Assessment of hydrological water balance in Lower Nzoia Sub-catchment using SWAT-model: towards improved water governance in Kenya

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ABSTRACT

Kenya’s catchments has both natural and disturbed environments. Within these environments, there has been interaction between hydrological, physical and ecological characteristics. Therefore, impacts of Land Use Land Cover (LULC) change on surface and sub-surface hydrology needs to be well understood due to the increasing population competing for scarce natural resources such as water, trees and forest land. The water balance components’ spatial and temporal dynamics in relationship to the LULC change between 2003 and 2018 in the Lower Nzoia Sub-Catchment (LNSC) in Kenya was therefore assessed. Landsat data with 30 m (m) spatial resolution was used in understanding LULC dynamics of the study area using Supervised Classification Approach (Interactive Classification Method) in ArcGIS 10.5. After landsat image classification, key water balance components including; surface runoff (SURFQ), lateral flow (LATQ), groundwater recharge (BASEQ), deep aquifer recharge (DEEPQ), evapotranspiration (ET) and groundwater revap (REVAP) for years 2003 and 2018 were estimated using SWAT model in ArcSWAT. The overall accuracies for 2003 and 2018 classified images were 75.9% and 98.9% respectively which are showing good values. The results of the study showed that agricultural land coverage reduced from 83.1% in 2003 to 78.6% in 2018. Rangeland on the hand increased from 6.3% to 9.8% while urban/built-up area increasing from 10.6% to 11.6%. The annual water balance components from the LULC distribution of the two time periods shows that ET reduced, SURFQ increased, BASEQ reduced, DEEPQ reduced, LATQ reduced and REVAP reduced. At catchment level, results show that 2018 had a higher water balance than 2003 which can partly be explained by land cover decrease. The relationship between rainfall distribution, Land Surface Temperature (LST) and LULC change were further compared. At the same time, the study found out that there is limited focus to date on rural communities climate adaptive capacity. Hence, water institutions in the sub-catchment such as Water Resources Authority (WRA) are yet to fully mainstream adaptive capacity into their organizational structure and policies.

1. Introduction

Water balance is a function that can be used in describing the flow of water in and out of a system (Sutcliffe, 2004). The hydrological domains of such systems include column of soil, water basin, irrigation area or a city (Vieussman and Lewis, 1996). For a closed system, the water balance equation uses the principle of conservation of mass whereby, precipitation entering the system is transferred into evaporation, transpiration, surface runoff and ground water recharge (Sharma et al., 2019). Kenya has two water systems which includes water use system and water resource system. These two systems requires various tools and institutions to ensure that there is water availability (High Level Panel on Water, 2021). Water resource system such as a river should have the same inflow and outflow. However, drivers such as climate change, population increase and bad management causes reduction of water volume after every decade (National Geographic, 2021) hence causing reduction of outflow in comparison to the inflow.

This paper explores how knowledge on Land Surface Temperature (LST), rainfall distribution, LULC change and Water Resources Authority (WRA) adaptive capacity constraints can be linked to water balance components such as surface runoff (SURFQ), lateral flow (LATQ), groundwater recharge (BASEQ) and deep aquifer recharge (DEEPQ) within a catchment hence increased or reduced water availability. Changes in vegetation cover have significant impacts on the surface

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water budget (Chemura et al., 2020). For instance, the changing climate over the years has led to altering of forest’s role in influencing water availability and regulating water flows (Bergkamp et al., 2003). Therefore, there is need to understand how LULC alters the hydrological cycle. Similarly, there is a need to develop institutional mechanisms to enhance synergies in dealing with issues related to LULC and water at catchment levels.

1.1. Background of the study

Globally, freshwater represents only 3% of existing water resources on the planet, of which 0.3% is available for human use (McGlade et al., 2012). At the same time, spatially and temporally, water is not equally distributed and yet continues to play a vital role in our daily upkeep. It is a resource not only for domestic use but also for supporting environmental systems. In the recent past, the state of water demand and water availability in every part of the world has drawn attention of national and regional actors. This is as a result of its fundamental importance in life with food production, hydropower production, and other industrial uses (Young, 2005). Therefore, assessment of water resources and water balance components is of importance for water resources management at global, continental and river catchment scales towards realizing sustainable use (Vörösmarty et al., 2015).

Furthermore, having hydrological information of the catchment systems can be of great use in conflict management, planning water conservation, agricultural design, drainage and flood control. Hydrologic responses are dependent on decisions that are accurate and predictions reliable in order to facilitate planning and managing water resources (Bao et al., 2012). As a result, water balance study is becoming extremely important in helping water practitioners and civil society to make informed decisions. The interconnected nature of water balance components has led to the need for information on the relationship between hydrological components and physical parameters. This helps in understanding the complexity of hydrologic processes being dealt with when carrying out any water resources related developments (Loucks and van Beek, 2017).

Nevertheless, changes in LULC, flow duration and state of water balance due to ever rapidly changing environment requires knowledge in order to support adaptive capacity measures in water governance. These components have cross-scale interactions between life, ecosystem dynamics, and governance (Barbara et al., 2018). The desired goal is to obtain resilience and transformation of a given water way. The study by (Ostrom, 2009) stated that self-organization of communities around governance of natural resources is demonstrated by the fallacy of neoclassical economic theory. The theory assumed that self-interest renders communities incapable of collaboration to solve serious societal problems.

Given the importance of Lower Nzoia Irrigation Development Project (LNIDP) by National Irrigation Authority, the increasing population and the increasing water demand called for planning and managing water resources (WRG, 2015). Hence, there is need for gable area (Kodiaga, 2013). The government recognizes that water in Kenya is a resource not only for domestic use but also for supporting environmental systems. In the recent past, the state of water demand and water availability in every part of the world has drawn attention of national and regional actors. This is as a result of its fundamental importance in life with food production, hydropower production, and other industrial uses (Young, 2005). Therefore, assessment of water resources and water balance components is of importance for water resources management at global, continental and river catchment scales towards realizing sustainable use (Vörösmarty et al., 2015).

2. Materials and methods

2.1. Study area

Lower Nzoia Sub - Catchment of Wuoroya River, a sub catchment in Lower Nzoia in Western Kenya, is located within latitudes of 0°3’N and 0°40’N and longitudes 34°13’E and 34°36’E (Figure 1). It consists of rural communal areas who mainly practice small – scale agriculture and peri - urban areas. The sub – catchment lies within Siaya, Busia and Kakamega counties. It was selected as the study area because it is in an area where Lower Nzoia Irrigation Projects are being constructed. Therefore, knowledge on LULC change, hydrology and adaptive capacity constraints of the area are very important in addressing water resources management. The outlet of the watershed was selected at Wuoroya river’s latitude and longitudes of 0’15’ North and 34°24’03’ East respectively, since river flow data was available for this section. Lower Nzoia Sub – Catchment has an area of 534.24 square kilometres (km²).

The climate of Nzoia catchment is mainly tropical humid, with average temperatures ranging from 16 °C in the highlands to 28 °C in the lower semi - arid areas. The area experiences four seasons in a year as a result of the inter - tropicalconvergence zone (ITCZ). There are two rainy seasons and two dry seasons, namely, long rains (March to May) and the short rains (October to December) associated with ITCZ. Generally in the drier months, the evapotranspiration exceeds rainfall amounts. LNSC is administered by Water Resources Authority (WRA) in Kakamega. It has three dominant LULC types which include agriculture, rangeland and built – up. Physiographically, LNSC covers lowlands and uplands of between 1179 m and 1524 m above sea level. The sub – catchment is predominantly sedimentary which controls the hydrogeological characteristics of the area. The most occurring lithology are clastic sediments, acid metamorphic rock, igneous rock, and unconsolidated fluvial (Table 1). The area is majorly covered by Haplic Acrisol which are grey soils on old alluvium.

2.2. Techniques and tools used

Digital Elevation Model (DEM), Land Use map, and Soil map were required in order to create a digital map for SWAT simulation. The maps were prepared using ArcGIS 10.5 with SWAT modelling done in ArcSWAT. SWAT model was developed by the United States Department of Agriculture–Agricultural Research Service (USDA–ARS). SWAT is a physically based, computationally efficient, process-based, distributed-parameter simulation model operating on a daily time step. In addition, apart from the ability to take into account land use and soil data, the model differs from other physical models in its ability to separate the watershed into sub-basins and Hydrologic Response Units (HRUs) (Neitsch et al., 2011). The model is a complex integrated river basin scale model which operate either on daily or hourly time step (Arnold et al., 1998).

2.3. Hydrologic, climate and physiographic data

Hydrologic, climate and physiographic data (Table 2) were collected and retrieved from different sources for this research. Landsat images which are; Landsat MSS for 1988, Landsat ETM – for 2003 and Landsat 8 (OLI) for 2018 Image for path 60 and 170 were downloaded at
Landsat images were used because according to (Lillesand et al., 2004), they have good spectral and temporal resolution while their spatial resolution is moderate. The DEM in ESRI grid format with 30 m resolution of Shuttle Radar Topography Mission (SRTM) was collected from (https://earthexplorer.usgs.gov). The daily precipitation for a period of 26 years (1988–2014) for data station 2344 situated within the watershed was retrieved from Global Weather Data for SWAT (https://globalweather.t...
The daily river flow of Wuoroya Catchment at Wuoroya outlet station 1GEO2 for a period of 40 years (1974–2014) was collected from Hydro-meteorological station in Lower Nzoia. Soil data of the sub-catchment was extracted from the Soil and Terrain Database for Kenya (KENSOTER) (ISRIC, 2007) as compiled by the Kenya Soil Survey. Since permeability and infiltration as principal parameters were required to classify soil types into hydrologic groups, Kenya's parametered soil was classified soil classification code from which the data were retrieved.

2.4.2. Hydrologic data

The daily river flow data was used in SWAT model calibration and validation as well as calculating Flow Duration Curve (FDC) of Wuoroya river using the FDC 2.1 tool in HydroOffice. The daily precipitation and the rest of the weather data (temperature, wind speed, relative humidity, sunshine hours and evaporation) were then used for SWAT model simulation. Inverse Distance Weighting (IDW) method was used for rainfall distribution mapping. Interpolation of Climate Hazards Group Infrared Precipitation with Station (CHIRPS) rainfall data of 19 stations for the years 2003 and 2018 were used. Thermal infrared, red and near infrared bands for the same time period of landsat 7 and landsat 8 images were used in estimating Land Surface Temperature using split window algorithm method in ArcGIS. For SWAT modelling purposes, the catchment was partitioned into sub-catchments and Hydrological Response Units (HRUs). The study opted for Sub-Catchment use in simulation because the number of HRUs and sub-catchments were the same. The hydrologic cycle was then simulated by the model and conformed to the hydrologic characteristics of LNSC.

The landsat image processing chain was performed for 1988 bands (1,2,3,4,5,6), 2003 bands (1,2,3,4,5,7,8) and 2018 bands (1,2,3,4,5,6,7,8,9,10,11) datasets. The criteria considered in choosing the satellites images for classification included: images with less than 10% of cloud coverage, and the images satellite series availability for a long time series. Each image was then georeferenced to the WGS-84 datum and Universal Transverse Mercator Zone 36 North coordinate system. The image for each year’s band were layer stacked in window image analysis using composite band button. The stacked image was then clipped using Wuoroya watershed to extract the Area of Interest (AoI). Red, Green, Blue (RGB) and Near-infrared (NIR) bands of the datasets were common and thus they were considered for LULC reclassification. Land use inventory was prepared using a Supervised Classification Approach (Interactive Classification Method) with feature identification of the AoI done using Google Earth Pro and Google Map. Area coverage of various LULC were then calculated using Zonal Geometry. Finally, the study integrated GIS and Remote sensing techniques in order to carry out accuracy assessment and LULC change detection.

2.4.3. Landsat image classification accuracy assessment

We used the error matrix to assess the accuracy of the classification process relative to reference data. User's accuracy (UA), producer's accuracy (PA) and overall accuracy (OA) were determined from the error matrix. Correctly classified number of pixels were summed up and divided by the total number of pixels in order to calculate OA. The

Table 2. Data used in SWAT model and their sources.

| Data                      | Resolution | Format | Source                                                                 |
|---------------------------|------------|--------|-----------------------------------------------------------------------|
| SRTM DEM                  | 30m        | Raster | USGS EROS Archive - Digital Elevation - Shuttle Radar Topography Mission (SRTM) 1 Arc-Second Global (https://earthexplorer.usgs.gov) |
| Soil layer                | N/A        | Vector | International Soil Reference and Information Centre (ISRIC, 2011) website (www.isric.org) |
| Landsat satellite images  | 60m, 30m   | Raster | 1.Landsat MSS: 1988 Image 2.Landsat ETM : 2003 Image 3.Landsat 8 (OLI): 2018 Image (https://earthexplorer.usgs.gov) |
| Streamflow                | N/A        | Vector | Kenya’s Hydrometeorological department                                 |
| Rainfall                  | Raster     |       | CHIRPS rainfall data                                                  |
| River/stream shapefile    | N/A        | Vector | MaMaSe Sustainable Water Initiative (http://maps.mamase.org/)          |
| Population                | N/A        | Vector | Kenya National Bureau of Statistics (https://www.citypopulation.de/php/kenya-admin.php) |
| River Gauging Station     | 1EG02      | 34.243 | 0.150 1974-2014                                                       |
ground feature correctly shown on the classified pixels was a measure used in indicating the PA. The actual classified pixels that are real on the ground was a measure used in indicating the UA. However, in assessing the image classification accuracy, the kappa coefficient and the error matrix have become a standard in determining the accuracy. Kappa is a measure that can be used in determining if the error matrix values obtained is a significant representative result that is better than the random (Jensen, 1996). The kappa coefficient (κ) is calculated using the Eq. (1).

\[ K = \frac{N \sum_{i=1}^{n} x_{0i} - \sum_{i=1}^{n} (x_{ri} \times x_{si})}{N^2 - \sum_{i=1}^{n} (x_{ri} \times x_{si})} \] (1)

2.5. SWAT model set-up

SWAT model's tabular data base and entire map base were generated for the study area. The delineation of the main watershed into sub watersheds was done based on the slope direction of the DEM. The outlet for this study was defined at the location of river flow monitoring station. All the main watershed topographic parameters and those of the sub watersheds were calculated. After inputting LULC and soil maps, a total of 21 Hydrologic Response Units (HRUs) were generated consisting of unique combinations of land use and soils.

The lookup tables for LULC category and soil type were then used in reclassifying the LULC and soil to make it SWAT model compatible. Retrieved soil data of the catchment were reclassified using a ‘User Soil’ database table that was created for the study area from the available interpretations. Furthermore, lookup tables were used to reclassify SOTER WISE soil data to SWAT coded data. In addition, the model required daily data for precipitation and temperature that is provided by the user in the text format and which were stored in the project database. The remaining climatic data used for visualization such as humidity, solar radiation and wind velocity were downloaded then stored in the project database. After all datasets required for running model simulation were prepared, the model was run to calculate the hydrologic processes like evapotranspiration, lateral flow, base flow and surface runoff.

2.6. SWAT calibration and validation

As a physically based distributed watershed model, SWAT model was calibrated before being used in the simulation of hydrologic processes. The purpose of this was to reduce the model prediction uncertainty. Observed river flow at Wuoroya River Gauging station was used for comparison with the results from the simulated data. The model was calibrated with 16 years of observed river flow data from 1991 to 2006 and was validated using 7 years data from 2007 to 2013. Prior to model calibration, most sensitive parameters were identified based on sensitivity analysis procedure in SWAT. The study by (Musau et al., 2015) addressing water balance sensitive parameters were identified based on sensitivity analysis procedures. The statistical representation of these measures is included in Equation (2), Equation 3 and Eq. 4.

\[ NSE = 1 - \frac{\sum_{i=1}^{n} (Q_{o,i} - Q_{s,i})^2}{\sum_{i=1}^{n} (Q_{o,i} - \overline{Q})^2} \] (2)

\[ PBIAS = \left[ 100 \times \frac{\sum_{i=1}^{n} (Q_{o,i} - Q_{s,i})}{\sum_{i=1}^{n} (Q_{o,i})} \right] \] (3)

\[ R^2 = \frac{\sum_{i=1}^{n} (Q_{o,i} - \overline{Q}) (Q_{s,i} - \overline{Q})}{\sqrt{\sum_{i=1}^{n} (Q_{o,i} - \overline{Q})^2 \sum_{i=1}^{n} (Q_{s,i} - \overline{Q})^2}} \] (4)

2.7. Water balance equation

The water balance equation (Equation 5) was used to simulate the hydrological balance for each HRU (Arnold et al., 1998).

\[ SW_i = SW_0 + \sum (R_{day} - Q_{surf} - E_i - W_{seep} - Q_{gw}) \] (5)

Where \( SW_i \) = the final soil water content (mm H2O), \( SW_0 \) = the initial soil water content on day \( i \) (mm H2O), \( t \) is the time (days), \( R_{day} \) = the amount of precipitation on day \( i \) (mm H2O), \( Q_{surf} \) = the amount of surface runoff on day \( i \) (mm H2O), \( E_i \) = the amount of evapotranspiration on day \( i \) (mm H2O), \( W_{seep} \) = the amount of water entering the vadose zone from the soil profile on day \( i \) (mm H2O), and \( Q_{gw} \) = the amount of return flow on day \( i \) (mm H2O).

2.8. Qualitative data

Qualitative data was collected using unstructured questionnaires in the form of interview schedule (appendix 1) and a checklist (appendix 2). Interview schedule was designed and used for the study by the researcher to facilitate collection and analysis of adaptive capacity of water governance data from WRA. The schedule was subjected to a validation process for face and content validity. In the validation process, copies of the interview schedule and research questions were shared with some soil and water practitioners to ascertain the appropriateness and adequacy of the instrument. WRA was chosen because of the central role they play in exploitation, conservation and protection of raw water at national and local level.

2.9. Ethics statement

There was no involvement of humans in lab or field experiments for this study. The primary data were obtained with the request from Pan African University Institute of Water and Energy Sciences (including Climate Change), and permission of Water Resources Authority. The data collected were intended to enable the understanding of policy and hydrological aspects of LNSC.

3. Results

3.1. Sensitivity analysis of the model

Sensitivity analysis for the flow parameters of the SWAT model shows that Curve Number (CN2) is the most sensitive parameter among all other parameters. Alpha base flow factor (Alpha_Bf) is the second most sensitive parameter followed by ground water delay time (GW DELAY) (Table 3). Subsequently, the task involving model calibration was made easier after undertaking the sensitivity analysis.

3.2. Performance of SWAT model

In order to get reliable results, calibration and validation of SWAT model was done before the analysis of hydrological water balance. Hydrographs in Figure 2a and 2b shows the performance of the model during calibration and validation processes for the 2018 LULC map. The NSE values were 0.89 and 0.74 for calibration and validation periods respectively. The R² values were 0.56 and 0.66 for both calibration and validation periods respectively. The PBIAS was estimated to be 10.2%
during the calibration and -12.6% during the validation. The positive PBIAS shows underestimation of the model while negative PBIAS indicating overestimation of the model.

The mean monthly river flow shows that the river is live from January to December.

The correlation between the observed and estimated flow for the calibration and validation time periods could be seen as unsatisfactory. This could be due to the use of Global Weather Data for SWAT to drive the model instead of using physically collected data in the watershed. As a result, causing observed and simulated flow data correlation not best.

### 3.3. Landsat image classification results

The highest producers’ accuracies were for agriculture class while the results for rangeland and built-up classes varied depending on the year. Rangeland and built-up for 2018 were the best classified classes from the user’s accuracy with 98.6% and 100% respectively (Table 4). For 2003, they were rangeland (95.6%) and urban/built-up (86.7%) and 1988, agriculture (93.7%) and built-up (79.2%). All LULC types had satisfactory classification accuracies with users’ accuracies averages for 1988, 2003 and 2018 time periods exceeding 82.5%. Table 5 shows overall accuracy and Kappa Coefficient Statistics for the years 1988, 2003 and 2018.

### 3.4. LULC distribution and changes

The LULC distribution map for 1988, 2003 and 2018 time periods (Figure 3) show agriculture, rangeland and urban/built-up as dominant LULC types. However, agriculture is the most dominant land cover type in the sub-catchment (Table 6). About three quarters of the study area was agricultural land for all the three time periods. Between 1988 and
2003, agricultural land increased by 1959.01 ha, urban/built-up area increased by 4283.34 ha and rangeland declining by 6224.3 ha. Between 2003 and 2018, agricultural land reduced by 2433.39 ha, built-up area increased by 561.33 ha and rangeland increasing by 1872.06 ha. The overall comparison was done over a period of 30 years (1988–2018).

Over this period, agricultural land declined by 474.38 ha rangeland reducing by 4352.24 ha and built-up area increasing by 4844.67 ha. LULC area coverage was presented in hectares (ha).

### 3.5. Water balance of the sub-catchment

Lower Nzoia Sub-Catchment's water balance (different components) were determined using the calibrated and validated SWAT model and the results are graphically presented in Figure 4. The most important water balance components considered were surface runoff (SURFQ), lateral flow (LATQ), groundwater recharge (BASEQ), deep aquifer recharge (DEEPQ), evapotranspiration (ET) and groundwater revap (REVAP). All the components are shown as a percentage of annual rainfall for the year 2003 and 2018. 2018 had a higher water balance as compared to 2003 (Table 7). Analysis of the results shows that for 2018 LULC map, ET has the highest share of the water balance, followed by SURFQ, then BASEQ, REVAP, DEEPQ and finally LATQ. In 2003, ET has the highest share of the water balance followed by SURFQ, then BASEQ, REVAP, DEEPQ and finally LATQ. Water present in each cycle component of the sub-catchment is expressed in millimetres (mm).

### 3.6. Comparing Land Surface Temperature, rainfall distribution and LULC change to water balance components

A comparative analysis of Land Surface Temperature (LST), rainfall distribution and LULC (Figure 5) for the years 2003 and 2018 was done to assess their relationship to water balance discharge components changes. The resampled LULC classes for 2003 and 2018 showed that there is increased urban/built-up area. Agricultural land reduced by 4.5%, rangeland increasing by 3.5% and urban/built-up area increasing...
by 1.6%. Most built-up areas in the study area are in the southern, south western and northern parts. These areas’ LST ranged between 20.4 °C and 25.5 °C in 2003 and 16.1 °C and 28.6 °C in 2018. The data on precipitation showed that southern and south western parts of the sub-catchment received less rainfall both in 2003 and 2018 as compared to north eastern parts. However, 2018 was wetter year as compared to 2003 but the general distribution of the annual precipitation in the sub-catchment remaining the same.

![Figure 4. Six water balance components of LNSC as a percentage of annual rainfall in 2003 and 2018 as derived from simulated SWAT model.](image)

![Table 7. Water balance components and total water balance of LNSC for years 2003 and 2018.](table)

![Figure 5. LST, rainfall distribution and LULC comparative analysis in LNSC for years 2003 and 2018.](image)
3.7. River flow assessment of Wuoroya River

Due to the difference in hydrological characteristics of the area, the shape of the constructed FDC (Figure 6) showed different river regimes. The highest flow (0–20 percentile) ranged between a flow of 21.33 m³/s and 4.89 m³/s; intermediate flow (20–60 percentile) ranged between 4.89 m³/s and 2.05 m³/s and low flow (60–100 percentile) ranged between 2.05 m³/s and 0.04 m³/s. By the year 2014, chances for the river discharge reaching 4.89 m³/s was at 20 percentile.

3.8. Adaptive capacity constraints

Dealing with water in Kenya means facing a dual governance system of service provision and resources management. At the same time, adaptive capacity constraints include: the concealed nature of adaptive capacity, the temporal trade-offs between coping and adaptive capacity, the limited focus to date on rural communities, and the lack of empirical evidence has hindered localised solutions. In addition, technological and financial inadequacies has further made learning on adaptive capacity hard hence, recognizing changes might be missed or take longer to be recognized when resources are available. As the area is becoming wetter, its population rapidly growing, land cover reducing due to the increasing built - up areas and there is still a narrow understanding of adaptive capacity, water availability of the area is threatened.

4. Discussion

4.1. LULC change assessment

The study determined quantified and spatial distribution of the three dominant LULC classes in the Lower Nzoia Sub – Catchment as shown by 1988, 2003 and 2018 maps. The accuracies achieved using Supervised Classification Approach (Interactive Classification Method) were good. Even though (Akali, Oteng’i, Masibayi, Mokua and Maloba, 2015) used unsupervised comparable classification using landsat data, supervised classification method has added advantage in that, the approach’s algorithm is applied systematically throughout the entire image relatively quickly (Horning, 2004). Therefore, there are a number of studies using Supervised Classification Approach in remote sensing image classification.

Three quarters of the sub – catchment (83.1%) was covered by agricultural land as compared to 78.6% in 2018 with both years exceeding 70% of agricultural production carried out in small – scale farms in rural settings (Route to Food, 2021). As a result of human – induced LULC types (agriculture and built - up) which account for 93.7% in 2003 and 90.2% in 2018, Lower Nzoia Sub – Catchment has been modified by human activities. The modification has been exacerbated by the increasing population growth in the area (Figure 7). Due to the sub - catchment agricultural development having high potential, demand for

Figure 6. Wuoroya River Flow Duration Curve between 1974 – 2014 using observed flow.

Figure 7. Population trend in Nzoia Catchment between 1989 and 2019.
agricultural land uses in the area is getting high at the expense of natural cover types. Population increase has led to land sub-division coupled with unsustainable land management practices hence, affecting land productivity. Therefore, forcing communities to intensify cultivation into water catchment areas thereby affecting the catchment water functions (Campbell et al., 2003; Rwanga and Ndambuki, 2017).

In addition, it was also observed that there is a co-occurrence of changes in land cover types and changes in urban/built – up land use in the sub – catchment. Between 1988 and 2018, approximately 9.1% of land for other uses became built- up thereby decreasing agricultural land by 0.91% and rangeland by 8.2%. The close association between land cover loss and built – up areas increase means that there can be significant impact on the catchment hydrology. The increased surface runoff has been linked to increased built – up areas (Ligtenberg, 2017). These findings shows that LULC changes are quantitative and spatial in nature hence important in addressing LULC change policy. For instance, adaptive capacity has to be incorporated in WRA structures and policies.

4.2. LULC change and water balance

Even though agriculture is the main land cover type in the sub – catchment, maize farming is the main crop being planted in the area. Conversion of rangeland or agricultural land to built-up area alters the water cycle of the catchment as it is likely to reduce evapotranspiration which causes increased runoff (Cao et al., 2009; Odongo, van Oel, van der Tol and Su, 2019). For example (Memarian et al., 2014), indicated that effects of LULC change on water cycle is evident in the variation of water balance components such as surface runoff. Similar impacts of LULC change have been reported elsewhere (Waithaka et al., 2020; Githui, 2022).

This study has demonstrated that there is ET shift in line with land cover changes. Hence, altering water availability in the sub - catchment. Improved management of the catchment requires a focus in term of reducing ET from the catchment in order to maximize discharge and water yield. Thus both positive and negative effects on water balance will be experienced depending on the type of changes in LULC at catchment scale. It is also important to note that the effects of the changes in LULC may be quantitative and qualitative hence impacting on the economic and environmental activities (Maingi and Marsh, 2001; Odada et al., 2004; Duveiller, 2018). The decrease of 6% in ET between 2003 and 2018 points to the significance of agriculture and built – up land in influencing water dynamics as evapotranspiration was shown as the most important water balance component accounting for between 64% (2018) and 70% (2003) of annual precipitation.

Changes in LULC explain the changes in water balance that was observed in many ways. For example (Mwangi, 2016), findings concludes that land use change is the main driver of the change in streamflow. Therefore, converting land cover to built-up area caused the increase in streamflow due to reduced water infiltration into the soil. On the contrary, the study by (Wang et al., 2017) shows that a 30-year averages of the streamflow decreased on agricultural land but increased in forest areas.

The hydrological characteristics changes of the sub-catchment are significant in understanding Wuoroya river flow as a result of non-uniform nature of rainfall distribution and the corresponding LULC changes. The unsustainable activities within and outside the sub-catchment such as increase in built-up areas and rangeland degradation can lead to unreasonable water abstraction from the catchment. Such a scenario is likely to impact on the river discharge. There is only 20 percentile chances that the streamflow will be 4.89 m³/s. However, in case of decrease in permeability as a result of converting vegetated land to built-up area and increase in annual rainfall, there is a possibility of increased water yield. This means that the flow duration curve will change due to high flows as a result of impervious surface causing increase in stormwater runoff and decrease in infiltration and ground water recharge hence resulting in high flows.

The changing hydrological characteristics has further been enhanced by changing climate (Adhikari, 2013; Githui, 2022). Hence, knowledge on state of adaptive capacity (Figure 8) in the catchment as adapted from (Cinner et al., 2018) is important.

![Figure 8. State of adaptive capacity in LNSC using adoptive capacity components (adopted from Cinner et al., 2018).](image-url)
4.3. Implications on catchment scale adaptive capacity

Changes in water balance components affect hydrological responses and has made learning on adaptive capacity hard in the face of limited financial resources, inadequacy in advanced technology as well as limited availability of reliable data of integrity. Even though there is urgency to change due to residents’ livelihoods dependence on natural resources, there is still a narrow understanding of adaptive capacity due to limited investment and research in this sector in rural areas. The complexity of this issue is further exacerbated by the physical, ecological and population changes.

Even though water resources management in LNSC has been hindered by external demands, “water quality has increased but not to the desired level, quantity improved but still equitable water allocation not fully realized, conflict reduced but there is still illegal water use, data availability improved but gaps are still there.” Eng. Reuben of WRA. This is because, the water sector introduced changes through institutionalization as well as policy reforms hence leading to the establishment of empowerment, permitting and regulations programs. Furthermore, launching of abstraction and pollution surveys has enabled understanding of who are polluting and using water sources in order to monitor the progress.

5. Recommendations

Considering Kenya has relatively similar socio-political, cultural, environmental, and water governance contexts, the water scarcity and water demand differing responses can provide an opportunity to explore adaptive capacity in practice while proposing innovative solutions. For instance, there is need for the adoption of current techniques such as decision support systems and artificial intelligence to facilitate understanding of LULC, water balance and adaptive capacity as interactive systems. At the same time, the studies should cover horizontal and vertical governance approaches adopted by WRA while collaborating with communities in shaping adaptive capacity policies. The study therefore recommends future research on the direct and indirect relationship between LULC change and water governance adaptive capacity.

6. Conclusion

The water cycle operates on a time and space scales. Since precipitation is the central component of hydrological water balance, accurate and timely knowledge of catchment-scale precipitation is essential for improving the ability to manage freshwater resources and for predicting high-impact weather events. As a result, the future of water availability depends on the understanding of the spatial and temporal variation and interaction of hydrologic components hence, could be instrumental to assisting water planners in the formulation of strategies for water conservation. Because of this, embracing the interface between science and policy through this paper is very key. This enables understanding of how knowledge on water balance components and LULC change can be used to streamline adaptive capacity at institutional level.

Study analysis of governance system and policy interventions as well as changing LULC in LNSC confirms that adaptive capacity is influenced by institutional and environmental contexts hence affecting how to safeguard our natural resources. The 1988–2018, a 30-year period saw a change in the land use in the area with built-up area and agricultural land increasing while rangeland decreasing. The area became wetter in 2018 as compared to 2003 and more built-up in 2018 as compared to 2003. At the same time, the area saw reduction in evapotranspiration, increased surface run-off, reduction in groundwater recharge, increased revap and increased lateral flow.

Water Resources Management Authority (WRMA) also changed to WRA hence change in the institution’s mandate. WRMA mandate was more on management aspects of water while WRA’s mandate is more on regulation aspects. This clearly shows how institutional changes and external demands such as deforestation or increased built-up can affect the structure and operations of WRA. Therefore, if these changes are not accompanied by deliberate efforts to ensure adoption of integrated approach, they will also negatively affect the status and use of water. This study concludes that water availability in a catchment is consequently affected by hydrological characteristics of a place.

Declarations

Author contribution statement

Lilian A. Juma: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Nsalambi V. Nkongolo: Contributed reagents, materials, analysis tools or data; Wrote the paper.

James M. Raude: Conceived and designed the experiments; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Caroline Kial: Contributed reagents, materials, analysis tools.

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Data availability statement

Data included in article/supplementary material/referenced in article.

Declaration of interests statement

The authors declare no conflict of interest.

Additional information

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Appendix

The guide for key informants was used for data collection in WRA. The checklist was used to collect and retrieve key information from primary and secondary data for the study.

1. Guide for Key Informants

Purpose: to get an overview of how to simplify complexities of water balance and water governance aspects of water resources management.

How are institutions responding to devolved plans on water governance issues? And to what extent are the responses shaping and are being shaped by the devolved governance policies in support of a more sustainable decision systems in Nzoia River Catchment in Kenya?

i. What is the role of your institution in water resources management?

ii. What are the external demands in your institution?

iii. Does prior management increase or decrease water use efficiency?

What worked or did not work?

iv. How does external factors affect your work?

v. What are your ideas and views about adoption of devolved water policies geared towards future sustainable decision systems targeting vulnerable communities within the catchment?
vi. How have the newly introduced reforms in water sector helped to solve/address water services problems for people occupying the catchment?

a) If now, how
b) If in the future, how

vii. Does your institution integrate new policies with the institution's overall mandate in order to have in place decision systems that work for everyone? Are the laws flexible? Yes, No, No = rigid laws

viii. Explain whether formulated and devolved systems share common water resources management values and interests among actors across all sectors in this area towards sustainable water access and consumption?

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