# An Assessment of Streamflow Linkage between Land Use or Land Cover Change and In Lilongwe River Basin, Malawi

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**Abstract**

World human population has grown very rapidly in the past century. In Malawi's Capital City (Lilongwe) it increased by more than 3000% between 1966 and 2008 (from 19,425 to 674,448). Such rapid population growth might contribute to Land Use and Land Cover Changes (LULCC) due to pressure on land resources to meet diverse livelihoods, which in turn significantly affects the flow of water in river catchments. This study was thus conducted to evaluate LULCC in Lilongwe between 1989 and 2004 in view of the exponential population increase, and to assess the effects of LULCC on the streamflow of Lilongwe River. To evaluate LULCC, change detection analysis was carried out on Landsat imagery of the Lilongwe River catchment for the years 1989 and 2004. Data on land cover classifications, soil, rainfall, temperature, elevation and water reservoir levels in the catchment were modelled using the Soil Water Assessment Tool (SWAT) to assess the effects of LULCC on streamflow in Lilongwe River. Results showed that between 1989 to 2004, a 10.7% decrease in forest cover occurred (from 63,112.6 ha to 51,034.3 ha). Furthermore, there was an increase in cropland (8.6%, from 19,249 ha to 28,911.3 ha), and a 3.5% increase in land use for settlement (from 23,535.9 ha to 27,526 ha). The resultant changes in average monthly streamflow were -0.058 $m^3/s$ during the dry season (August –November) and +1.432 $m^3/s$ during the wet season (December–March). The results establish the link between LULCC and streamflow in the catchment. Integrated catchment management practices are therefore recommended to ensure that further LULCC does not adversely affect streamflow in Lilongwe River, and the livelihoods of its beneficiaries.

**Key words**: *Land use and land cover change, Lilongwe, Lilongwe River, Streamflo, Soil Water Assessment Tool.*

# 1 INTRODUCTION

Integrated catchment management is an essential resource management approach in the modern era as it recognizes the full cycle of processes which affect natural and human systems in a watershed (Alemayehu et al., 2009; Heathcote, 2009). Implementation of the approach, however, faces many challenges especially in developing countries, such as climate change, over-reliance on agricultural livelihoods, and population growth (IWMI, 2005; Bahri et al., 2011; United Nations, 2017).

Malawi is one such country facing difficulties in realising the goals of this approach with issues ranging from deforestation in areas such as the Mulanje Forest Reserve (Shanmugaratnam & Kafakoma, 2014), to climate induced disasters and subsequent encroachment of protected areas in Dzalanyama forest reserve (Munthali, 2013). One persistent issue exacerbating such challenges has been the rapid population growth in the country. This is most evident in the country's most populous city, Lilongwe, where NSO (2008) reported a more than 3000% increase in population between 1966 and 2008, from 19,425 to 674,448 people respectively.

Population growth of this kind greatly contributes to land use and land cover change (LULCC) as land is required for various purposes such as agriculture, and industry (Pimentel, 1997; Singh, 2017). Land cover simply refers to the physical features that cover a land surface, such as crops, whilst land use refers to the purpose for which humans use land cover, such as agriculture (Di Gregorio & Jansen, 2005).

Since land and water resources are intimately linked through the hydrological cycle (Guo & Jiang, 2008; Mbano, 2009; Palamuleni, 2009; Geremew, 2013), the population growth in Lilongwe has been a major cause of concern in the environmental sector (Munthali, 2013, GoM, 2017). The Lilongwe River which runs through the centre of the district is currently the only sanctioned source of water for the city's residents and as a result, has in recent years noticeably felt the pressure of the growing population (GoM, 2012). Low water levels in the river especially during the dry season have led to rationing of water by the city's water supply utility, Lilongwe Water Board (LWB), and a push for new or improved sources to be developed (World Bank, 2017).

Studies show that LULCC such as deforestation can lead to higher streamflow after rainfall events by facilitating runoff and vice versa (Palamuleni, 2009; Geremew, 2013). This raises the question of whether there have been significant changes in land use and land cover in the Lilongwe River catchment that may have adversely affected the quantity of water flowing in Lilongwe River.

Considering the importance of using up-to-date information in integrated catchment management (Pahl-Wostl, 2005; Stewart, 2015), this study aimed at evaluating the extent of LULLC that has occurred in the Lilongwe River catchment and assessing how these changes are linked to streamflow changes in the Lilongwe River using remote sensing and hydrological modelling techniques.

# 2 MATERIALS AND METHODS

## 2.1 Description of Study Area

The study was conducted using data from part of the Lilongwe River which originates from the Dzalanyama catchment (also known as Catchment 4D) located in the south western part of Lilongwe (**Figure 1**). The catchment generally exhibits a warm tropical climate with mean annual rainfall ranging between 800 and 1000 mm (Malawi Department of Climate Change and Meteorological Services (MDCCMS), 2014). The Lilongwe River has two main tributaries, Likuni, and Lisungwi River. The river also has two reservoirs, Kamuzu Dam 1 and 2, which were constructed along its path in 1966 and 1989 respectively for municipal water supply purposes.

The gauging station officially known as 4D4 (located at 4.04 $^{\circ}$S, 33.71 $^{\circ}$E) was taken as the outlet for the catchment. This was done due to the relatively extensive availability of data at station 4D4, and to minimize the influence of unquantified water abstractions on the results of the study by downstream users.

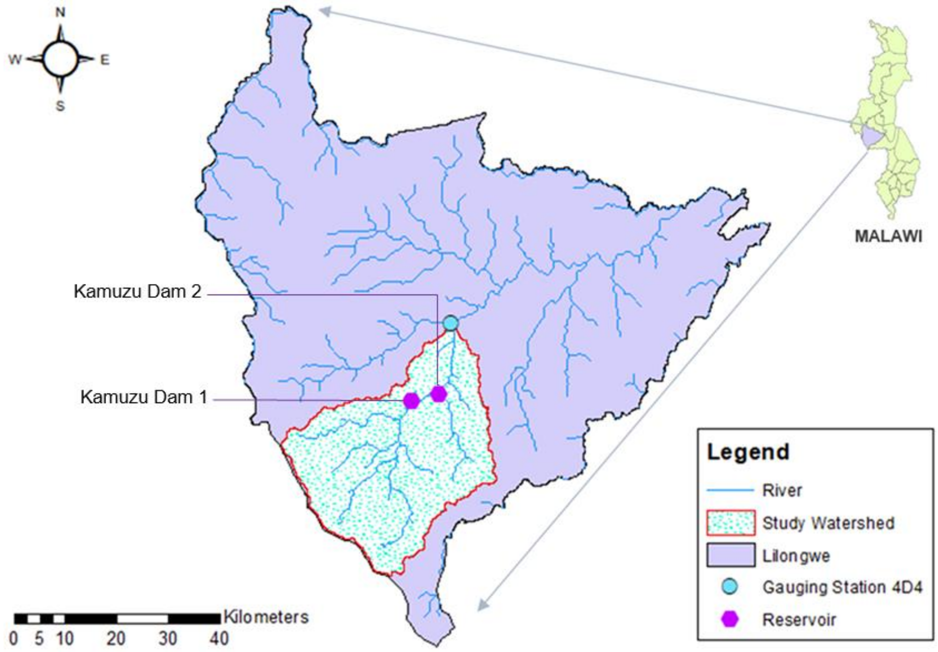


***Figure 1:*** *The study area showing all its major rivers, and reservoirs Kamuzu Dam 1 and 2.*

## 2.2 Data Collection

### *Climatic Data*

Climatic data recorded at Chitedze Meteorological Station from 1970 to 2004 was obtained from the Malawi National Meteorological Services Department. Due to lack of complete data, only four measured historical data sets namely: daily precipitation, maximum and minimum temperature, and wind speed; were input into the Soil Water Assessment Tool (SWAT). Other climatic variables, namely, solar radiation, and relatively humidity, were thus left out to be simulated by the model.

### *Land Cover and Soil Data*

ArcGIS 10.1 was used for all processing of geospatial data in this study. Landsat 5 images from 1989 and 2004 were used to identify changes in land use and land cover within part of the Lilongwe River watershed. To ensure that observed changes in vegetation cover were not as a result of seasonal variations, all Landsat images acquired were captured around the same time of the year during the dry season which normally occurs between the months of June and October. The images were downloaded from the United States Geological Survey (USGS) website (https://earthexplorer.usgs.gov).

For lack of a higher resolution source, the soil data for the watershed was extracted from a global soil map (Daggupati et al. 2018; Kangsabanik & Murmu, 2017) obtained from the Food and Agriculture Organisation (FAO) archive (FAO, 2007). Due to its low resolution, this soil map only shows three major soil types within the study watershed.

***Digital Elevation Model and Reservoir Data***

The Shuttle Radar Topography Mission (SRTM) archive was used to obtain a 90 x 90 m Digital Elevation Model (DEM) raster from the USGS online database (Jarvis et al., 2008). The DEM was necessary for delineation of sub-basins and identification of stream networks in the study area (Arnold, 2012a).

Lilongwe River has two dams that were constructed along it mainly to serve as a water storage facility and ensure adequate water supply for the population in Lilongwe. Therefore, to properly model flow within the river, parameters referring to the structural design of the reservoirs such as size, height of spillways, average daily outflow and beginning year of operation of the dam were required by the model. This data was acquired from survey reports provided by the Lilongwe Water Board (NIRAS, 2001; Aurecon, 2013).

## 2.3 Data Processing and Analysis

Data analysis was carried out in two phases, the first of which involved assessment of land use and land cover change while the second phase involved modelling streamflow in Lilongwe River Catchment.

### *2.3.1 Land Use/Cover Change Detection*

To detect changes in land cover, the spectral signatures of different land cover types had to be classified and analysed in the acquired Landsat images. There are two main categories of image classification techniques, these are; unsupervised (calculated by software) and supervised (human-guided) classification (Al-doski et al., 2013). This study used unsupervised image classification because it is useful for detecting land use/cover when and where primary data of the site is considered insufficient and/or of low quality for use in training classifiers in supervised classification.

After a review of literature on land cover classes in the area, five main classes were identified using the Isodata clustering algorithm to perform unsupervised image classification in ArcGIS. These classes were Forest; Water; Marshland/Cultivated Dambo; Cropland; and Grassland/Settlements. The latter class also included areas with bare ground or unused cropland since such areas were spectrally indistinguishable from dry grasslands.

Using a 2004 Google Earth image, the land use/cover present at 56 random points within the study watershed was checked against that of the classified 2004 image. Correct classifications were thus measured using a common accuracy assessment technique known as a confusion matrix (Congalton & Green, 2009; Geremew, 2013). The overall accuracy of the classified image determines the validity of the classification process and in this context determined whether the produced images were worth using as valid data to evaluate changes in streamflow (Congalton & Green, 2009; Al-doski, 2013). Cohen’s kappa coefficient was also calculated from the confusion matrix to measure the classification performance (Pontius, 2000; Liu et al., 2007; Congalton & Green, 2009). According to Muzein (2006), the accepted level of accuracy for any classification process is determined by the users themselves depending on the type of application the map product will be used for. Accuracy levels accepted by some users may not be accepted by others for specific tasks. Considering resource constraints, an overall accuracy of at least 80% was considered sufficient for this study.

### *2.3.2 Hydrological Modelling*

Several factors can affect streamflow in a river apart from LULCC. Therefore, to single out LULCC as the only causative factor of potential streamflow changes, the SWAT model was used. The SWAT model is a semi-distributed physically based simulation model that can predict the impacts of land use change and management practices on hydrological regimes in watersheds with varying spatial conditions (Arnold, 2012a). The model was selected for this study because it is open source, has been widely used in semi-arid regions (Palamuleni, 2009; Geremew, 2013), and always produces the same output for any given input. Being semi-distributed and deterministic, the model is also less demanding on input data than fully distributed models (Gassman et al., 2012; Arnold et al., 2012a), and allows objective comparison of model outputs arising from different land-cover scenarios

### **Model Run**

The DEM was loaded into SWAT to enable identification of stream networks and delineation of sub-basins in the study watershed. The location of the two Kamuzu Dams were then identified on the rendered stream networks. Climatic and reservoir data were then entered, and the model was run on a monthly time step from 1970 to 2004.

## Model Calibration and Validation

The next step in the modelling process was calibration of the model to ensure that it was able to adequately emulate conditions in the studied watershed. An auto-calibration program known as SWAT-CUP version 5.1.5.4, specifically designed to be used with SWAT, was used for calibration and validation in this study because it produced very quick and detailed results (Abbaspour, 2013).

This study used the Sequential Uncertainty Fitting version 2 (SUFI2) calibration and uncertainty program in SWAT-CUP which only allowed auto-calibration of up to four parameters at a time. To ensure calibration of only the most sensitive parameters, multiple flow parameters listed in SWAT-CUP were set four at a time for calibration. Several trial iterations were done to reveal the most sensitive parameters used for final calibration. The tool was then run for 1000 simulations for calibration using recorded streamflow data from a 6-year period (1970–1976). The same approach was later followed (Arnold, 2012b), for validation of the model using streamflow data from the same gauging station for a 4-year period (1977–1981) without making further adjustments to any input parameters. More data was used for calibration to ensure the model captured a wider range of streamflow scenarios, and due to the persistence of streamflow data gaps after 1981.

Model validation is a crucial step in the modelling process that allows a user to determine the accuracy of their model by statistically comparing observed and simulated variable outputs (Arnold, 2012b). Two statistical parameters were used for validation, namely: the coefficient of determination ($R^2$) and the Nash-Sutcliffe Efficiency coefficient (*NSE*) (McCuen et al., 2006). According to Moriasi et al. (2007) and Santhi et al. (2001), values of $R^2$ greater than 0.6 can be considered as acceptable indicators of good model performance. The Nash-Sutcliffe Efficiency coefficient indicates how well the plot of observed versus simulated data fits the 1:1 line. According to Moriasi et al. (2007), the acceptable values for *NSE* based on reported performance ratings from several other studies are Satisfactory ($NSE > 0.5$); Adequate ($NSE = 0.54 – 0.65$); and Very Good ($NSE > 0.65$).

### 2.3.3 Evaluation of Streamflow Change Due to Land Use/Cover Change

To evaluate the effect of LULCC on streamflow, the calibrated SWAT model was run from 1989 to 2004 with the different land cover maps of 1989 and 2004, while keeping all other parameters constant. Since SWAT is a deterministic hydrologic model, any differences in the model output from the two runs were a direct result of the LULCC only. LULCC can cause the model to produce ambiguous results if streamflow is analysed on an annual time scale, hence streamflow changes were evaluated by examining seasonal differences (i.e. from dry and wet season months) from the two model outputs since these are the periods in which the effect of LULCC is most prominent (Palamuleni, 2009; Geremew, 2013).

# 3 RESULTS AND DISCUSSIONS

## 3.1 Land Use/Cover Detection

The classification process yielded a satisfactory overall accuracy of 82%. The Cohen's kappa coefficient calculated also revealed that the classification process performed 74% better than if it had been done by randomly assigning values to land cover classes.

Figure 2 shows the map outputs of the unsupervised classification carried out on the Landsat imagery acquired for 1989 and 2004. Table 1 summarises the results of the land cover changes between 1989 and 2004. The image classification showed the largest change in forests compared to all land cover classes in the watershed in the years between 1989 and 2004. This reduction in forest cover represented 11% of the total catchment land area. Although the reduction appears to be small, such a percentage translates to astounding 12,078 hectares of Dzalanyama forest reserve. Similar results have been reported by FAO (2012) and Munthali (2013).

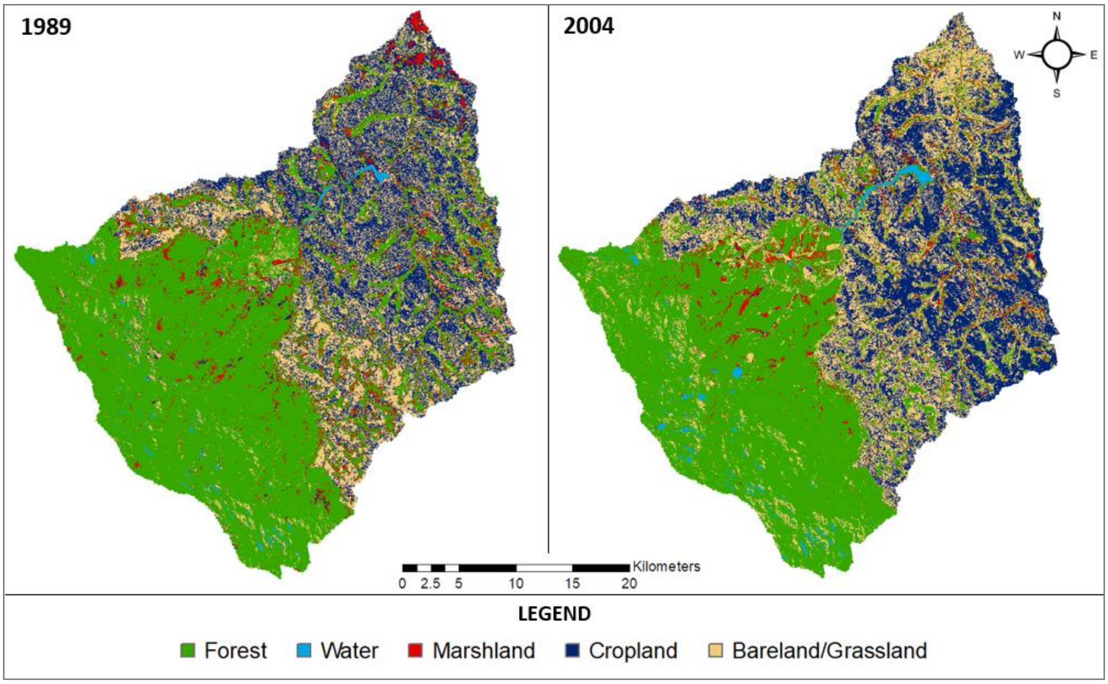


***Figure 2:*** *Land cover classification outputs for 1989 and 2004.*

The results also showed that marshland/cultivated dambo areas had decreased by 1.84%, translating to 2,078.73 hectares. Crops grown in dambo areas usually include vegetables and short crops which are often cash crops. Therefore, this land class may have been converted to cropland where crops such as maize and sorghum are grown mainly for subsistence farming. Conversely, results also showed that cropland, and areas featuring grassland, bare ground and or settlements had increased quite significantly by 8.55% (9,662.33 ha) and 3.53% (3,990.08 ha), respectively. This might be the result of the rapid population growth experienced in Lilongwe in the 1990's (with a population of 223,318 people in 1987 to 440,471 in 1998, (NSO, 2008) which increased the demand for land for settlement and farmland since a large number of people in Malawi rely on agriculture for subsistence and sourcing of income.

From the findings, it is evident the area covered by the water bodies also increased by 0.45% or 504.58 ha in the 15-year period. The increase could be attributed to the expansion of the Kamuzu Dam 2 reservoir's area of inundation which resulted from raising of the dam by 5 meters in 1999.This could also be attributed to the interference of a few clouds which were present in the Landsat imagery and caused a few areas in the Dzalanyama forest to be classified as water and bare ground. Considering that this misclassified area constitutes less than 0.5% of the catchment, this false positive was simply ignored as an insignificant error.

***Table 1:*** *Land cover change results for the study watershed from 1989 to 2004*

| **Land Cover Type** | **Area 1989** | | **Area 2004** | | **Area (2004 – 1989)** | |
|---|---|---|---|---|---|---|
| | **km$^2$** | **%** | **km$^2$** | **%** | **km$^2$** | **%** |
| Forest/Trees | 631.13 | 55.86 | 510.34 | 45.18 | -120.78 | -10.69 |
| Grassland/Settlements | 235.36 | 20.83 | 275.26 | 24.37 | 39.90 | 3.53 |
| Cropland | 192.49 | 17.04 | 289.11 | 25.59 | 96.62 | 8.55 |
| Marshland/Cultivated Dambo | 64.63 | 5.72 | 43.84 | 3.88 | -20.79 | -1.84 |
| Water | 6.06 | 0.54 | 11.10 | 0.98 | 5.05 | 0.45 |

## 3.2 Hydrological Modelling

The results of the SWAT model calibration showed that there is an acceptable agreement between average monthly observed flow and simulated flow with a coefficient of determination ($R^2$) of 0.65 and Nash-Sutcliffe Efficiency coefficient (NSE) of 0.6. These values are well within the accepted value minimum of 0.5 for the Nash-Sutcliffe efficiency and 0.6 for the coefficient of determination (Santhi et al., 2001). In addition, **Figure 3** also illustrates these results with a line chart describing simulated and observed average monthly flow from the calibration period. The chart also depicts the 95% prediction uncertainty (95PPU) band which is a distribution of parameter prediction uncertainty measured between the 2.5th and 97.5th percentiles.

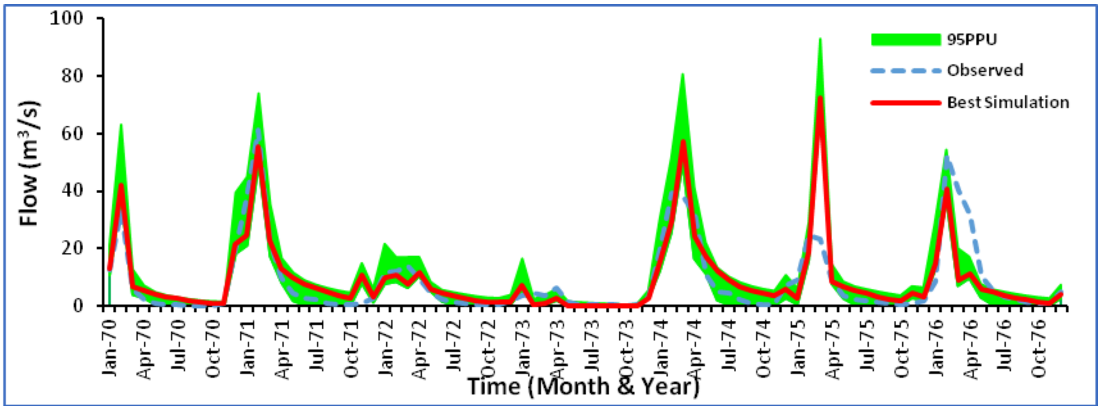


***Figure 3:*** *Calibration results for average monthly streamflow.*

Model validation was performed with the same calibration parameters using streamflow data for a 4-year period from 1977 to 1981. According to the results (**Figure 4**), the simulated data also show an acceptable correlation with observed data with a Nash-Sutcliffe Efficiency coefficient of 0.57 and coefficient of determination of 0.60.

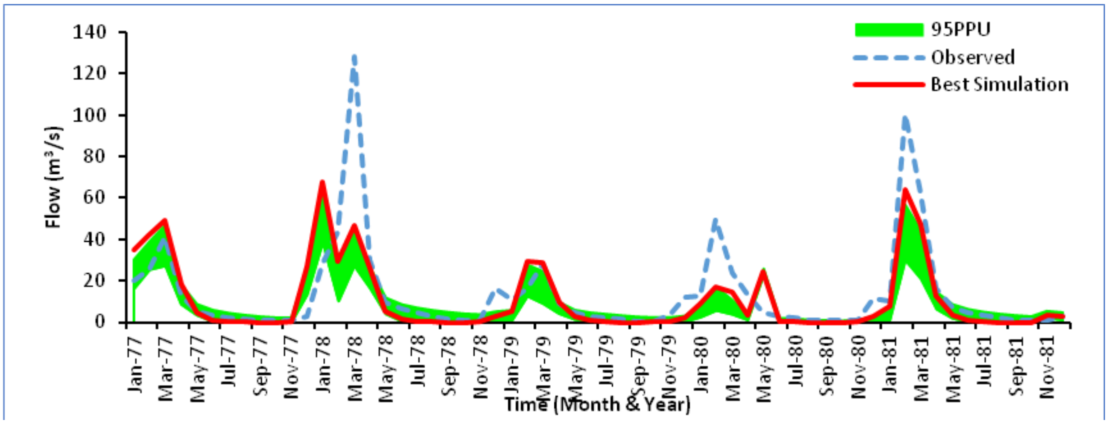


***Figure 4:*** *Validation results for average monthly streamflow.*

**Table 2** shows the comparison of observed and simulated average monthly flow from calibration and validation periods. From this data, the table shows that the model performance values for calibration and validation of the flow simulations were satisfactory according to the NSE and $R^2$ values. This confirms that the physical processes involved in generation of streamflow in the watershed were adequately captured by the model. The model could thus be used to make fairly accurate conclusions about changes in streamflow.

***Table 2:*** *Comparison of observed and simulated average monthly flow from calibration and validation periods*

| **Period** | **Mean Monthly Flow** | | | |
|---|---|---|---|---|
| | **Observed $m^3s^{-1}$** | **Simulated $m^3s^{-1}$** | **NSE** | **$R^2$** |
| Calibration period (1970-1976) | 8.46 | 9.998 | 0.60 | 0.65 |
| Validation Period (1977-1981) | 13.63 | 10.94 | 0.57 | 0.60 |

The mean monthly flow change for the dry season (July, August, September, and October) and for the wet season (December, January, February, and March) was used to compare the two model outputs (Table 3). The percent change was calculated using Equation 1. The results confirm that LULCC is indeed linked to streamflow change in the Lilongwe catchment as flow during the wet season months increased by 1.432$m^3$/s, which is 6.50% of the original value (Equation 2), and decreased during the dry months by 0.058$m^3$/s, which is 4.80% of the original value (Equation 3).

$$Percentage\ Change = \frac{Mean\ Flow\ Change}{1989\ Mean\ Flow} \times 100 \quad \text{(1)}$$

$$Wet\ Months\ \%\ Change = \frac{1.432}{22.047}\% = 6.50\ \% \quad \text{(2)}$$

$$Dry\ months\ \%\ Change = \frac{-0.058}{1.211}\% = 4.80\ \% \quad \text{(3)}$$

***Table 3:*** *Changes in mean monthly flow for wet and dry season months using 1989 and 2004 land use/cover maps.*

| **Mean Monthly Flow ($m^3$/s)** | | | | **Mean Monthly Flow Change ($m^3$/s)** | |
|---|---|---|---|---|---|
| **Land use/cover map 1989** | | **Land use/cover map 2004** | | **2004 – 1989** | |
| Wet Season | Dry Season | Wet Season | Dry Season | Wet Season | Dry Season |
| 22.05 | 1.21 | 23.48 | 1.15 | + 1.43 | - 0.06 |

A critical aspect of this study was to establish the link between LULCC and hydrologic responses of the Lilongwe River. This is well demonstrated by the results which showcase the significant role played by forests and vegetated areas in reducing runoff after precipitation events in the catchment. Results show an increase in runoff over crop land and bare land converted from forest. This runoff collects in streams and subsequently increases streamflow in the Lilongwe River during the wet season. The lack of infiltration during the wet season as a result of this phenomena consequently also reduces the amount of water stored underground to feed streams through base flow and this leads to reduced streamflow in the dry season.

Comparing the simulation outputs using the 2004 and 1989 land use maps (Figure 5), the above assertions are apparent with increases in peak flows as high as 4.53 $m^3/s$ during the wet season and decreases in streamflow as much as -1.57 $m^3/s$ afterwards. The decreases are most apparent immediately after the end of the wet season in April, likely because this is when the highest volume of subsurface water is available to replenish streams and the differences in infiltration rates between the two model outputs is reflected in the baseflow maintaining streamflow.

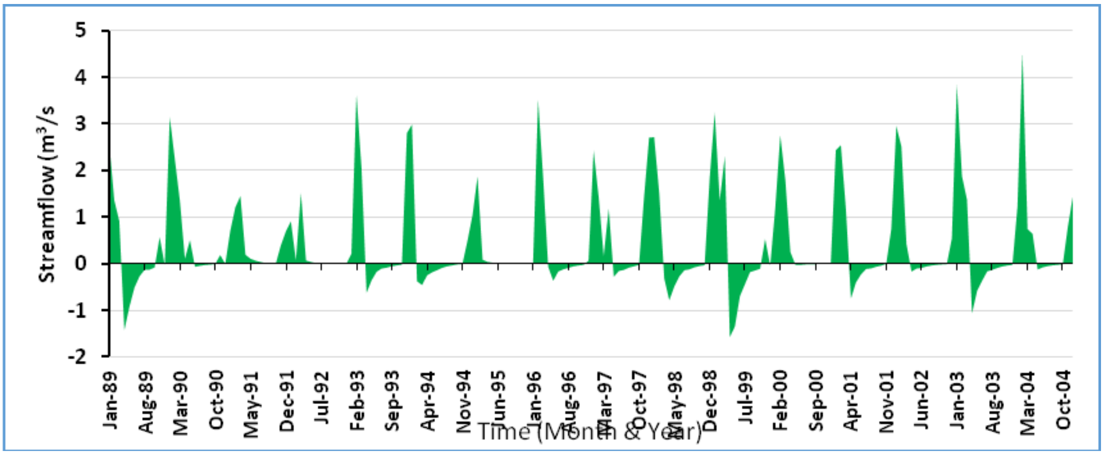


***Figure 5:*** *Streamflow simulation outputs produced using 2004 and 1989 land use maps.*

Since climatic conditions were kept constant, the changes in streamflow detected from the 1989 and 2004 land cover model outputs were a direct result of LULLC alone. These results are potentially of high socio-economic significance to the people of Lilongwe. According to the LWB Annual Report of 2004, a peak water demand of 0.971$m^3/s$ (83,919.5$m^3$/day) was observed during the dry season of the same year. This therefore implies that the change in average streamflow in the Lilongwe River between 1989 and 2004 could have supplied Lilongwe City with water for a complete 2 days during that same season. This lost water is particularly significant in recent years with the water shortage problems facing the city since 2016, especially during the dry season (World Bank, 2017). On the other hand, the city has also been experiencing flooding during the wet season in 2017, 2018, and 2019 (UNICEF, 2017) which may have been exacerbated by the effects of LULCC since streamflow in the wet season increased.

Further changes to streamflow are likely to occur considering the trend of LULCC implied by this study, as well as predicted in a study by Munthali (2013) which revealed that the Dzalanyama forest reserve may lose up to 26, 721 ha of forest between 1990 and 2030. Such a large change can greatly affect the hydrology of a watershed and has the potential to induce very high and low river flows in the wet and dry season respectively. It is worth noting however, that lack of enough data to model the catchment more accurately may have affected the results of this study. This data includes soil, and climatic data current data sets of which are not spatially detailed enough to truly represent the heterogeneity of the study watershed. The results may have also been affected by inaccuracies in image classification since according to the accuracy assessment performed, 18 percent of land cover was not accurately classified and as LULCC over those areas was missed.

## 4 CONCLUSIONS AND RECOMMENDATIONS

This study evaluated the changes in streamflow that resulted from the changes of land use and land cover (LULCC) in the 15-year period between 1989 and 2004. An integrated approach coupling the use of the SWAT hydrological model along with other GIS based methodologies was used in the study. The study revealed changes in land use and land cover had indeed occurred in the catchment resulting in changes in streamflow. These streamflow changes bear great significance to the Lilongwe Water Board and the residents of Lilongwe especially in terms of water losses in the dry season due to the LULCC as the city faces water scarcity problems. An integrated approach to management of the catchment is therefore recommended to ensure that the effects of escalated LULCC are foreseen and mitigated or enhanced accordingly. Considering that this study was conducted using limited secondary data, some variables governing streamflow may not have been fully accounted for. Further research is therefore recommended with regards to use of more detailed data about the catchment, and advanced land use detection techniques, such as object-based image classification, which may yield better land classification accuracies. Coupling land change modelling with streamflow modelling may also facilitate prediction of changes in land cover and streamflow over an extended period of time.

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