification of rainfall extremes across Malawi. At monthly timescale, a significant negative trend was shown by Neno Station, while Mwanza Station had a negative but not significant trend at $\alpha = 0.05$ level. The monthly trend for the areal mean rainfall was also negative but not significant $\alpha = 0.05$ level. For the individual months, rainfall increased with statistical significance in January whereas June, September and October experienced significant decreases.

Annually, the mean areal rainfall during 1981–2015 was 1,116.2 mm with a coefficient of variability (CV) of 26%. Both stations (Mwanza and Neno) and the areal mean rainfall did not show any significant trends at $\alpha = 0.05$ level. However, linear regression trends for the annual rainfall at the three series (Figure 4(a)–4(c)) show a slight decrease in the annual rainfall. The slope of the areal mean rainfall suggests a decrease of $-0.74$ mm/year. These findings are in agreement with those from previous studies by Ngonzongo et al. (2011, 2015) among others who reported that annual rainfall over Malawi decreased during 1971–2000. Declining rainfall trends over southern Africa were also reported by other studies (e.g. McSweeney et al. 2010; Morishima & Akasaka 2010).

The monthly and annual mean temperature trends in the catchment show decreasing trends (Figure 5 and Table 5), though not statistically significant at $\alpha = 0.05$ level with slopes of $-0.02$ and $0.06$ $^\circ$C/year, respectively. The monthly and annual maximum mean temperatures, however, had a decreasing trend that was statistically significant with a slope of $-0.052$ $^\circ$C/year. On the other hand, the monthly and annual minimum mean temperatures had an increasing trend that was not statistically significant with a slope of $0.012$ $^\circ$C/year. Overall, it can be noted that there is no trend in the annual temperature regime of the basin and this has a considerable influence on the evaporative demands.

At inter-decadal timescales, the basin did not experience significant changes in the mean, maximum and minimum mean annual temperatures during the period from 1981 to 1989 as compared to the period from 1990 to 1999 and from 1990 to 1999 compared to the period from 2000 onwards. However, the results show that the period 1981–1999 was generally warmer than the period after the 2000s.

Historical river flows in the Wamkurumadzi basin during 1984–2015 had a mean of 3.03 m$^3$/s with the CV of 43%. Trend results of the flows suggest a predominance of increasing trends at monthly and annual timescales (Figure 6(a) and 6(b)). However, the MK statistics for monthly and annual discharge were not significant at $\alpha = 0.05$ level. For the individual months, January, May, June, July, August and September had significant flow increases. In addition, the months of March and December had insignificant flow increases. In addition, the months of March and December had insignificant increases at $\alpha = 0.05$ level, while the rest of the months registered insignificant flow decreases at $\alpha = 0.05$ level. The MK statistic trend direction and significance results of the rainfall and discharge from the MK showed good agreement in the rainy season months of January, February, March, April, November and December. On the other hand, the dry season months between May and October had a predominance of opposing trends, some statistically significant.
SWAT model calibration and validation

A comparison of the observed and simulated monthly flows is shown in Figures 7–10. It can be seen from Figure 7 that the SWAT model can capture the sequencing of high and low flow pattern associated with the nature of seasonal climate of the area during both calibration and validation. The calibration and validation results showed that during the calibration period (1984–1999), Wamkurumadzi River experienced relatively lower monthly mean discharge as compared to the validation period (2000–2015) as shown in Figure 8(a) and 8(b). The mean monthly discharge was highest in the month of January, i.e 6.37 and 5.97 m$^3$/s for validation and calibration, respectively, while the month of September had the lowest mean discharge of 0.16 and 0.14 m$^3$/s during validation and calibration, respectively.

There are, however, some slight overestimations of the peak flow especially during the calibration period. Such
peak flows normally occur during the wet season. According to Suryavanshi et al. (2017), this can arise due to overestimation of the base flow at the onset of the rainy season, assigning a lower curve number (CN) parameter or using a lower density of meteorological stations which fails to accurately predict the runoff. The last (lower density of meteorological stations) would seem the more likely reason as the study area is indeed sparsely gauged and there are no weather stations in the headwater highland areas. However, there are also some underestimations of the observed flows, especially in the dry season.

Scatter plots for the observed and simulated discharge during the calibration and validation period were plotted, as shown in Figure 9(a) and 9(b). The results showed a strong correlation between the observed and simulated river discharge during both the calibration and validation periods. The scatter of the points also shows that they are not far from the line of perfect fit, the regression line between the observed and simulated discharge that passes through the origin. In addition, the FDCs in Figure 10 show that the SWAT model can capture the extremely high flows with exceedance probability below about 2% and the lower flows with exceedance probability above 40%. There is, however, a slight mismatch between observed and simulated flows in the middle section of the FDC where the observed flows are underestimated. The middle section of the FDC normally represents the delayed flow component of the total flow (Yaeger et al. 2012). This is the part that was also underestimated by the simulated flows, as shown in Figure 7.

The statistical summaries of the observed and simulated discharge are shown in Table 6. During the calibration period (1984–1999), the observed and simulated mean flows were 2.82 and 2.33 m³/s. On the other hand, the observed and simulated mean flows during the validation period were 3.23 and 2.50 m³/s. These observed and simulated flow results were quite comparable, although the monthly distributions of the annual discharge regime suggest some underestimation of the observed discharge. Statistically, analysis of the observed and simulated discharge based on the NSE and $R^2$ had values of 0.78 and 0.96, respectively, during calibration. The same had values of 0.93 and 0.98, respectively, during validation. The values of RSR were 0.47 and 0.27 during calibration and validation, respectively. In addition, PBIAS values were 17.2 and 22.9 during calibration and validation. The calibration and validation statistical indices results are all in the ‘very good ranges’ according to Moriasi et al. (2007), consequently suggesting acceptable SWAT model performance in the Wamkurumadzi Basin. The results are also comparable with other studies which applied the SWAT model such as Palazón & Navas (2016) in the Spanish Pyrenees, Ndomba et al. (2008) in the Pangani Basin in Tanzania and Gyamfi et al. (2016) in the Olifants Basin of South Africa.

### Impacts of CC and LUC scenarios on river flow

The response of the Wamkurumadzi River discharge to CC and LUC for the entire period and three decadal intervals (1980s, 1990s and 2000s) in each of the seven scenarios are shown in Figure 11 and Table 7. The two cases (CC and LUC) were considered both separately and integrated. Two scenarios were consequently needed to evaluate their

### Table 6 | Statistical indices for observed and simulated discharge during model calibration and validation

<table>
<thead>
<tr>
<th>Period</th>
<th>Mean discharge m³/s</th>
<th>PBIAS %</th>
<th>NSE</th>
<th>$R^2$</th>
<th>RSR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Calibration (1984–1999)</td>
<td>2.8</td>
<td>2.3</td>
<td>17.2</td>
<td>0.78</td>
<td>0.96</td>
</tr>
<tr>
<td>Validation (2000–2015)</td>
<td>5.2</td>
<td>2.5</td>
<td>22.9</td>
<td>0.93</td>
<td>0.98</td>
</tr>
</tbody>
</table>
respective impacts on river discharge: scenarios SC1 (as a baseline) and SC2 and SC4 (as a baseline) and SC5 (Table 7) were compared, respectively, for the LUC impacts only; scenarios SC1 (as a baseline) and SC3 and SC4 (as a baseline) and S6 (in Table 7) were compared for CC only. On the other hand, scenarios SC1, SC4 and SC7 were then used to evaluate the integrated impacts of LUC and CC.

The results show that both CC and LUC had varying impacts on the river discharge which were also decade-dependent. Under SC2, the results show that LUC alone resulted in a reduction of the mean river discharge by 11.67% in the 1980s. However, the student’s t-test results showed that there were no significant differences in the mean discharges at $\alpha = 0.05$ level during the baseline scenario (SC1, mean discharge $= 3.17 \text{ m}^3/\text{s}$) and S2 scenario simulations (mean discharge $= 2.8 \text{ m}^3/\text{s}$). Consequently, LUC did not result in significant changes in mean river discharge between 1980 and 1990 in the catchment. Under scenario 5 (SC5), LUC alone resulted in increased mean river discharge by 16.56% between the 1990s and 2000s. The t-test results showed that this LUC-induced change in river discharge was significant at $\alpha = 0.05$ level. The 1990s period coincides with a considerable reduction in the forest-covered area and a sprawl of the urban area (Figure 3). In many areas, studies in similar environments (e.g. Guzha et al. 2018; Kambombe et al. 2018) have found that decreased forest cover results in increased surface runoff and discharge with a corresponding decrease in base flow.

On the other hand, CC alone (SC3) resulted in decreasing the river discharge by 49.8% between the 1980s and 1990s and increased the river discharge by 108.61% between the 1990s and 2000s (SC6). In both scenarios SC3 and SC6, the CC-induced changes in river discharge were statistically significant at $\alpha = 0.05$ level. Overall, the contributions of CC to river discharge can be attributed to changes in the rainfall regime where a relatively high rainfall period in the 1980s was followed by relatively lower rainfall with lower temperatures in the 1990s which subsequently picked up again in the 2000s. Figure 12 shows the inter-decadal variations of the mean annual rainfall and discharge from the 1980s to 2015s demonstrating this aspect.

In addition, the combined impacts of CC and LUC were represented by scenarios SC1, SC4 and SC7. The results show that annual mean river discharge decreased from

![Figure 11](image1.png) 

**Figure 11** | Climate and land use change scenarios.

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>Climate</th>
<th>Land use</th>
<th>Simulation (m$^3$/s)</th>
<th>Discharge change (m$^3$/s)</th>
<th>Discharge change (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SC1</td>
<td>LU and climate data from the 1980s</td>
<td>1980s</td>
<td>1980s</td>
<td>3.17</td>
<td>0</td>
</tr>
<tr>
<td>SC2</td>
<td>Changing LU while holding climate constant</td>
<td>1980s</td>
<td>1990s</td>
<td>2.8</td>
<td>-0.37</td>
</tr>
<tr>
<td>SC3</td>
<td>Changing climate while holding LU constant</td>
<td>1990s</td>
<td>1980s</td>
<td>1.59</td>
<td>-1.58</td>
</tr>
<tr>
<td>SC4</td>
<td>LU and climate data from the 1990s</td>
<td>1990s</td>
<td>1980s</td>
<td>1.51</td>
<td>-1.41</td>
</tr>
<tr>
<td>SC5</td>
<td>Changing LU while holding climate constant</td>
<td>1990s</td>
<td>2000s</td>
<td>1.76</td>
<td>0.25</td>
</tr>
<tr>
<td>SC6</td>
<td>Changing climate while holding LU constant</td>
<td>2000s</td>
<td>1990s</td>
<td>3.15</td>
<td>1.64</td>
</tr>
<tr>
<td>SC7</td>
<td>LU and climate l data from the 2000s</td>
<td>2000s</td>
<td>2000s</td>
<td>3.22</td>
<td>1.71</td>
</tr>
</tbody>
</table>

![Figure 12](image2.png) 

**Figure 12** | Inter-decadal comparison of rainfall and discharge.
3.17 m³/s in the 1980s to 1.51 m³/s in the 1990s (SC1 and SC4), representing a total reduction of 44.48% from the 1980s mean discharge. The annual mean river discharge then increased to 3.22 m³/s in the 2000s, representing a total increase of 113.3% from the 1990s annual mean discharge. Consequently, the results show that the discharge increased by a total of 0.05 m³/s or 1.6% between the 1980s and 2000s.

From the foregoing, it seems that CC through rainfall changes had had a higher impact on the river flows as compared to LUC. However, the results of the rainfall climatology pattern (Section ‘SWAT model calibration and validation’) suggested no trend, although there were minimal decreases during 1984–2015. The results also show that mean annual rainfall had decreased from 1,224.7 mm in the 1980s to 979.3 mm in the 1990s. The mean annual rainfall then increased to 1,140.6 mm in the 2000s (Figure 11).

CONCLUSIONS

The combined impacts of CC and LUC on river discharges in many key basins in Malawi remains an area to be fully understood. Such information is now crucial for water resources management especially in the key river basins owing to considerable evidence of CC and LUC. In this study, the semi-distributed SWAT model was set up in the Wamkurumadzi River basin in southern Malawi to understand the impacts of LUC and CC. The river is a major tributary of the Shire, Malawi’s socio-economic development lifeline along which over 90% of the hydropower is generated. The impacts of LUC and CC on river discharge were evaluated both in isolation and integrated. In the historical period, LUC analysis results suggest that the reforestation measures introduced in the basin since 1999 are being effective with the recovery of previously deforested areas. The hydroclimate analysis results show that the basin largely experienced reductions in rainfall that were not statistically significant, with an increasing pattern since 2000. On the other hand, the mean annual temperature has been decreasing whereas the mean annual discharge has been increasing, both without statistical significance. In spite of the insignificant changes in the rainfall and temperature regimes, the river responded significantly to the climate variability, especially changes in the rainfall. These results highlight the sensitivity of the Wamkurumadzi River to climate forcing mechanisms and have significant consequences for water resources management for the area. According to model evaluation criteria composed of statistical indices and graphics, the model’s performance during calibration (1984–1999) and validation (2000–2015) periods was very good. The model outputs showed that the climate forcing had larger impacts on the historical river discharge as compared to LUC. In part, the reforestation measures introduced in the basin have helped attenuate the LUC impacts.

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DATA AVAILABILITY STATEMENT

Data cannot be made publicly available; readers should contact the corresponding author for details.

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MacDonald, M. 2015 *Final Management Plan for Wamkurumadzi Sub-Catchment 4*. 


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