**Impact of Land Use Land Cover Change on Water Quality of Athi River Basin, Kenya**

**ABSTRACT**

Studies on Land use/land cover (LULC) changes from 2015 to 2023 were analyzed to understand the spatial variation in water quality within the Athi River Basin. Data was extracted from Landsat 8 imagery from the USGS archive and analyzed using Google Earth Engine. Land use land cover (LULC) changes analyzed include six categories namely Bare-lands, Built-up, Farmlands, Forestlands, Grasslands, and Open-waters. Pearson correlation analysis was employed to assess the spatial LULC differences in water quality at different sampling stations within the mid-reaches of the Athi River Basin. Ground truthing surveys involving interviews were conducted to determine land use activities influencing water quality. The findings revealed significant LULC changes between 2015 and 2023. Barelands decreased by 7.06%, while built-up areas rose slightly by 0.29%. Farmland grew by 0.52%, forestlands by 4.54%. Grasslands increased by 2.77%, while open waters declined by 1.24% from 2015 to 2023. The result on spatial LULC differences indicated significant influence on water quality. Urbanization and agricultural activities generate pollutants such as Total Dissolved solids (TDS), Electrical Conductivity (EC), Biological Oxygen Demand (BOD5), cadmium, and chromium across the stations. Drought in open water with a -0.85 correlation result increases pollutants and dilution effect which worsens the water quality over time. The interview survey identified four land use drivers and a natural factor affecting water quality. Respondents cited climatic factors, agriculture, and settlement as primary drivers of water quality degradation, with industry and commercial activities as secondary drivers in the Athi River Basin. Climatic factors were associated with Grasslands and Farmlands. Agriculture impacted Forestlands and open waters, and Settlement influenced Bare-lands, Grasslands, and Forestlands. Industry affected Built-up/others and open waters, while commercial activities relate to Built-up. In conclusion, the Government of Kenya should enforce the regulations on environmental management, water resource conservation, sustainable land use, public health protection, irrigation control, forest preservation, and aquatic ecosystem conservation to safeguard the water quality of the Athi River Basin.

**Keywords:** LULC, water quality, interview survey, agriculture, spatial variation, Pearson correlation analysis

1 **INTRODUCTION**

Land use/land cover (LULC) change driven by human activities has significantly degraded natural water bodies. The global increase in population, as a key factor in urban development and economic activities, has affected the quality of watersheds and disrupted natural hydrological systems (Nimi *et al*., 2018). In low-income countries, LULC change has destabilized ecosystems and disrupted ecological balance. Rapid urbanization, and industrial, and agricultural expansion are major contributors to land cover changes (Lacher *et al*., 2019; Dewan & Yamaguchi, 2009). The reliance on natural resources for survival and ineffective pollution management systems, especially in developing countries, have heavily damaged riparian ecosystems and riverbanks, leading to water quality degradation. Nimi et al. (2018) found that LULC change impacts livelihoods, displaces habitats, increases flood risks, and affects watersheds. Changes in land cover, such as deforestation and prolonged droughts, exacerbate pollution transport into water bodies. Studies have shown that LULC change influences water quality through the spatial and temporal effects of population growth, urban development, industry, and agriculture (He *et al*., 2008). River water pollution varies by location and time due to the release of organic and inorganic effluents into water bodies. Addressing the rapid changes in land cover, soil encroachment, riverbank expansion, and increasing river sediments requires mitigation efforts at global and regional levels.

In Kenya, agriculture is a widespread land use activity that degrades the water quality of major rivers, particularly the Athi River Basin. Increased use of agrochemicals, animal farming, and irrigation runoff contribute to the deterioration of water bodies (Wilson *et al*., 2021). Agricultural and industrial activities affect water quality through the presence of nutrient loads, raw sewage, and solid waste effluents (Ngatia *et al*., 2023; Ontumbi *et al*., 2015). The impact of industrial, demographic expansion and agricultural intensification on land cover is particularly evident in arid and semi-arid regions in Kenya. For instance, Langat et al.(2019) observed that agricultural lands and built-up areas increased, while open land, water bodies, and vegetation decreased in the Tana River Basin from 1987 to 2015. Chepkorir et al. (2021) discussed that rapid LULC changes occurred in the Lake Nakuru drainage basin, including the entire Eastern Mau, where the Njoro River catchment has been affected over the last three decades. They found that LULC in Njoro and Kamweti river catchments changed at spatial and temporal scales, indicating anthropogenic effects on increased demand for food and building construction. The impacts of urbanization and agricultural activities contributed to seasonal water quality pollution in the Ruiru and Ndarugu river Basins (Wambugu *et al*., 2017). Agricultural practices and building constructions affected the water quality of the Tambayakbayan River (Putri *et al*., 2021). A study on LULC trends showed river encroachment affecting water quality in Mokopane, Limpopo, South Africa, from 2016 to 2019 (Molekoa *et al*., 2021). The decreased trend in land cover demonstrated a complex impact of cultivated land on the water quality of the Chaohu Lake Basin (Huang *et al*., 2013).

Despite the importance of riparian vegetation and forests, which act as natural water filters, regulate water temperature, and stabilize riverbanks, in the Athi River Basin, these areas face threats and destruction in certain sections of the river basins, affecting water quality. The upper, middle, and riparian sections of the Athi River Basin are exposed to economic activities, including industrial processing, agricultural runoff, land scalping runoff, atmospheric deposition, sand mining, and brick burning, all contributing significant pollution to water quality. Poor regulation of land use activities, including agricultural practices and industrial processing, exacerbates water quality degradation. It is on this basis that Land use activities, including commercial, industrial, agricultural, and human settlements (both formal and informal), were examined across different spaces of the river. The ultimate goal of the study was to investigate the impact of LULC change on the water quality of the Athi River Basin from 2015 to 2023.

**2 MATERIALS AND METHODS**

2.1 STUDY AREA

The study was conducted in the mid reaches of the Athi River Basin. The upper mid-sampling point is located in Athi River town with coordinates of 1°26'38.29''S, 36°58'52.49''E, extending down to the Kibwezi bridge sampling location with coordinates of 2°12'09.45''S, 38°03'30.36''E as illustrated in Figure 1. The Athi Basin has an area of 66, 559 km2 covering 11 % of land surface and borders Tanzania to the south, the Indian Ocean coastline to the east, the Tana Basin to the north, and the Rift Valley Basin to the west (WRA, 2022).

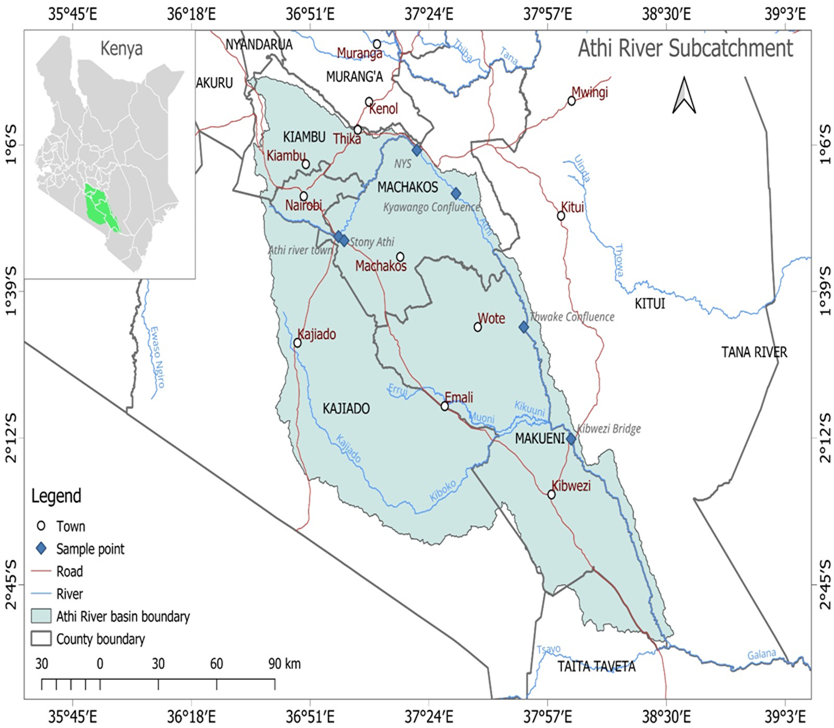


Figure 1: The Location of the Study Area

Athi River traverses the plains and valleys of Kenya, forming Fourteen Falls, meandering through Nairobi, and passing through Tsavo National Park (Kenya Wildlife Service, 2024). The river flows through informal settlements and industrial areas in cities and towns including Nairobi and Machakos Counties, including suburban and rural communities, where it collects various effluents (Figure 1).

The topography of the Athi River Basin ranges from sea level in the Indian Ocean to approximately 2,740 meters in the Aberdare Range (WRA, 2022). Higher elevations (1,800 to 2,735 meters) include the Aberdare Range, Ngong Hills, and surrounding areas. Mid-reaches (1,200 to 1,800 meters) encompass Nairobi, Kajiado Town, Machakos, Makueni, and Kitui (Wikipedia, 2024). The lowest elevations (0 to 1,200 meters) span the Sabaki River Mouth, Mombasa, Kilifi Town, Malindi, and the river's estuary at the Indian Ocean.

The basin's headwaters are in the central Kenya highlands, specifically the Kikuyu Escarpment. The Southern Aberdare ranges and the Ngong Hills also receive significant precipitation. Rainfall distribution is influenced by altitude, the Inter-Tropical Convergence Zone (ITCZ), and orographic effects (Kitheka *et al*., 2022). The basin experiences two main rainy seasons: long rains from March to May and short rains from October to December, essential for sustaining agriculture, replenishing water levels, and maintaining river flow in the Athi River. Annual precipitation ranges from 481mm to 1,764mm, with temperatures varying from 6°C to 28°C (Wambugu *et al*., 2017). During the dry season, temperatures can range from 28°C to 32°C in some months. Daytime temperatures average around 23°C, while nighttime temperatures typically hover around 17°C. The basin experiences dry periods from July to September (Kitheka *et al*., 2022; Kithiia, 2006). April is the wettest month, averaging 159mm (6.3 inches) of precipitation, while July is the driest with only 11mm (0.4 inches) of precipitation (Kithiia, 2006).

**2.2 SAMPLE COLLECTIONS AND ANALYTICAL METHODS**

Data for the study was collected in six sampling stations within the mid-reaches of the river basin, namely Athi River town, Stony Athi, National Youth Service (NYS), River Kyawango confluence, River Thwake confluence, and Kibwezi Bridge as shown in Figure 1. The study determined land cover change and their impacts on water quality. Remote Sensing (RS) and Geographic Information Systems (GIS) were applied in monitoring trends in spatiotemporal land cover. The historical data on land cover was acquired from the United States Geological Survey (USGS) website. Enhanced Thematic Mapper (ETM) Landsat 8 Data from January 1st to December 31st for three reference years namely 2015, 2020, and 2023 was used. The images from the period 2015 were considered as the baseline for the change detection due to the best quality satellite image Data. The study used Google Earth Engine (GEE) for analysis. Land use/land cover (LULC) was classified into six (6) categories namely bare-land, open-water, forest, grassland, farmland, and built-up/others. This data was used to validate land use and land cover interpretation from the satellite images for a qualitative description of the characteristics of each land use/land cover. A similar approach was used by Ruttoh et al. (2022) on ecosystem service values in Cherangany Hills Water Tower, Kenya. Pearson correlation analysis was used to examine spatial LULC differences across the sampling stations in the river basin. An interview survey was conducted to support the dataset.

**3 DATA ANALYSIS**

**3.1 Supervise Method**

The study employed a supervised classification technique to develop the spectral signatures of known categories (Richard & Jia, 2006; Eastman, 2003).

**3.2 Training and Testing Samples**

The study tested the Random Forest classifier by using survey data collected from Google Earth. Random Forest was performed in GEE using ee.Classifier.smileRandomForest function and then trained it. Random Forest algorithm classified land cover types based on input features, including the Normalize Difference Vegetative Index (NDVI). Manual digitization of areas of interest (AOI) such as barelands, crop/farmlands, grasslands/vegetation, built-up areas, forest, and water was done using high spatial resolution satellite imagery in GEE. The study used 129 samples for training and 100 samples were generated for testing purposes. The class of interest and the number of training samples were Farmlands 22, Grasslands 31, Forest 36, Barelands 14, Built-up/others 12, and Open-water 14. The training and sampling were acquired using Google Earth Engine (GEE) and then imported into the analysis script. The production of different land cover categories applied visual interpretation of Landsat ETM backed by a field survey using Google Earth similar to the study conducted by Rotich & Ojwang (Rotich & Ojwang, 2021).

**3.3 Normalized Difference Vegetation Index (NDVI)**

Normalized differences in spectral bands of Landsat mosaics were used to analyze bands 1, 2 .3, 4, 5, 6, and 7. In addition, the Normalized Difference Vegetation Index (NDVI) detected land cover changes and served as one of the covariates for image classification (Rotich & Ojwang, 2021; Meng *et al.,* 2019; Elmore *et al*., 2000). NDVI was derived from band 3 (red band) and band 4 (Near Infrared band). According to Elmore et al. (2000), the index quantifies vegetation’s reflective difference between the NIR and RED. It is useful for environmental monitoring, mainly for vegetation growth measurement (Tamiminia *et al.,* 2020). The formula is as follows;

NDVI = (NIR + RED) / (NIR + RED) (1)

Where,

NIR = near-infrared and RED = red wavelengths band, in Landsat Image.

**3.4 Cloud Masking and Generation of Image Composite**

Data filtering was done using Google Earth Engine (GEE) for cloud-free imagery relative to the years from the Landsat image collection. The study used a function to handle and detect clouds in a multi-temporal image collection. Google Earth Engine (GEE) provides many statistical classifiers for pixel-based image classification of land use mapping.

**3.5 Accuracy Assessment and Image Classification**

Accuracy assessment was quantitatively used to assess how effectively the pixels were sampled into the corrected land cover classes (Rwanga & Ndambuki, 2017). It is the most important, difficult, and last stage in the land cover classification process of the images (Foody, 2002). The primary accuracy measure is the overall accuracy, which is calculated by dividing the correctly classified pixels by the total number of pixels checked (Banko, 1998).

This study performed an accuracy assessment for a trained Random Forest (RF) classifier which predicted the generated LULC maps. The classification results were compared with ground truth data using the confusion matrix, which indicated the number of correctly or incorrectly classified pixels in each land cover category. Adjustment were made to improve the accuracy based on error matrix. The RF classifier quantified accuracy by estimating the percentage of correctly classified test Data (Plourde & Congalton, 2003). Accuracy assessment was successfully determined using Kappa coefficient, error matrix, producer accuracy and consumer accuracy. User's accuracy represent the proportion of an area classified on the map which correspond to the actual map on ground.

Both user and producer accuracies were calculated using confusion matrix to evaluate the class performance.

Google earth engine (GEE) function techniques were used with the following equations to generate accuracy statistics.

 (2)

 (3)

 (4)

Where;

nii denotes the number of suitably classified pixels,

N denotes the total number of pixels,

r is the number of rows, and

ni col and ni row denote the column and row total.

**3.6 Kappa Coefficient**

The kappa coefficient measured the overall agreement of the matrix. The equation below shows the accurate Kappa coefficient for stratified random measurement (Petropoulos *et al*., 2015).

 (5)

Where,

T denotes the test pixels,

C denotes the correctly classified pixel observations, and

G is the sum of the multiplied total value.

GEE was utilized for user accuracy and producer accuracy analysis of land cover classification.

**3.7 Temporal Change Detection**

The change detection analysis was conducted in ArcGIS software. The classification images were converted to vector format for geoprocessing of the six (6) land cover classifications through the intersection tool. The intersection processing tool allowed the conversion of land cover information for the years 2015, 2020, and 2023, into one database in tabular form for change detection (Rotich & Ojwang, 2021).

The spatiotemporal change was quantified using the gain and loss method. The land cover change was calculated with the equations adapted from Lin *et al.,* 2020).

Kgain = Sb – Sa (6)

K0 = Sbi - Sai  (7)

Kloss = Sa – K0  (8)

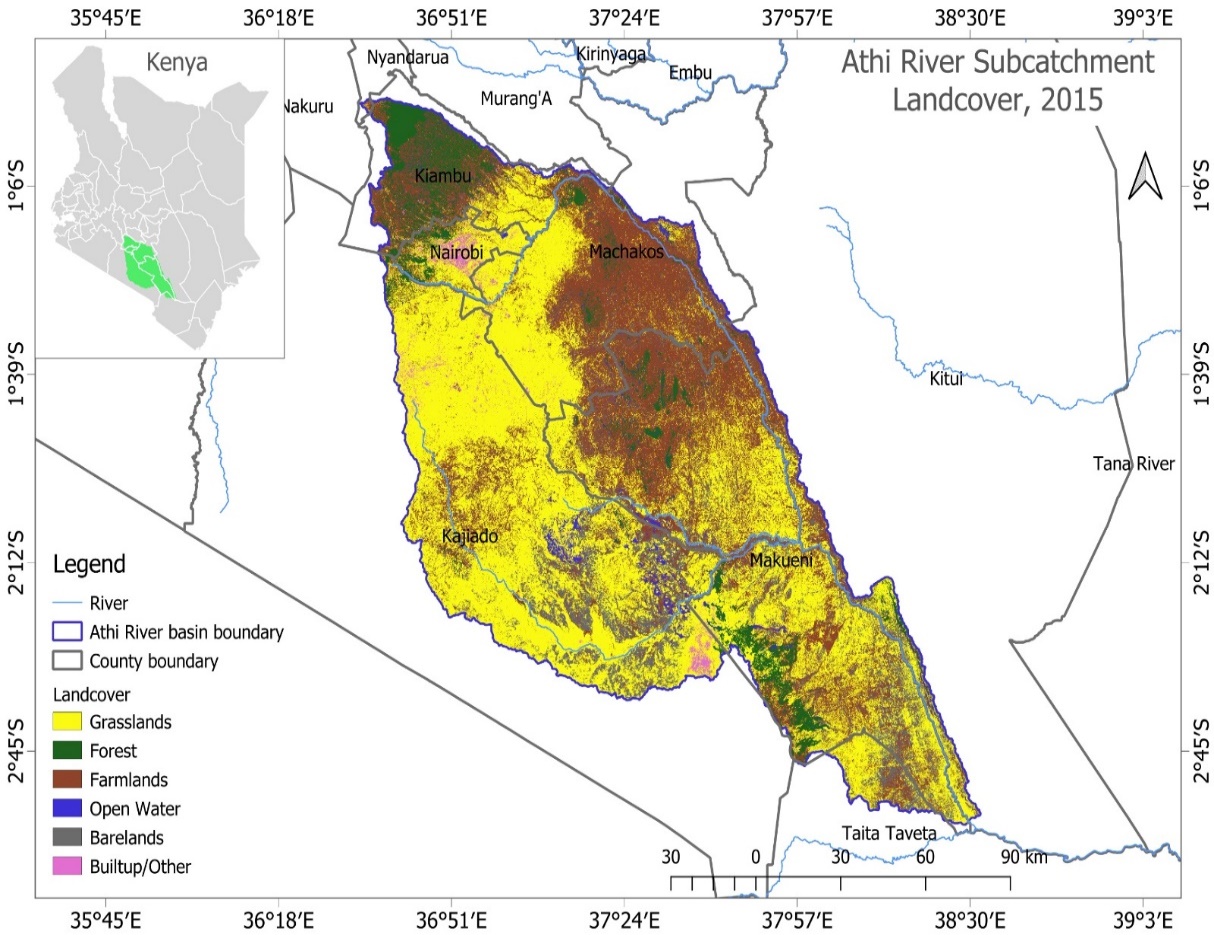
Where;

Sa and Sb = land cover types at the beginning and end-year (time) in a given period.

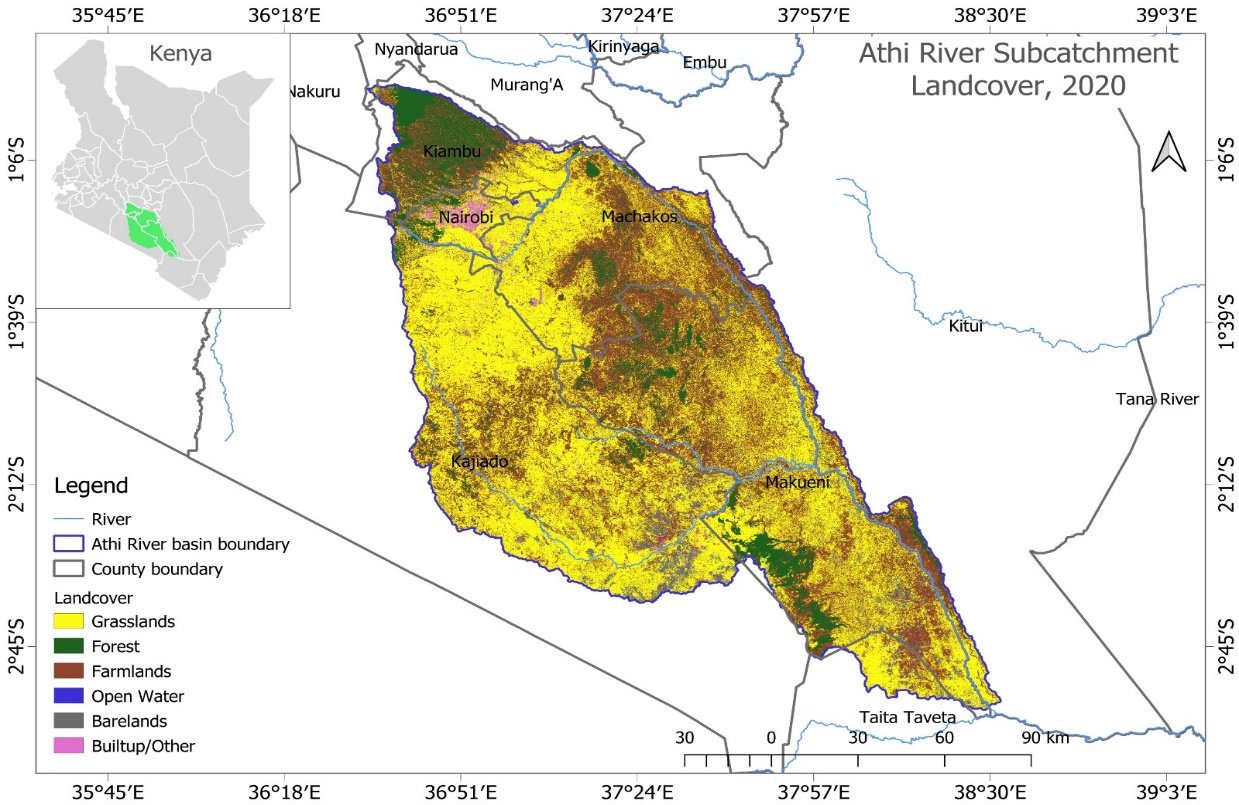
Sai and Sbi = land cover types with no change between the beginning and end (time). The total area covered by each class to detect a change was calculated and summarized into percentage change.

**4 RESULTS AND DISCUSSIONS**

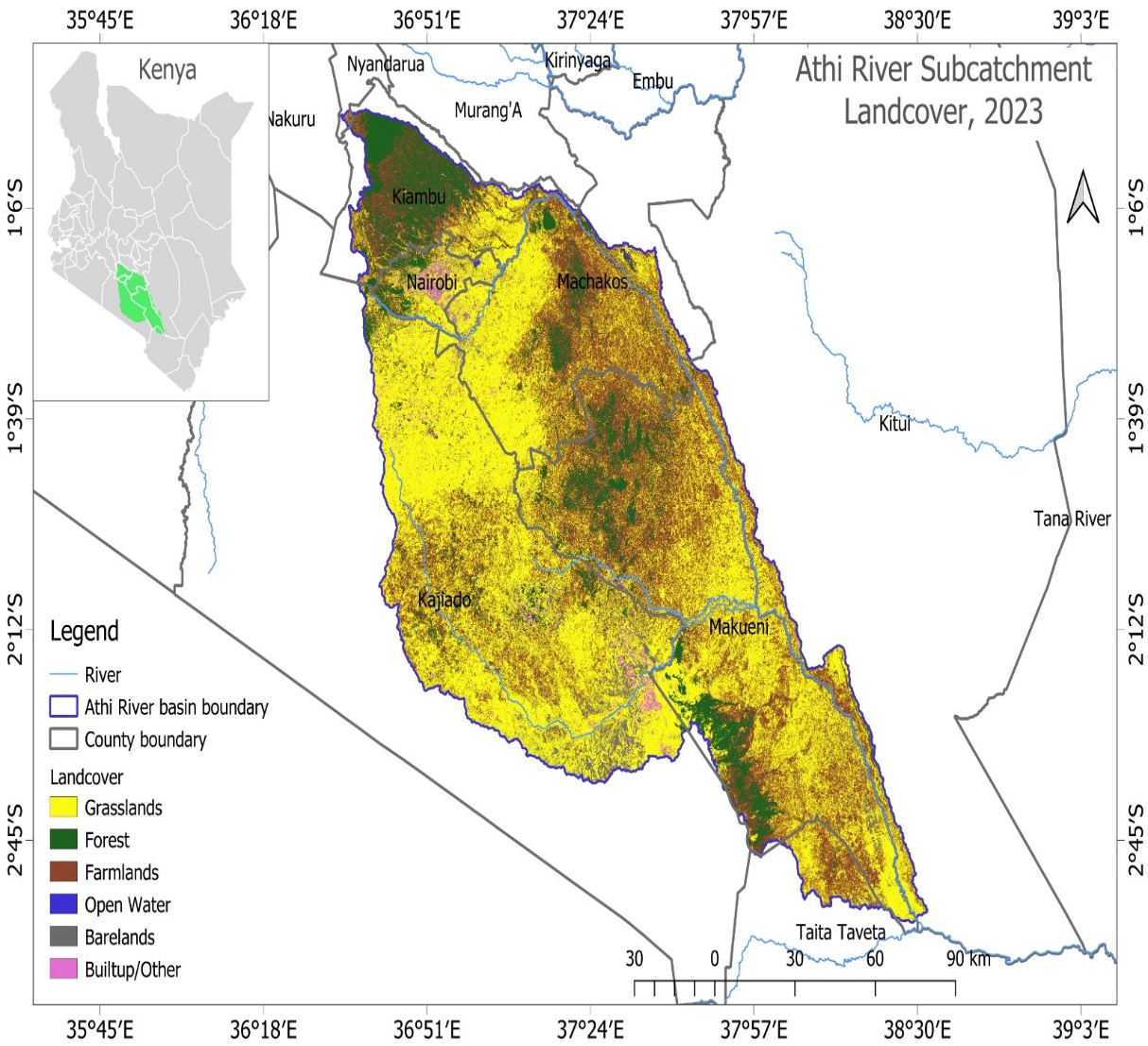
The land cover maps of the mid-reaches of the Athi River Basin for 2015, 2020, and 2023 highlight different colors representing various land cover types in the study area. These types include built-up areas, bare lands, farmlands, forestlands, grasslands, and open water areas. It features County boundaries and rivers. The legend uses colors such as yellow, brown, green, blue, and pink to represent these land cover types. The yellowish color, identifying grasslands, appears to be dominant in the basin, coupled with the brownish color indicating farmlands. Built-up areas, bare lands, and forestlands are present in smaller proportions. The open water areas indicate the Athi River and a wastewater treatment plant (WWTP). Built-up areas include urban, semi-urban, and parts of rural areas. The 2015 land cover map represents the baseline distribution of different land cover types. The 2020 and 2023 maps highlight significant shifts due to urban development, agricultural practices, reforestation, and other factors, as illustrated in Figures 2, 3, and 4 respectively.



**Figure 2:** River Athi Basin Land Use/Land Cover (LULC) Classification, 2015



**Figure 3:** River Athi Basin Land Use/Land Cover (LULC) Classification, 2020

****

**Figure 4:** River Athi Basin Land Use/Land Cover (LULC) Classification, 2023

**4.1 Land Cover Area (Ha) and Gross Percentage Change from 2015 to 2023**

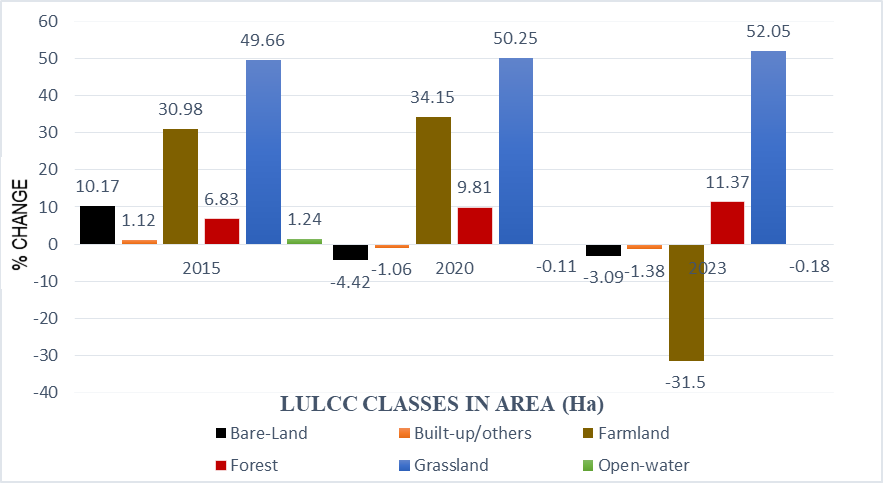
The land use/land cover (LULC) indicated overall percentage changes in the area per ha from 2015 to 2023 (Table 1). **Barelands** decreased from 10.17% in 2015 to 3.11% in 2023, a total decrease of 7.06%. This suggests repurposing for agriculture, reforestation, or urban development. **Built-up Areas** declined from 1.12% in 2015 to 1.08% in 2020 and increased to 1.41% in 2023. This fluctuation indicates a gradual urbanization trend, with a total increase of 0.29% since 2015. **Farmlands** increased from 30.98% in 2015 to 34.17% in 2020, it decreased to 31.50% in 2023, resulting in a net increase of 0.52% since 2015. This was due to changes in agricultural activities and potential land conversion. **Forestlands** increased from 6.83% in 2015 to 11.37% in 2023, with a total increase of 4.54%, due to successful reforestation and conservation efforts. **Grasslands** increased from 49.66% in 2015 to 52.43% in 2023, with a total increase of 2.77%, which is linked to a reduction in agricultural pressure. **Open waters** decreased from 1.24% in 2015 to 0.18% in 2023, with a total decrease of 1.06%, suggesting water conversion or climate change effects.

**Table 1: Land Cover Area per Hectare and Percentage (%) Change**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Land cover | Area (Ha) | % 2015 | Area (Ha) | % 2020 | Area (Ha) | % 2023 |
| Bare-land | 246677.5 | 10.17% | 107746.7 | 4.44% | 75475.66 | 3.11% |
| Built-up/other | 27048.07 | 1.12% | 26190.68 | 1.08% | 34225.7 | 1.41% |
| Farmland | 751223.9 | 30.98% | 828480.6 | 34.17% | 763771.9 | 31.50% |
| Forest | 165602.2 | 6.83% | 238494.6 | 9.84% | 275587.3 | 11.37% |
| Grassland | 1204176 | 49.66% | 1218805 | 50.26% | 1271276 | 52.43% |
| Open-waters | 30046.26 | 1.24% | 5055.926 | 0.21% | 4437.723 | 0.18% |

**4.2 Gross Percentage Change in LULC Classes from 2015 to 2023.**

The overall changes in the basin’s area coverage, vary by land use/land cover (LULC) class (Figure 5). Grasslands indicated the largest increase in area, followed by farmlands and forestlands, whereas open water and built-up have the smallest area coverage. Figure 5 illustrates variations in multiple land cover categories, indicating where specific land use types have expanded or contracted between 2015 and 2023. Notably, the 31.5% decline in forest areas in 2023 compared to the increases in 2015 and 2020, due to changes in land cover may signal environmental issues like deforestation.



**Figure 5:** Gross Percentage Change in LULC of the River Basin.

**4.3 Classification Accuracy**

The overall classification accuracy was 77.5%, showing a good level of accuracy and reliability in differentiating various land cover types in the basin (Table 2). A Kappa value of 72.3% indicated substantial agreement, showing that the model's performance is significantly better than random classification. The land cover indicates 24 True positive grasslands, with 1being misclassified as Forest, 3 as Farmlands, and 2 as Bare-lands (high accuracy, 24/31 correctly identified). **Forest** showed 23 true positives, with 1 misclassified as Farmlands (high precision). **Farmlands** indicated 18 true positives, with 6 misclassified as Grasslands and 1 as Forest (accurate most of the time despite some confusion). **Open-Waters** showed perfect classification with all 12 instances correctly identified (high effectiveness). **Barelands** had 8 true positives, with 5 misclassified as Grasslands, 1 as Farmlands, and 1 as Built-up (the majority correctly identified despite some confusion). **Built-up** had 15 true positives, with 6 misclassified as Grasslands and 2 as Bare-lands (the majority correctly identified despite some confusion) as depicted in Table 2.

**Table 2: Accuracy Confusion Table**

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Class** | **Cover** | Class | 1 | 2 | 3 | 4 | 5 | 6 | Total |
| 1 | Grasslands | 1 | **24** | 1 | 3 | 0 | 0 | 2 | 31 |
| 2 | Forest | 2 | 0 | **23** | 1 | 0 | 0 | 0 | 24 |
| 3 | Farmlands | 3 | 6 | 1 | **18** | 0 | 0 | 0 | 19 |
| 4 | Open Water | 4 | 0 | 0 | 0 | **12** | 0 | 0 | 12 |
| 5 | Bare-lands | 5 | 5 | 0 | 1 | 0 | **8** | 1 | 14 |
| 6 | Built-up | 6 | 6 | 0 | 0 | 0 | 2 | **15** | 16 |
| **Total** |  |  | 41 | 25 | 23 | 12 | 10 | 18 | **100** |
|  | Overall Class Accuracy |  |  |  |  |  |  |  | 77.5% |
| Kappa Coefficient Test |  |  |  |  |  |  |  | 72.3% |

**4.4 Change Detection Analysis from 2015 Base Year to 2020 and 2023**

The findings on change detection analysis for 2020, in Table 3, depict bare land areas accounting for a significant 8.45% of transitions to farmland and grassland, indicating that growing vegetation or agriculture occupied previously underutilized or less fertile land. However, only a small amount was converted to grassland. The results for built-up were relatively stable as depicted in Table 3, suggesting minimal urban sprawl, though some conversions involved natural or semi-natural land cover. Table 3 also depicts that while farmland remained stable, 3.19% was reforested and part was converted back to grassland. Additionally, 1.34% was converted to farmland between these periods. The data in Table 3 demonstrated that forestlands were generally well-maintained, indicating a shift in land use priorities. The results for grasslands indicate significant stability; however, 10.35% of the area was converted to farmland, reflecting ongoing agricultural activity (Table 3). The 2.44% conversion to bare ground may signal land clearing or deterioration. Open-water areas declined dramatically, with some areas transitioning to forest (0.35%) and farmland (0.46%), showing the potential impact of climate change.

**Table 3: Change Detection Matrix for 2015 and 2020**

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  | **2020** | | | | | | |
| LULC Type | Bare-lands | Built-up | Farmlands | Forests | Grasslands | Open waters |
|  | Area in % | Area in % | Area in % | Area in % | Area in % | Area in % |
| 2015 | Bare-lands | 1.33 | 0.08 | 4.37 | 0.31 | 4.06 | 0.009 |
| Built-up | 0.12 | 0.36 | 0.03 | 0.001 | 0.58 | 0.008 |
| Farmlands | 0.51 | 0.07 | 17.60 | 3.12 | 9.63 | 0.031 |
| Forest | 0.003 | 0.007 | 1.34 | 5.24 | 0.22 | 0.004 |
| Grasslands | 2.44 | 0.53 | 10.35 | 0.79 | 35.50 | 0.036 |
| Open-waters | 0.02 | 0.017 | 0.46 | 0.35 | 0.26 | 0.119 |
|  | **Grand Total** | **4.423** | **1.064** | **34.152** | **9.811** | **50.25** | **0.486** |

Change detection depicted in Table 4 indicates that in 2023, land use intensification and grassland regeneration, had a substantial percentage of bare lands from 2015 shifting to other land cover types, primarily farming (3.90%) and grassland (4.61%). The table also reveals that some land uses have been reclassified or resettled, due to shifts from the built-up category to grassland (0.66%) and bare land (0.13%). The Farmlands category remains largely stable, with noticeable shifts to grasslands (9.61%) and forests (3.86%), suggesting either land abandonment or reforestation activities. Findings show that forestlands were largely constant, with only a small percentage (1.13%) converted to farmlands (Table 4). Land conversion predominantly transformed areas into farmland (9.18%) and forests (1.33%), while grasslands experienced minimal change. This pattern reflects a balance between land use conversion and preservation. Data in Table 4 depict a notable decrease in open waters, with most of the land changing to grassland (0.28%) and forestland (0.45%). This suggests that water bodies are drying up or experiencing altered hydrological conditions due to climate change. The significant declines in open water, with a sizable portion shifting to other LULC types such as forest and grassland, are primarily caused by natural processes affecting water bodies and flora in the Athi River Basin.

**Table 4: Change Detection Matrix for 2015 and 2023**

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  | **2023** | | | | | | |
| LULC Type | Bare-land | Built-up | Farmland | Forest | Grassland | Open-water |
|  | Area in % | Area in % | Area in % | Area in % | Area in % | Area in % |
| **2015** | Bare-land | 1.15 | 0.11 | 3.90 | 0.36 | 4.61 | 0.013 |
| Built-up | 0.13 | 0.27 | 0.02 | 0.012 | 0.66 | 0.002 |
| Farmland | 0.35 | 0.11 | 16.99 | 3.86 | 9.61 | 0.028 |
| Forest | 0.003 | 0.007 | 1.13 | 5.32 | 0.003 | 0.007 |
| Grassland | 1.46 | 0.74 | 9.18 | 1.33 | 36.89 | 0.045 |
| Open-water | 0.004 | 0.15 | 0.25 | 0.45 | 0.28 | 0.084 |
|  | **Grand Total** | **3.097** | **1.387** | **31.47** | **11.362** | **52.053** | **0.179** |

**4.5 Spatial Analysis of LULC Trends on Water Quality of the Athi River Basin.**

A Pearson product-moment correlation coefficient assessed the relationships between water quality and spatial land use/land cover alterations as presented in Table 2.

Table 5: Pearson Correlation Matrix of Water Quality

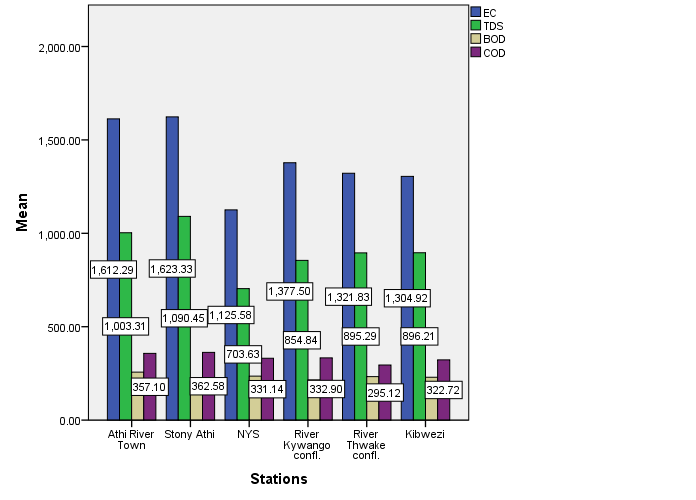
|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | pH | EC | TDS | NO3 | K | PO4 | BOD5 | COD | Cd | Cr |
| pH | 1 |  |  |  |  |  |  |  |  |  |
| EC | 0.67\*\* | 1 |  |  |  |  |  |  |  |  |
| TDS | 0.61\*\* | 0.93\*\* | 1 |  |  |  |  |  |  |  |
| NO3 | 0.61\*\* | 0.75\*\* | 0.65\*\* | 1 |  |  |  |  |  |  |
| K | 0.38\*\* | 0.62\*\* | 0.55\*\* | 0.63\*\* | 1 |  |  |  |  |  |
| PO4 | 0.43\*\* | 0.67\*\* | 0.57\*\* | 0.71\*\* | 0.74\*\* | 1 |  |  |  |  |
| BOD5 | 0.55\*\* | 0.78\*\* | 0.73\*\* | 0.63\*\* | 0.48\*\* | 0.54\*\* | 1 |  |  |  |
| COD | 0.65\*\* | 0.82\*\* | 0.73\*\* | 0.67\*\* | 0.51\*\* | 0.59\*\* | 0.91\*\* | 1 |  |  |
| Cd | 0.10 | 0.26\*\* | 0.23\*\* | 0.24\*\* | 0.52\*\* | 0.35\*\* | 0.32\*\* | 0.36\*\* | 1 |  |
| Cr | 0.29\*\* | 0.47\*\* | 0.35\*\* | 0.51\*\* | 0.54\*\* | 0.45\*\* | 0.28\*\* | 0.36\*\* | 0.35\*\* | 1 |

# **4.5.1 Built-Up Areas and Urbanization**

Urban and semi-urban areas, at the Athi River Town, Stony Athi, and NYS sampling stations, exhibit elevated levels of EC and TDS, due to reduced runoff. The influence of built-up areas due to urban expansion also contributes to increased cadmium (Cd) and chromium (Cr) levels, the NYS sampling station exhibits higher cadmium levels as shown in Figure 8.

# **4.5.2 Decrease in Openwater Areas**

Reduced open-water areas are correlated with higher concentrations of pollutants such as TDS, EC, BOD, and COD, as indicated by the correlation analysis (Table 5). The decline in open water reflects the concentrations of these pollutants across the sampling stations.



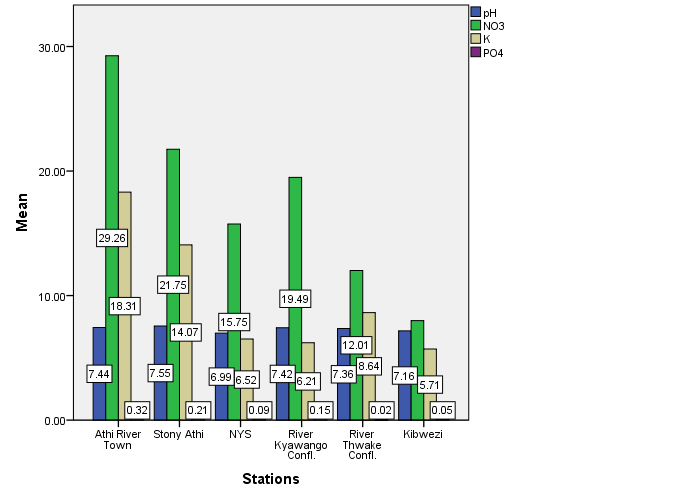
**Figure 6:** Spatial LULC Difference on Physicochemical Water Quality in Athi River Basin

# **4.5.3 Bare-Lands and Sediment Runoff**

A decline in bare-land areas within the basin likely contributes to decreased sediment runoff. This reduction in runoff may account for the relatively stable Total Dissolved Solids (TDS) levels (range from 1125.5 to 1623.3 dS/m) in recent years (Figure 6).

**4.5.4 Farmlands and Agricultural Expansion**

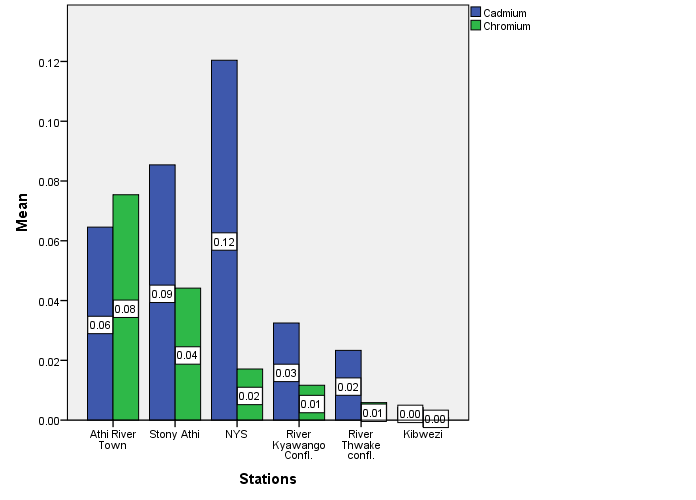
Athi River Town, Stony Athi, and River Kyawango Confluence sampling stations exhibit higher levels of NO₃, K, and PO₄, than NYS, River Thwake, and Kibwezi Bridge sampling stations (Figure 6). These higher concentrations are closely linked to nutrient release from agricultural waste into the stagnated water and low-flow water at Athi River Town and Stony Athi areas, as well as the River kyawango confluence station during the dry season (Figure 7).



**Figure 7:** Spatial LULC Differences on Physicochemical Water Quality in Athi River Basin.

**4.5.5 Grasslands and Forests**

River Thwake Confluence and Kibwezi contain extensive grassland areas with relatively lower levels of BOD, TDS, Cd, and Cr pollutants(Figures 6 & 8). Higher levels of Cadmium concentrations were found at the NYS sampling station and declined at Stony Athi, and Athi River Town stations. Chromium levels increase at Athi River Town with decreasing levels as the river flow progresses downstream to Kibwazi Bridge (Figure 8).



**Figure 8:** Spatial LULC Differences on Water Quality in Athi River Basin

**4.6 Interview Survey on Land Use Drivers of Change**

The study utilized open-ended interviews to investigate the sources and drivers of land use changes within the Athi River basin. The interviews were conducted within a range extending from the river bank to 10 kilometers away. Table 6 outlines various activities occurring within the river basin, including industry, agriculture, climatic factors, settlements, and commercial activities. Additionally, the study identifies non-point sources like urban and agricultural runoff, seasonal circle, commercial release, and Waste disposal. Residents around the six sampling stations, Athi River Town (S1), Stony Athi (S2), NYS (S3), River Kyawango confluence (S4), River Thwake confluence (S5), and Kibwezi (S6) were assigned twenty interview questions each.

**Table 6: Interview Result on Sources of Water Pollution of the Athi River Basin.**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Number of People Targeted and Interviewed** | | | | |
| S.S | No. of Target | No. of Respondents | Number of Factors | Number of listed Drivers |
| S1 | 20 | 20 | Industry, agriculture, commercial, settlement, and climatic factors. | 5 |
| S2 | 20 | 17 | Industry, agriculture, commercial, settlement, and climatic factors. | 5 |
| S3 | 20 | 13 | Agriculture, settlement, commercial, and climatic factors. | 4 |
| S4 | 20 | 8 | Agriculture, sand harvesting, settlement, and climatic factors. | 4 |
| S5 | 20 | 3 | Sand harvesting, agriculture, and climate | 3 |
| S6 | 20 | 9 | Agriculture, climatic factors, commercial, settlement, and runoff | 5 |
| **Total** | **120** | **70** |  | **27** |

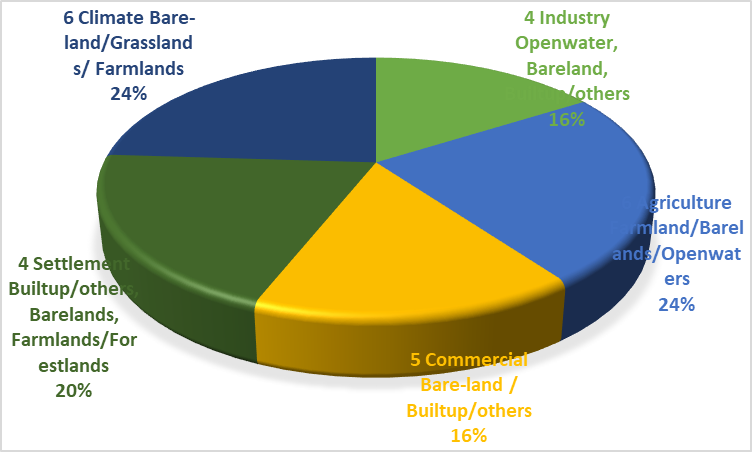
Figure 9, depicted 20 respondents and 5 drivers of change listed at the Athi River Town (S1) sampling station, 17 respondents and 5 drivers at the Stony Athi (S2) sampling station, 13 respondents and 4 drivers at the NYS (S3) sampling station, 9 respondents and 5 drivers of change at the Kibwezi (S6) sampling station, 8 respondents and 4 drivers at the River Kyawango (S4) sampling station, and 3 respondents and 3 drivers of change at the River Thwake Confluence (S5) sampling station.

**Figure 9:** Respondents and Drivers of Change on Water Quality

**Table 7: Comparative Studies on Community Perception on Factors Influencing Water Quality of the Athi River Basin**

|  |  |  |
| --- | --- | --- |
| **S/N** | **Natural & Anthropogenic Factors** | **Land Cover Categories** |
| 1 | **Industry:** Wastewater treatment plant, cement particles, Sand harvesting, solid waste, plants, and sewage | Open-waters (WWTP) /  bare lands, built-up/others |
| 2 | **Settlement:** population/lifestyle, wastewater, washing & bathing, landscape, plants, waste dumpsites. | Built-up/others, bare lands, farmlands, and forest lands |
| 3 | **Agriculture:** irrigation, walking animals, fishing, wastewaters, biological waste, sewages, runoff, and stone burning. | Farmlands, bare lands, and open-waters |
| 4 | **Climate**: temperature, seasonality (dry and rainfall), and atmospheric deposition. | Bare-lands, grasslands, and farmlands |
| 5 | **Commercial:** Road network, Stages, and Vehicular release of CO2, NO2, CO, and SO4 | Bare-lands, built-up/others |

Five sources of change alongside the percentage classification of land cover associated with each are illustrated in Figure 10. A detailed examination reveals that, based on their sources and percentage within the basin, the five drivers of water quality degradation and land cover categories reported frequencies of four for industry, six for agriculture, six for commercial, five for settlement, and six for climate across six land cover categories. The results indicate that while industrial and commercial activities have some minor or less noticeable effects on the decline in the river water quality, climatic factors such as rainfall-runoff, agriculture, and settlement are the primary drivers.



**Figure 10:** Drivers of Change and Related Land Cover Classification in Percentages.

The findings on land use land cover (LULC) studies in the Athi River Basin,as depicted in Figures 2, 3, and 4, as well as Table 3 & 4, demonstrate changes in land cover over time, from 2015 to 2023.

Built-up category remained relatively stable between 2015 and 2020, with overall increase of 0.29% from 2015 to 2023, highlighting a gradual trend of urbanization and infrastructure development in the area (Table 1). This trend is consistent with global research on urban sprawl driven by economic growth and population expansion (Chen *et al*., 2014). However, the observation made by Kithiia (2021) indicated an increase in built-up, due to ongoing infrastructure development, in response to population growth and economic demands. Athi basin only depends on baseflow with changes in flooding during rainfall, which might affect buildup lands near the riparian zones.

The Barelands category indicated a substantial reduction from 10.17% in 2015 to 3.11% in 2023, with an overall decrease of 7.06%, suggesting that some portions of Barelands have been substituted for other land uses. This could be due to agricultural expansion, reforestation, and urbanization activities. A similar finding in a study conducted by Mbayaki (2015) on land use changes in Mumias District, Kenya, demonstrated a significant decrease in barelands, due to an increase in population, infrastructure development, and changes in agricultural practices. Studies also emphasized the importance of sustainable land management techniques, such as conservation agriculture and integrated soil-crop system management, to maximize land use and minimize environmental degradation (Ismail *et al*., 2016). These findings are essential in preventing land degradation, restoring soil health, and promoting sustainable agricultural productivity (Gaikwad *et al*., 2023).

The Farmlands category expanded by 3.19% between 2015 and 2020, indicating an increase in agricultural activities (Table 1). Farmlands had a net increase of 0.52% from 2015 to 2023, due to temporary agricultural expansion and land abandonment or conversion to other land uses (Table 1). JICA (2012) found that decline in farmlands could be cause by an increase in grasslands, reforestation or builtup (urban development). This finding correspond to a report by FAO (2020), that agriculture influences land use changes in a river basin, highlighting how agricultural land expanded by 3.2% from 2015 to 2020, due to an increase in agricultural activities, declined by 2.5%, leading to a net increase. In addition, Tilman et al. (2002), identified a dynamic balance between agricultural expansion and conversion to other land uses, including natural grasslands, due to conservation efforts.

Forestlands category increased progressively from 6.83% in 2015 to 11.37% in 2023, representing an overall gain of 4.54% for 8 years as depicted in Figure 2, 3, & 4. This growth suggests successful reforestation and conservation programs in the Country and individual aesthetic or commercial land reforestations and natural forest regrowth in the basin (Table 1, 3, & 4). Similar to this finding is a study by Kenya Forest Service (KFS) which projected an increase in forest from 6.9% in 2015 to 10% in 2022 due to successful reforestation and conservation programs (Juma & Atieno, 2021). These positive trends are crucial for mitigating climate change impacts, enhancing biodiversity, and supporting ecosystem services (Jwaideh *et al*., 2022).

The grasslands category indicated a significant growth between 2015 and 2023, showing a 2.77% increase, with geometric expansion from 49.66% to 52.43% within the study area (Table1, 3, & 4). This increase in grasslands indicates a decrease in agricultural pressure within the river basin, likely due to changes in land use regulations, low yields, and lack of capital investment. Similar findings showed that grasslands increases due to restoration efforts and sustainable management practices, which suggests a reduction in agricultural pressure (IUCN, 2024). According to Pretty (2003), the growth of grasslands indicates biodiversity protection, as grasslands are crucial for preserving ecological balance and providing habitats for various species. In addition, Jafarabadi et al. (2018) noted that trends in grasslands help preserve soil health and minimize erosion. This increase could also be attributed to successful conservation efforts and sustainable land management practices aimed at reducing agricultural expansion and promoting natural habitats.

The open-waters category experienced a significant decline, dropping by 1.06% from 1.24% in 2015 to 0.18% in 2023 (Table 1, 3, & 4). This decline, especially in surface water, can be attributed to urbanization and the effects of climate change. These findings were supported by the findings made by NASA (2024), that the average amount of freshwater stored on land such as rivers, lakes, and aquifers has decreased drastically between 2015 and 2023 compared to previous years. This phenomenon is attributed to a severe drought, exacerbated by climate change and global warming causing surface water deficits and an increase in groundwater reliance. The decline in open-water areas not only affects water availability but also has broader implications for ecosystem health and sustainability. Despite the base flow of the Athi River Basin, the decline in open-water bodies is at increase. This trend could negatively affect groundwater recharge, aquatic habitats, food production, and the overall health of the river basin ecosystem. This phenomenon was supported by Kitheka (2019) and Rodell et al. (2024) that the loss of open waters in the basin may have detrimental impacts on local ecosystems, biodiversity, and groundwater recharge and supply.

The influence of spatial land use land cover (LULC) differences across the study stations demonstrate anthropogenic and natural factors shaping the basin. Urbanization induced a significant rise in built-up areas, which increased the concentrations of Cr, Cd, TDS, and EC (Figures 6 & 8). This increase is attributed to stormwater runoff carrying pollutants from commercial, industrial, and residential sources, impermeable surfaces, and industrial emissions from the upper mid-reaches and commercial areas in the basin. The sampling stations at Athi River Town, Stony Athi, and NYS, were situated within these built-up or urban and semi-urban areas. In contrast, the more pronounced swings seen in rural areas and urban activities buffer pH variations. These findings are similar to Waturu et al. (2023) who found that an increase in industrial and urban expansions induced encroachments and destructions of wetlands and riparian ecosystems including degradations of water quality of the Athi River Basin. Urbanization increases nutrient and organic pollution, according to correlations between built-up lands and parameters like NO₃ (0.75), PO₄ (0.67), and BOD (0.78). This align with the study by Maris et al. (2025), who observed a strong positive relationship between built-up areas and water quality parameters. Similar results were reported by Rahman et al. (2014), where residential land use positively correlated with TDS. Research by Huang et al. (2022) and Ling et al. (2017), highlights how urbanization increases the levels of organic matter, heavy metals, and pollutants in water bodies. Additionally, higher levels of Cd and Cr in these populated areas also suggest that stormwater runoff and industrial operations are contributing factors (Figure 8). Rainfall worsens the problem by flushing accumulated pollutants into the river, aggravating downstream pollution. During periods of high rainfall, the Mbagathi River, a tributary of the Athi River, plays a crucial role in carrying these pollutants, impacting downstream communities, including those near the National Youth Service (NYS) headquarters sampling station, before emptying into the Indian Ocean. These findings are similar to international research on urban river pollution, highlighting the impact of untreated wastewater and the damage rapid urbanization causes to river ecosystems (Omer, 2019).

The reduction in open-water areas leads to increased TDS, BOD, and COD levels, which restricts water diluting capacity, especially during the dry season (Figure 6). Open waters negatively correlated with EC (-0.93), TDS (-0.93), and BOD (-0.96), indicating that reduced open water due to climate change and drought enhances pollutant dilution and decreases organic pollution in the basin (Table 5). Widodo (2013) concluded that water distribution and mixing in open systems contribute to pollution dispersion and purification. Extreme rainfall and flooding increased Cd (0.97) and Cr (0.93) levels through soil erosion (Table 5). This finding align with the studies conducted by Ezemokwe & Ezigbo (2016), who found that soil erosion during intense rainfall transports heavy metals into water bodies. However, land cover change not only influences water quality but also interacts with urbanization which further destroys hydrological processes. However, decrease in open water across the sampling stations suggests low recharge and discharge of groundwater reservoir and aquifer decline during the dry season. This finding is similar to work done by Wang et al.(2020) who found that decrease in water level in the reservoir degrades water quality, leading to increasing pollutants such as Ammonia Nitrogen (NH3-N), Permanganate index, and total Nitrogen. It is similar to the findings by Ling et al. (2017), who documented comparable impacts in the Batang Rajang River. Decreased open-water areas make aquatic ecosystems more susceptible to contamination.

In the Bare-land areas, the decrease influence the reduction in sediment runoff, which may help maintain reasonable stable TDS and EC levels. However, barelands positively correlate with TDS (0.61), indicating that they contribute sediments during rainy or dry seasons (Table 5). This finding aligns with Gyimah et al. (2020), who noted that barelands contribute to increased concentrations of conductivity elements, total suspended solids (TSS), and turbidity due to the absence of vegetation cover. Ndugga (2021) conducted a similar study on a stream catchment in Uganda and observed a negative correlation, which can be attributed to factors such as increased runoff, erosion, lack of filtration, nutrient leaching, and temperature changes. The study highlights that bare lands, due to their lack of vegetation, contribute to higher runoff and erosion. Ling et al. (2017) discovered that exposed soil significantly contributes to greater dissolved solids during erosive rainstorm events. This observation underscores the link between exposed soil and increased dissolved solids in the river. The association between barelands and TDS (0.61) further supports this conclusion (Table 5). It is evident from these studies that the presence of bare lands, resulting from insufficient vegetation, plays a crucial role in exacerbating runoff and erosion. Consequently, this leads to elevated levels of dissolved solids in water bodies, particularly during heavy rainfall. The findings emphasize the need for effective land management practices to mitigate these impacts and preserve the health of river ecosystems.

Farmlands in the basin are dominated by agricultural activities, which contribute to high levels of phosphates (PO₄) and nitrates (NO₃) through nutrient loading and fertilizer runoff. Farmlands exhibited strong positive correlations with pH (0.93), NO3 (0.93), PO4 (0.93), and Cd (0.70), reflecting an increase in nutrient loads due to agricultural expansion (Table 5). This corresponds with Guerra (2022), who concluded that fertilizers and lime application in farmlands increase pH by altering water chemistry. Agricultural runoff also elevates nitrate and phosphate concentrations in water systems, as supported by Egbueri (2019). Intensive agricultural practices induce stream water quality due to correlation with nutrients (NO3 and PO4) (Crooks *et al*., 2021). The Athi River Town, Stony Athi, NYS, and River Kyawango Confluence sampling stations observed higher nutrient levels, particularly, farmlands in the River Kyawnago area are evidence of nutrient contaminants. In River Kyawango, the river water is widely used for domestic activities like washing, bathing, and drinking, it also supports extensive irrigation practices. Large farmlands, such as French bean farms near Mwala, rely heavily on the river's water resources, highlighting the river’s economic importance for local agriculture. Additionally, during the dry season, communities in nearby sub-counties like Kaaoni, Kamuthakya, Wamuyu, and Katangi engage in fishing and sand harvesting at various points along the river, emphasizing the dependence of local livelihoods on the river’s resources. Sand harvesting and frequent use of the river disrupt aquatic habitats and degrade water quality, mainly in areas where agricultural runoff accumulates during periods of heavy rainfall. The high levels of nitrate at Athi River and Stony Athi sampling stations reflect the release of agricultural byproducts by farmers and local industries or direct discharges. Peripheral et al. (2020) have highlighted how high nutrient levels worsen eutrophication, decreasing oxygen availability and lowering water quality. Although a small decline in farming from 31% in 2020 to 30.5% in 2023 would reduce nutrient pollution, these gains might be undone by the shift to urban areas (Tables 3 & 4). This dynamic implies that sustainable land use strategies are necessary to strike a balance between protecting water quality and agricultural productivity. These studies have consistently shown that agricultural activities within the river basin, including irrigation, fertilizers and pesticide applications, and livestock farming, contribute significantly to Athi River water pollution.

Grassland as a natural filter, covers up to 52.43% of the basin in 2023, reduces runoff velocities, traps sediments, and buffers pollutants (Table 4). These areas have a crucial role in reducing both organic and inorganic pollution, as evidenced by their negative connection with BOD and TDS. Grasslands showed moderate to strong positive correlations with EC (0.91) and TDS (0.95), highlighting their role in increasing dissolved solid concentrations (Table 5). Pragasan et al. (2024) observed that grasslands deposit nutrients and organic matter into water bodies, increasing EC and TDS levels. Sirimarco et al. (2017) reported that grasslands influence water retention and filtration, affecting the chemical composition of water, including EC and TDS levels. However, the effectiveness of grasslands in enhancing water quality is supported by sampling stations close to grasslands, such as River Thwake and Kibwezi Bridge, which exhibit relatively lower pollution levels. The importance of grasslands in improving sediment control, decreasing erosion, and stabilizing soil is also highlighted by Ling et al. (2017). These grasslands are essential for preserving water quality since without them, the basin's TDS and other pollutant levels would probably be greater. Grasslands cover roughly 30% of the planet’s terrestrial landscape, contributing to a variety of essential ecosystem services (Editorial Team, 2022). However, the riverbed at these sampling stations acts as a filtration medium rather than a complete decontaminant, as residents consume the water, this process is insufficient to eliminate all toxins.

Forestlands faced deforestation and soil erosion, which exacerbate the presence of heavy metals such as Cd and Cr in the water (Figure 8). Forestlands filter pollutants and control sediment and nutrient runoff, among other vital ecosystem services, despite their restricted size. Similar to a review by Kumar (2022) who concluded that the removal of forestlands destabilizes soil, which causes erosion, heavy metals, and sedimentation. Given the inverse correlations with BOD (-0.48), TDS (-0.61), EC (-0.67), and COD (-0.51), a minor increase in wooded areas is associated with improved water quality (Table 5 & Figure 6). These results support research by Omer (2019) and Ling et al. (2017), which highlight the importance of forest conservation as a tactic or strategy for improving water quality. The findings by Forestry (2024) also support the idea that forests act as natural filters, trapping sediments, nutrients, and pollutants from runoff before they reach the aquatic environment. The proximity to forested areas, which have lower nutrient and sediment loads, is advantageous for sampling stations farther away from urban and agricultural effects, such as River Thwake, Kibwezi Bridge, and part of the River Kyawango confluence. Residents at these stations particularly the Kibwezi Bridge, utilize shallow ditches dug on sand dunes for collection of filtered water, often aided by donkeys, which inadvertently deposit waste into the river and nearby collection points. Fischer (2024), discussed how forests naturally filter water through vegetation, soil, and organic matter, which helps in removing pollutants and managing water flow. The dense vegetation and forest floor litter capture particles and chemicals, preventing them from entering water.

The Interview Survey and the impacts of land use change on water quality highlighted various relationships between LULC categories and water quality pollution, considering factors such as climate, agriculture, human settlement, industry, and commercial activities. Climate influences Grasslands and Farmlands. Increased runoff can lead to soil erosion, transforming forest and grassland areas into barelands, while more rainfall might enhance agricultural productivity, expanding farmlands. Rainfall variability is a key driver of land cover changes, especially in regions dominated by agriculture and natural vegetation [Omondi *et al*., 2019). Agriculture affects Forestlands and Open-waters. The expansion of Farmlands can lead to deforestation as more land is cleared for cultivation. Irrigation practices might pollute Open-waters. Gibbs et al.(2010) noted that agricultural activities contribute to deforestation and land cover change, as more land is converted for cultivation to meet growing food demands.

Settlement impacts Barelands, Farmlands, and Grasslands due to urban sprawl and dispersed settlements. Urban expansion driven by settlement growth transforms natural landscapes into built-up areas UN-Habitat, 2016). Industry affects Built-up/other areas and Water, reflecting minimal changes observed in built-up areas and water treatment plants due to industrial activities in the area. Commercial activities impact Built-up/other areas, leading to the expansion of stages or motor parks that release dispersed waste pollutants, including hydrocarbons and carbon monoxide.

However, further studies should be conducted on rainfall variability, temperature changes, and extreme weather events that influence land cover changes (agriculture and natural vegetation areas). Secondly, Study on temporal LULC trend on water quality of the Athi River Basin using Land use policy should be conducted for 30 years period. Thirdly, an assessment of urban expansion and infrastructure development in riparian areas on water quality, flood patterns, and water retention in the Athi River Basin, is should be conducted to understand how impermeable surfaces contribute to increased runoff and pollution of the river.

**6 CONCLUSION**

The study on LULC changes in the Athi River Basin from 2015 to 2023, spatial LULC differences, and interview surveys indicates significant transformations in land cover, propelled by anthropogenic and natural factors. The studies identified similar drivers influencing water quality of the Athi River Basin. The upper mid reaches namely Athi River Town and Stony Athi sampling stations are the most sources of pollution with river Kyawango station generating nutrient loads in the basin. The studies show higher concentrations of NO3, PO4, BOD, COD, Cd, TDS, and Cr pollutants attributed to runoff from agriculture, urbanization, open water reduction, and high population. These findings call for an urgent response to mitigate water resource deficits and control pollution in the river basin. Therefore, we recommend climate change adaptation strategies to address water resource depletion, climate change variability, and their impacts on land use and water quality in the basin.

**Disclaimer (Artificial intelligence)**

Option 1:

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of this manuscript.

Option 2:

Author(s) hereby declare that generative AI technologies such as Large Language Models, etc. have been used during the writing or editing of manuscripts. This explanation will include the name, version, model, and source of the generative AI technology as well as all input prompts provided to the generative AI technology.

Details of the AI usage are given below:

1. There is no use of Large Language Models, etc. in this manuscript.

2.

3.

**10 REFERENCE**

Banko, G. (1998). A review of assessing the accuracy of classifications of remotely sensed data and methods including remote sensing data in forest inventory. *Interim Report IR-98–081/November 1998*.

Chepkorir, J. K., Ogendi, G. M., M'erimba, C. M., & Maina, G. M. (2021). Spatial and temporal variations in land use and land cover in the Njoro and Kamweti river catchments, Kenya. *East African Journal of Science, Technology and Innovation, 2*(3), 1-16.

Chen, M., Zhang, H., Liu, W., & Zhang, W. (2014). The global pattern of urbanization and economic growth: Evidence from the last three decades. *PLoS ONE, 9*(8), e103799. <https://doi.org/10.1371/journal.pone.0103799>.

Crooks, E. C., Harris, I. M., & Patil, S. D. (2021). Influence of land use land cover on river water quality in rural North Wales, UK. *Journal of the American Water Resources Association, 57*(3), 357-373.

Derwan, A.M., & Yamaguchi, Y. (2009). Land use and land cover change in Greater Dhaka, Bangladesh: Using remote sensing to promote sustainable urbanization. *Applied Geography, 29*, 390-401.

Eastman, J. R. (2003). *Guide to GIS and image processing* (14th ed.). Clark University Manual, USA.

Editorial Team. (2022, April 12). Nature-based benefits in focus: Protecting grasslands reduces soil erosion and improves water quality. *The Climate Trust*. Retrieved from The Climate Trust website: <https://www.climatetrust.org>.

Egbueri, J. C. (2019). Water quality appraisal of selected farm provinces using integrated hydrogeochemical, multivariate statistical, and microbiological techniques. *Modeling Earth Systems and Environment, 5*(4), 997–1013.

Elmore, A. J., Mustard, J. F., Manning, S. J., & Lobell, D. B. (2000). Quantifying vegetation change in semiarid environments. *Remote Sensing of Environment, 73*(1), 87–102.

zemokwe, D.E., & Ezigbo, J.I. (2016). Heavy Metal Contamination in Soils around Onyeama and Okpara Coal Mines in Enugu, Southeastern Nigeria. IOSR Journal of Environmental Science, Toxicology and Food Technology, 10(1), 1-8.

Fischer, R. (2024). The role of forest ecosystems in regulating hydrological cycles and water quality. *Opinion Journal of Biodiversity, Bioprospecting and Development, 10*(3). Department of Ecological Modelling, University of Osnabrück, Osnabrück, Germany.

Food and Agriculture Organization of the United Nations. (2020).World food and agriculture: Statistical yearbook. 2020; Retrieved from http://www.fao.org/publications/yearbook

Foody, G. M. (2002). Status of land cover classification accuracy assessment. *Remote Sensing of Environment, 80*(1), 185-201.

Forestry. (2024, August 15). Forest ecosystem services: Carbon sequestration, water filtration, and more. Forestry.

Gaikwad, A. S., Margal, P. B., & Titirmare, N. S. (2023). Soil degradation and remediation: Strategies for restoring soil quality. In S. A. Chaware et al. (Eds.). *Advances in soil science, 1*(16), 349–390.

Gibbs, M. M. (2000). Nitrate contamination in freshwater systems: Sources, effects, and management. *Science of the Total Environment, 246*(2-3), 127-136.

Government of Kenya (GoK). (2012). *Vision 2030: Development strategy for Northern Kenya and other arid lands*. 114 p.

Guerra Tamara, B., Torregroza-Espinosa, A. C., Pinto Osorio, D., Moreno Pallares, M., Corrales Paternina, A., & Echeverría González, A. (2022). Implications of irrigation water quality in tropical farms. *Global Journal of Environmental Science and Management, 8*(1), 75–86.

Gyimah, R. A. A., Karikari, A. Y., Gyamfi, C., Asantewaa-Tannor, P., & Anornu, G. K. (2020). Spatial evaluation of land use variability on water quality of the Densu Basin, Ghana. *Water Supply, 20*(8), 3000–3013.

He, H., Zhou, J., Wu, Y., Zhang, W., & Xie, X. (2008). Modeling the response of surface water quality to urbanization in Xi’an China. *Journal of Environmental Management, 86*, 731-749.

Huang, J., Zhan, J., Yan, H., Wu, F., & Deng, X. (2013). Evaluation of the impacts of land use on water quality: A case study in the Chaohu Lake Basin. *The Scientific World Journal, 329187*.

International Union for Conservation of Nature (IUCN). (2024, December 20). *Grasslands rising: Restoring vital ecosystems for a sustainable future*. Riyadh, Saudi Arabia.

Ismail, A., Toriman, M. E., Juahir, H., Md Zain, S., Abdul Habir, N. L., Retnam, A., Kamaruddin, M. K. A., Roslan Umar, R., & Azid, A. (2016). Spatial Assessment and Source Identification of Heavy Metals Pollution in Surface Water Using Several Chemometric Techniques. *Marine Pollution Bulletin, 107*(1), 292-300. https://doi.org/10.1016/j.marpolbul.2016.03.060.

Jafarabadi, A. R., Bakhtiari, A. R., Spano, N., & Cappelloc, T. (2018). First report of geochemical fraction distribution, bioavailability, and assessment of potentially toxic inorganic-elements in sediments of coral reef islands of Persian Gulf, Iran. *Marine Pollution Bulletin, 137*, 185-197.

JICA. (2012). The Development of the National Water Master Plan, 2030. Draft Report: Kenya. *Japan International Cooperation Agency*.2012.

Juma, A., & Atieno, S. (2021). Africa news, climate change, environment, top stories in Science Africa. *Science Africa*. Retrieved from [https://scienceafrica.co.ke/].

Jwaideh, M. A. A., Sutanudjaja, E. H., & Dalin, C. (2022). Global Impacts of Nitrogen and Phosphorus Fertilizer Use for Major Crops on Aquatic Biodiversity. *International Journal of Life Cycle Assessment, 27*, 1058-1080.

Kenya Wildlife Service. (2024). Fourteen Falls. Kenya Wildlife Service [Internet], [cited 2025 Mar 18].

Kitheka, J. U. (2019). Salinity and salt fluxes in a polluted tropical river: The case study of the Athi River in Kenya. *Journal of Hydrology: Regional Studies, 24*, 100614.

Kitheka, J. U., Kitheka, L. M., & Njogu, I. N. (2022). Suspended sediment transport in a tropical river basin exhibiting combinations of land uses/land covers and hydro-climatic conditions: A case study of Upper Athi Basin, Kenya. *Journal of Hydrology: Regional Studies, 38*, 100614.

Kithiia, S. M. (2006). *Effects of land-use types on the hydrology and water quality of the Upper-Athi River Basin, Kenya* (Unpublished PhD thesis). University of Nairobi, Kenya.

Kithiia, S. M. (2021). A critical analysis of the water quality impacts on water resources in the Athi River drainage basin, Kenya. *IntechOpen*.

Kumar, R., Kumar, A., Saikia, P. (2022). Deforestation and Forests Degradation Impacts on the Environment. In: Singh, V.P., Yadav, S., Yadav, K.K., Yadava, R.N. (eds) Environmental Degradation: Challenges and Strategies for Mitigation. *Water Science and Technology Library*,104. Springer, Cham.

Lacher, T.E., Davidson, A.D., Fleming, T.H., Gómez-Ruiz, E.P., McCracken, G.F., Owen-Smith, N., Peres, C.A., & Vander Wall, S.B. (2019). The functional roles of mammals in ecosystems. *Journal of Mammalogy, 100*, 942–964.

Ling, T.Y., Soo, C.-L., Phan, T.-P., Nyanti, L., Sim, S.-F., & Grinang, J. (2017). Assessment of water quality of Batang Rajang at Pelagus Area, Sarawak, Malaysia. *Sains Malaysiana, 46*(3), 401–411.

Lin, Y., Zhang, L., Wang, N., Zang, X., Cen, Y., & Sun, X. (2020). A change detection method using spatial-temporal-spectral information from Landsat images. *International Journal of Remote Sensing, 41*(2), 772-793.

Marisi, D. P., Suprihatin, S., Hariyadi, S., & Kaswanto, R. L. (2025). The impacts of land use and cover change on water quality of watershed basin. *Global Journal of Environmental Science and Management, 11*(2), 1–20.

Mateo-García, G., Gómez-Chova, L., Amorós-López, J., Muñoz-Marí, J., & Camps-Valls, G. (2018). Multitemporal cloud masking in the Google Earth Engine. *Remote Sensing, 10*(7), 7–9.

Mbayaki, H. (2015, December). *Assessment of land use land cover change and decline in sugarcane farming using GIS and remote sensing - A case study of Mumias District, Kenya* (Master's thesis). Dedan Kimathi University of Technology.

Meng, Y., Liu, X., Wu, L., Liu, M., Zhang, B., & Zhao, S. (2019). Spatio-temporal variation indicators for landscape structure dynamics monitoring using dense normalized difference vegetation index time series. *Ecological Indicators, 107*, 105607.

Meybeck, M. (2004). The global change of continental aquatic systems: Dominant impacts of human activities. *Water Science and Technology, 49*(7), 73-83.

Molekoa, M. D., Avtar, R., Kumar, P., Minh, H. V. T., Dasgupta, R., Johnson, B. A., Sahu, N., Verma, R. V., & Yunus, A. P. (2021). Spatiotemporal analysis of surface water quality in Mokopane area, Limpopo, South Africa. *Water, 13*, 220.

National Aeronautics and Space Administration. (2024). NASA satellites reveal an abrupt drop in global freshwater levels. NASA's Earth Science News Team. By James R. Riordon.

Ndugga, P. (2021). *Correlation between land use and stream water quality: A case study of Kinawataka stream catchment in Uganda* (Master's thesis). *Kyambogo University.*

Ngatia, M., Kithiia, S. M., & Voda, M. (2023). Effects of anthropogenic activities on water quality within Ngong River sub-catchment, Nairobi, Kenya. *Water, 15*(3), 660.

Nimi, G. D., Marc, J. M., & Andrew, P. C. (2018). Urban land-use dynamics in the Niger Delta: The case of Greater Port Harcourt Watershed. *Journal of Urban Science, 2*(1), 108.

Omer, N. H. (2019). Water quality parameters: Science, assessments, and policy. *IntechOpen Journal.* 1–18.

Omondi, O. C., Ndolo, I. J., Nyandega, A. I., & Cohen, A. (2019). Impact of rainfall variability on surface water resources in Homa Bay County, Kenya. *Journal of Sustainable Environment Peace, 1*(3), 84-89.

Ontumbi, G., Obando, J., & Ondieki, C. (2015). The influence of agricultural activities on the water quality of the River Sosiani in Uasin Gishu County. *International Journal of Research in Agricultural Science, 2*(1), 2348-3997.

Petropoulos, G. P., Kalivas, D. P., Georgopoulou, A., & Srivastava, P. K. (2015). Urban vegetation cover extraction from hyperspectral imagery and geographic information system spatial analysis techniques: Case of Athens, Greece. *Journal of Applied Remote Sensing, 9*(1), 096088.

Plourde, L., & Congalton, R. G. (2003). Sampling method and sample placement: How do they affect the accuracy of remotely sensed maps? *Photogrammetric Engineering & Remote Sensing, 69*(3), 289-297.

Pragasan, L. A., & Prasad, P. V. (2024). Assessment of soil carbon stock potential in different soil layers of grassland ecosystems. *Asian Journal of Research in Agriculture and Forestry, 10*(3), 129–138.

Pretty, J. (2003). Social capital and the collective management of resources. *Science, 302*(5652), 1912-1914. https://doi.org/10.1126/science.302.5652.1912.

Putri, R. J., Florensia, A. S., Asmara, A. A., Yulianto, A., & Brontowiyono, W. (2021). A spatiotemporal analysis of water quality and land use in Tambayakbayan River, Yogyakarta. *IOP Conference Series: Earth and Environmental Science, 933*(1), 012045.

Rahman, M. W., Purwanto, M. Y., & Suprihatin, S. (2014). Water quality status and land use conservation effort in the Upper Citarum Watershed, Bandung Regency. *Journal of Natural Resources and Environmental Management, 4*(1), 24–34.

Richards, J., & Jia, X. (2006). *Remote sensing digital image analysis: An introduction* (4th ed.). Springer.

Rodell, M., Barnoud, A., Robertson, F. R., Allan, R. P., Bellas-Manley, A., Bos-ilovich, M. G., Chambers, D., Landerer, F., Loomis, B., Nerem, R. S., O’Neill, M. M., Wiese, D., & Seneviratne, S. I. (2024). An abrupt decline in global terrestrial water storage and its relationship with sea level change. *Surveys in Geophysics, 45*, 1875–1902.

Rotich, B., & Ojwang, D. (2021). Trends and drivers of forest cover change in the Cherangany Hills forest ecosystem, Western Kenya. *Global Ecology and Conservation, 30*, e01755.

Rotich B, Kindu M, Kipkulei H, Kibet S, Ojwang D. (2022). Impact of land use/land cover changes on ecosystem service values in the Cherangany Hills water tower, Kenya. *Environ Challenges, 20*; 100576.

Rwanga, S. S., & Ndambuki, J. M. (2017). Accuracy assessment of land use/land cover classification using remote sensing and GIS. *International Journal of Geosciences, 8*, 611-622.

Santhosh Kumar, T. M., & Prakash, K. L. (2020). Surface water quality in the forest catchment: A case study of Tunga and Bhadra River stretches, Karnataka. *Current World Environment, 15*(2). Available from https://bit.ly/3dGKFi4

Sheela, M. S., & Kumar, P. S. (2014). Metal mobilization and physicochemical parameters of water around mangrove forests in Manakudy Estuary, on the southwest coast of India. *International Journal of Environmental Sciences, 4*(5).

Shelestov, A., Lavreniuk, M., Kussul, N., Novikov, A., & Skakun, S. (2017). Exploring Google Earth Engine platform for big data processing: Classification of multi-temporal satellite imagery for crop mapping. *Frontiers in Earth Science, 5*, 1-10.

Sidhu, N., Pebesma, E., & Câmara, G. (2018). Using Google Earth Engine to detect land cover change: Singapore as a use case. *European Journal of Remote Sensing, 51*(1), 486-500.

Sirimarco, X., Barral, M. P., Villarino, S. H., & Laterra, P. (2017). Water regulation by grasslands: A global meta-analysis. *Ecohydrology, 11*(2).

Tamiminia, H., Salehi, B., Mahdianpari, M., Quackenbush, L., Adeli, S., & Brisco, B. (2020). Google Earth Engine for geo-big data applications: A meta-analysis and systematic review. *ISPRS Journal of Photogrammetry, 164*, 152–170.

Tilman, D., Cassman, K. G., Matson, P. A., Naylor, R., & Polasky, S. (2002). Agricultural sustainability and intensive production practices. *Nature, 418*, 671-677.

Turner, M. G. (1989). Landscape ecology: The effect of pattern on process. *Annual Review of Ecology and Systematics, 20*, 171-197.

UN-Habitat. (2016). World Cities Report 2016: Urbanization and development – Emerging futures. United Nations Human Settlements Programme.

Wang, Z., Chen, J., & Zhou, Y. (2020). Assessment of Electrical Conductivity Levels in Urban Rivers: Case Study and Management. *Science of the Total Environment, 735*, 139212.

Water Resources Authority (WRA). (2022). Basin area: Athi River Basin. Accounting for every drop. WRA, Kenya.

Waturu, M., Sitoki, L., Lalah, J., Chasia, S., & Mbao, E. (2023). Effect of land use/land cover changes on water quality in the upper Athi River sub-catchment in Kenya. *African Journal of Aquatic Science, 1*-13.

Widodo, B. (2013). The influence of hydrodynamics on the spread of pollutants in the confluence of two rivers. *Applied Mathematical Sciences, 7*(123), 6115–6123.

Wikipedia. (2024). Athi River. Wikipedia [Internet], [cited 2025 Mar 18]. Available from: <https://wikipedia.org/wiki/Athi_River>

Wilson MM, Michieka RW, Mwendwa SM. (2021). Assessing the influence of horticultural farming on selected water quality parameters in Maumau Stream, a tributary of Nairobi River, Kenya. *Heliyon,. 7*(12):E08593.

Zubair, O. A., Lawal, H., & Abdulkadir, M. (2018). Exploring the relationship between land-use change and water quality in the River Niger Basin. *African Journal of Environmental Science and Technology, 12*(5), 167-179.