**INFLUENCE 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 spatiotemporal variations 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 includes six categories namely Bare-lands, Built-up/others, Farmlands, Forestlands, Grasslands, and Open-waters. Pearson correlation analysis was employed to assess the influence of spatial LULC differences on 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. Bare-lands decreased by 7.06%, Built-up/others had a slight increase of 0.29%. Farmland areas had a net increase of 0.52% from 2015 to 2023. Forestlands increased by 4.54%, Grasslands expanded by 2.77%, and Open-waters declined by 1.24%. The result on spatial LULC variations indicated significant influence on water quality, with urbanization and agricultural activities generating pollutants such as Total Dissolved solid (TDS), Electrical Conductivity (EC), Biological Oxygen Demand (BOD5), cadmium, and chromium. 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 being secondary drivers in Athi River Basin. Climatic factors were associated with Grasslands and Farmlands. Agriculture impacted Forestlands and Open-waters, Settlement influenced Bare-lands, Grasslands, and Forestlands. Industry affected Built-up/others and Open-waters, while commercial activities relates to Built-up/others. In conclusion, the government and non-governmental organizations should implement strict regulations and monitoring program to control land cover changes and enforce management practices that can help protect the water quality of the Athi River.

**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 watershed and disrupted natural hydrological systems [38]. In low-income countries, LULC change has destabilized ecosystems and disrupted ecological balance. Rapid urbanization, industrial, and agricultural expansion are major contributors to land cover changes [27, 5]. 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. [38] 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 [15]. 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 agrochemical, animal farming, and irrigation runoff contribute to the deterioration of water bodies [60]. Agricultural and industrial activities affect water quality through the presence of nutrient loads, raw sewage, and solid waste effluents [37, 40]. 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.[28] 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. [2] 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 [57]. Agricultural practices and building constructions affected the water quality of the Tambayakbayan River [44]. A study on LULC trends showed river encroachment affecting water quality in Mokopane, Limpopo, South Africa, from 2016 to 2019 [34]. The decreased trend in land cover demonstrated a complex impact of cultivated land on the water quality of the Chaohu Lake Basin [16].

Despite the importance of riparian vegetation and forests, which act as natural water filters, regulate water temperature, and stabilize riverbanks, in 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, and 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 bases that Land use activities, including commercial, industrial, agricultural, and human settlements (both formal and informal), were examined across different spaces and seasons of the river. The ultimate goal of the study was to investigate the influence 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 shown in Figure 1. The Athi Basin has an area of 66, 559 km2 covering 11 % 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 [57].

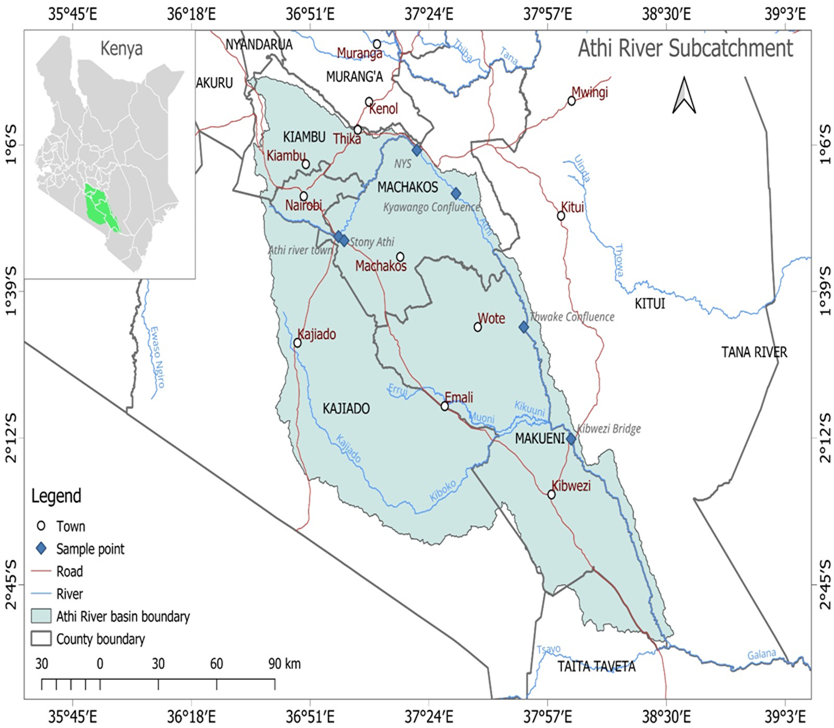


Figure 1: The Location of the Study Area

Athi River traverses the plains and valleys of Kenya, forming Fourteen Falls, meandering through Nairobi, and passing through Tsavo National Park [22]. The river flows through informal settlements and industrial areas in cities and towns including Nairobi and Machakos Counties as well as suburban and rural communities, where it collects various effluents.

The topography of the Athi River Basin ranges from sea level at the Indian Ocean to approximately 2,740 meters in the Aberdare Range [57]. 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 [59]. 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 [24]. 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 [57]. 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 [24, 25]. 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 [25]. The area encounters a low incidence of Harmattan in January.

**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 System (GIS) were applied in monitoring trends in spatiotemporal land cover. The historic data on land cover was acquired from United State 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 was considered as the baseline for the change detection due to best quality satellite images 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 descriptions of the characteristics of each land use/land cover. Similar approach was used by [50] on ecosystem service values in Cherangany Hills Water Tower, Kenya. Pearson correlation analysis was use to examine spatial LULC differences across the sampling stations in the river basin. Interview survey was conducted to support the dataset.

**3 DATA ANALYSIS**

**3.1 Supervised Method**

The study employed supervised classification technique to develop the spectral signatures of known categories [6, 45].

**3.2 Training and Testing Samples**

The study tested 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 Normalize Difference Vegetative Index (NDVI). Manual digitization of area of interest (AOI) such as bare-lands, crop/farmlands, grasslands/vegetation, built-up area, 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 number of training samples were Farmlands 22, Grasslands 31, Forest 36, Bare-lands 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 [47].

**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 [47, 32, 8]. 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 on vegetation growth measurement [52]. The formula is as follow;

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

Where,

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

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

Data filtering of this study was done in 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 effective the pixels were sampled into the corrected land cover classes [49]. It is the most important, difficult, and the last stage in land cover classification process of the images [10]. The study performed an accuracy assessment for trained Random Forest (RF) classifier to make predictions on the map production. The overall accuracy was used to assess the performance of Random Forest (RF) for easy interpretation and effective accuracy estimation method [42]. This method quantifies the correctly classified test data by the classifier as a percentage (Table 2).

The user’s accuracy gives a chance that an area classified on the map is actually the land cover on ground [1]. Confusion matrix provided by the classifier to evaluate the class-level performance also calculated user and producer accuracies.

In order to generate accuracy statistics free GEE function techniques was used with the following equations.

 (2)

 (3)

 (4)

Where;

nii denote the number of suitably classified pixels,

N denote 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**

Kappa coefficient measured the overall agreement of the matrix. The equation below showed the accurate Kappa coefficient for stratified random measurement [41].

 (5)

Where,

T denote the test pixels,

C denote the correctly classified pixels observations, and

G is the sum of 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 classification through intersection tool. The intersection processing tool allowed the conversion of land cover information for the year 2015, 2020, and 2023, into one database in tabular form for change detection [47].

The spatiotemporal change was quantified using gain and loss method. Land cover change was calculated with the equations adapted from Lin et al. [29].

Kgain = Sb – Sa (6)

K0 = Sbi - Sai  (7)

Kloss = Sa – K0  (8)

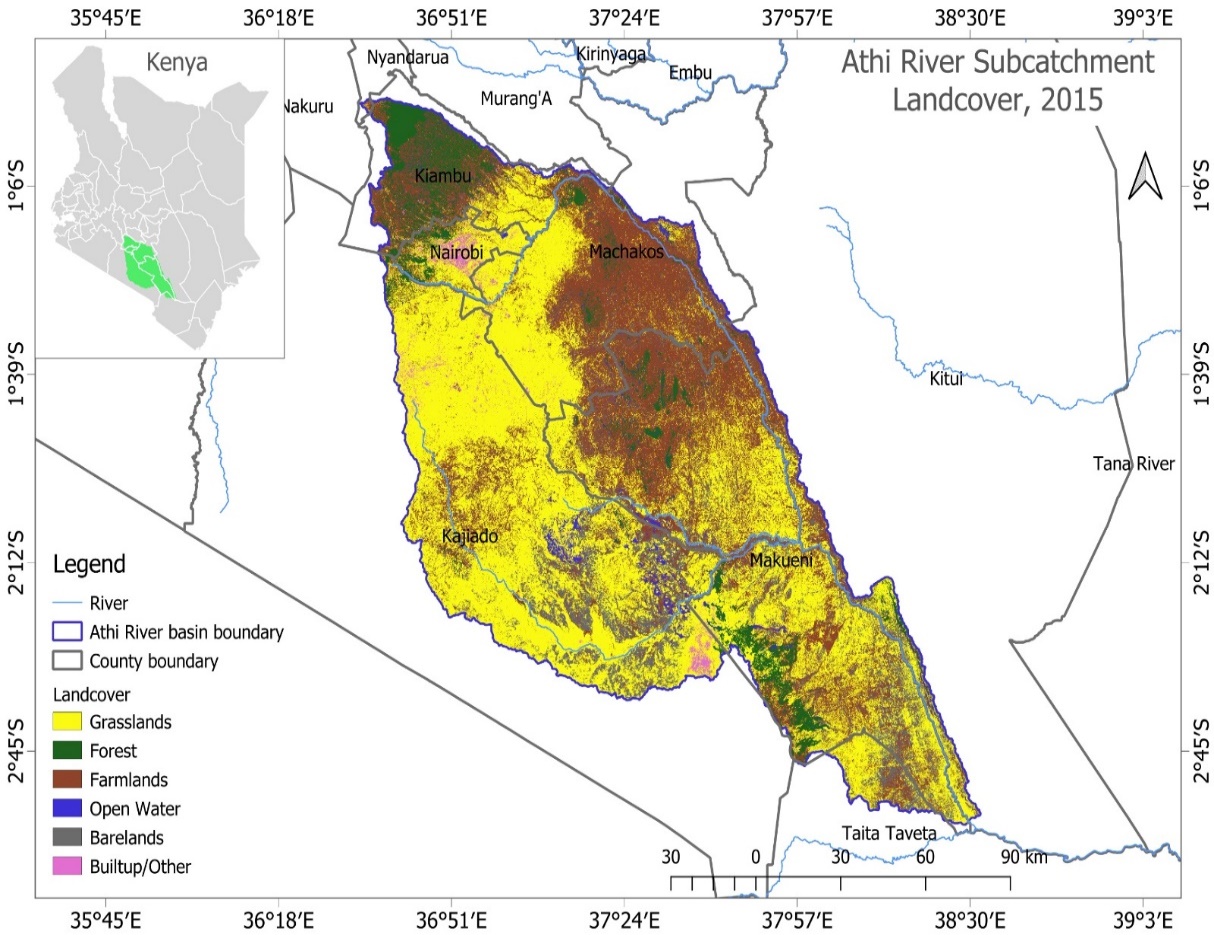
Where;

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

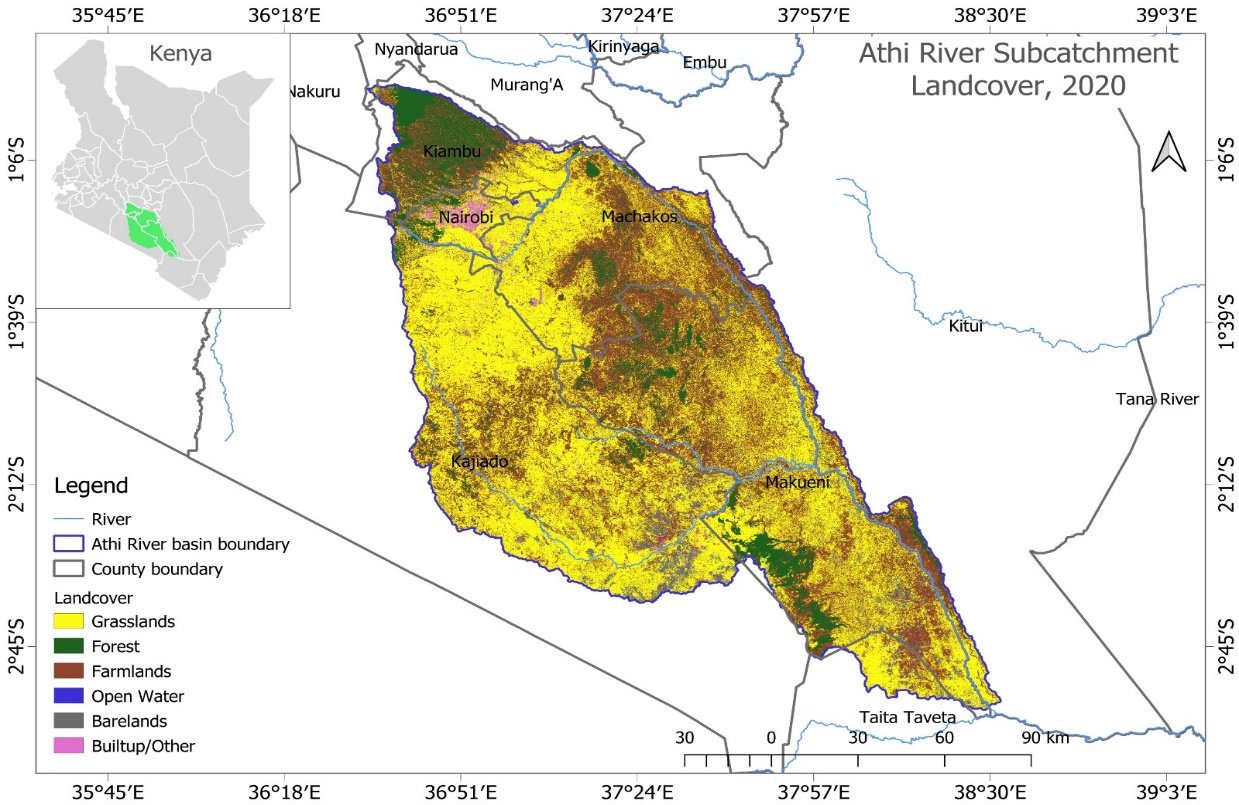
Sai and Sbi = land cover types with no change between the beginning and end year (time). The total area covered by each class to detect a change was calculated and summarized into percentage change.

**4 RESULTS AND DISCUSSIONS**

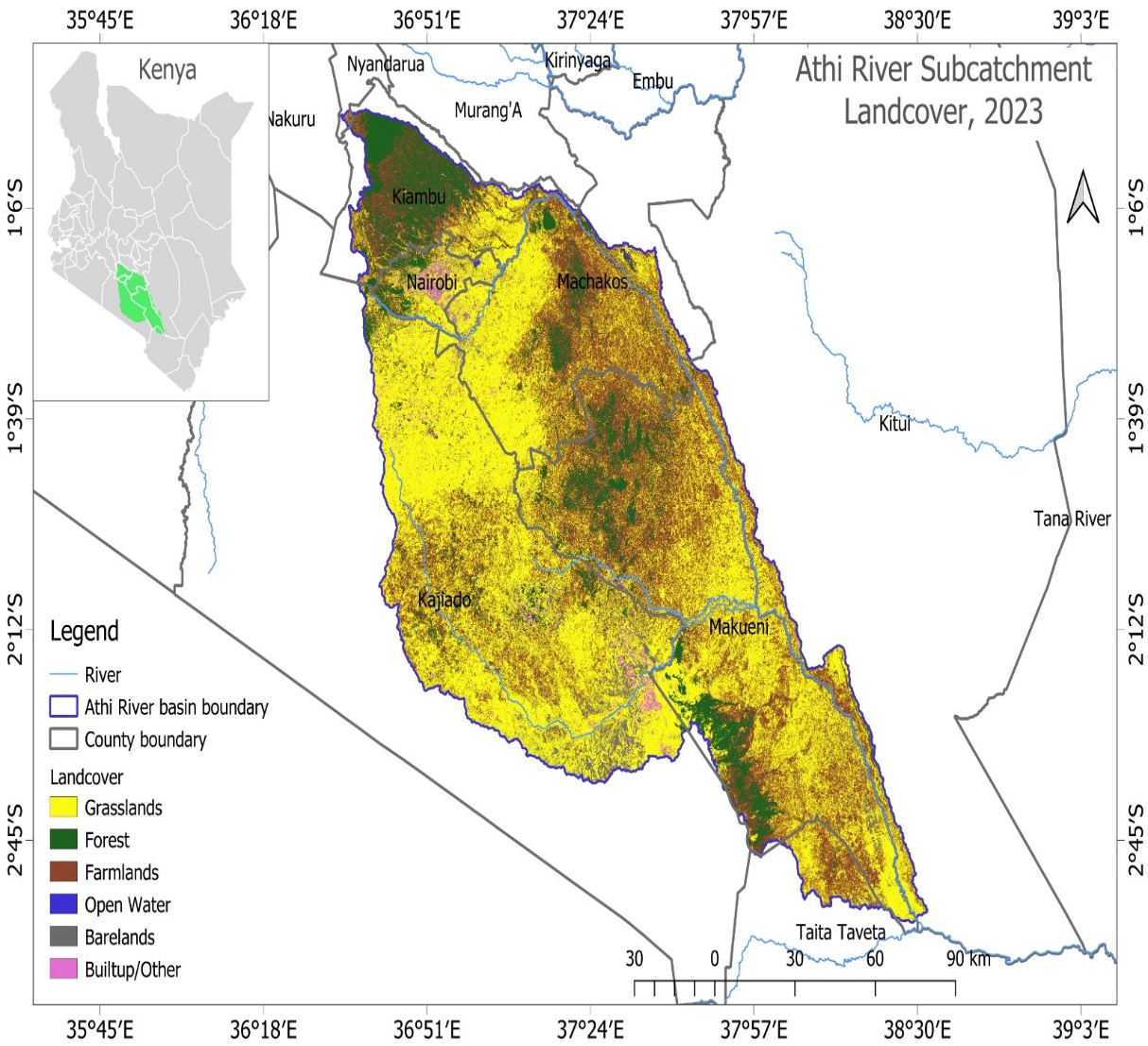
The land cover maps of the mid-reaches of the Athi River Basin for 2015, 2020, and 2023 show different colors representing various land cover types in the study area. These types include built-up areas, bare lands, farmlands, forestlands, grasslands, and open water areas. The maps also feature county 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 waste water 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 show significant shifts due to urban development, agricultural practices, reforestation, and other factors, as depicted in Figures 2, 3, and 4.



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



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

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**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**

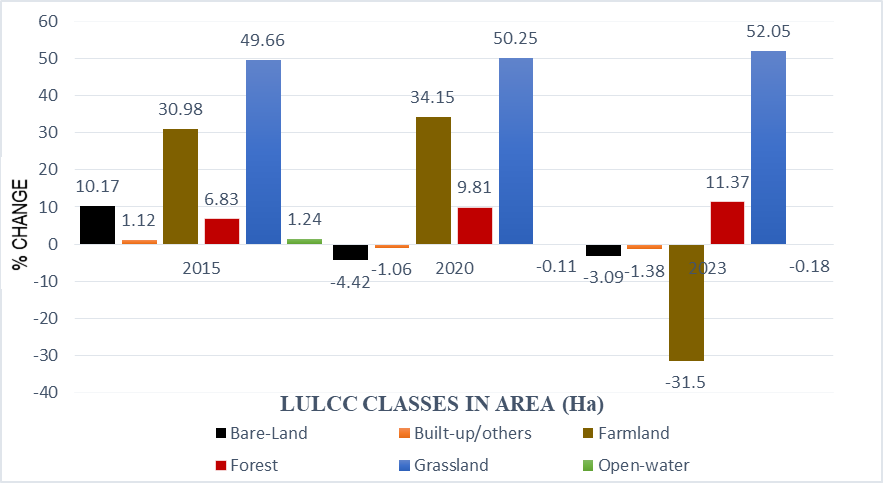
The land use/land cover (LULC) indicated over all percentage changes in the area per ha from 2015 to 2023 (Table 1). **Bare-lands** decreased from 10.17% in 2015 to 3.11% in 2023, a total decrease of 7.06%. This suggests repurposing for agriculture, reforestation, or urban development. **Built-up Areas** declined from 1.12% in 2015 to 1.08% in 2020, then increased to 1.41% in 2023, indicating 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, then decreased to 31.50% in 2023, resulting in a net increase of 0.52% since 2015, suggesting fluctuating agricultural activities and potential land conversion. **Forestlands** increased from 6.83% in 2015 to 11.37% in 2023, a total increase of 4.54%, indicating successful reforestation and conservation efforts. **Grasslands** increased from 49.66% in 2015 to 52.43% in 2023, a total increase of 2.77%, indicating a reduction in agricultural pressure. **Open-waters** decreased from 1.24% in 2015 to 0.18% in 2023, 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/others have the smallest area coverage. The Figure 5 highlights 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 indicate 24 true positives grasslands, with 1 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). **Bare-lands** had 8 true positives, with 5 misclassified as Grasslands, 1 as Farmlands, and 1 as Built-up/Others (majority correctly identified despite some confusion). **Built-up/Others** had 15 true positives, with 6 misclassified as Grasslands and 2 as Bare-lands (majority correctly identified despite some confusion) as shown 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/Other | 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, shows that bare land areas accounted 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/others were relatively stable as shown in Table 3, suggesting minimal urban sprawl, though some conversions involved natural or semi-natural land cover. Table 3 also shows that while farmland remained stable, a notable 3.12% was reforested and part was converted back to grassland. Additionally, there was some conversion to farmland (1.34%). 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%), illustrating 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 shown in table 4 indicates in 2023, land use intensification and grassland regeneration, showing 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, evidenced by shifts from the built-up/others category to grassland (0.66%) and bare land (0.13%). While the farmlands category remains largely stable, noticeable shifts to grasslands (9.61%) and forests (3.86%) suggest either land abandonment or reforestation activities. Findings from Table 4 show that forestlands were largely constant, with only a small percentage (1.13%) converted to farmlands. 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 from Table 4 shows 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, as well as anthropogenic activities including agriculture, urbanization, and conservation initiatives.

**Table 4: Change Detection Matrix for 2015 to 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 Influence of Spatial LULC Differences on Water Quality across Sampling Stations in 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

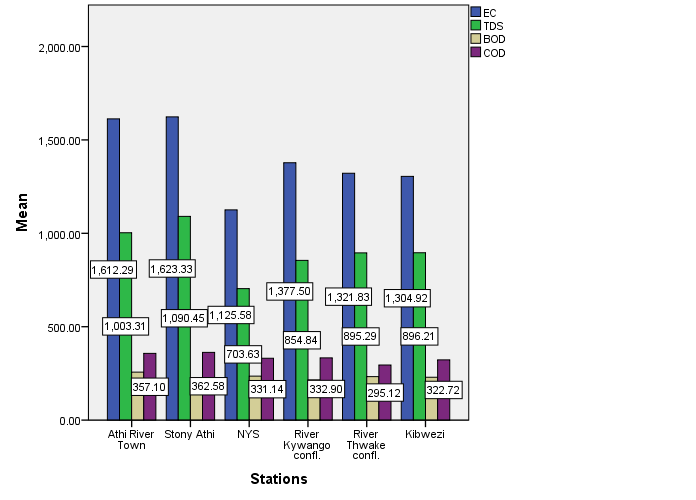
|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | pH | EC | TDS | NO3 | K | PO4 | BOD5 | COD | Cd | Cr |
| pH | 1 |  |  |  |  |  |  |  |  |  |
| EC | 0.67\*\* | 1 |  |  |  |  |  |  |  |  |
| TDS | 0.61\*\* | 0.93\*\* | 1 |  |  |  |  |  |  |  |
| 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, particularly at the Athi River Town, Stony Athi, and NYS sampling stations, exhibit elevated levels of EC and TDS, due to reduced runoff (Figure 6). The influence of built-up areas as a result of urban expansion, also contribute to increase cadmium and chromium levels, while the NYS sampling station exhibiting higher cadmium level as shown in Figure 8.

# **4.5.2 Decrease in Open Water 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).



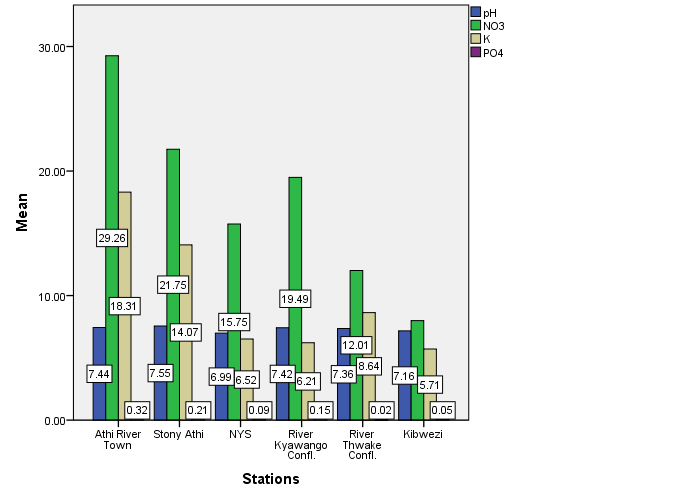
**Figure 6:** Spatial LULC Difference on physicochemical Water Quality in Athi River Basin

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

A decline in bare-land areas within the basin, which 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).

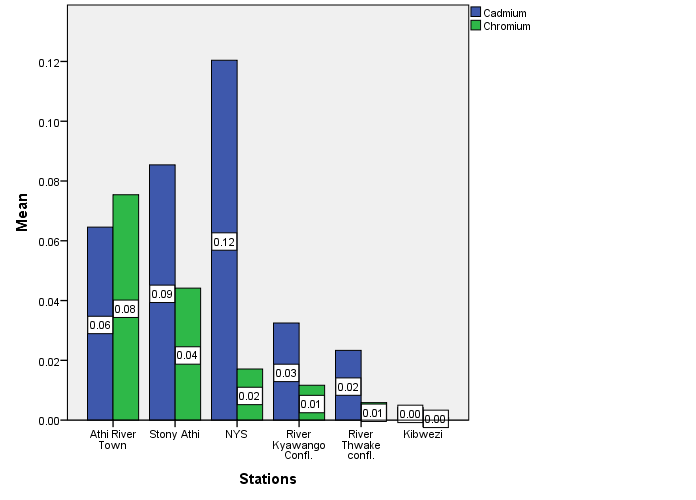
**4.5.4 Farmlands and Agricultural Expansion**

Athi river Town, Stony Athi and River Kyawango Confluence sampling stations exhibits higher levels of NO₃, K, and PO₄, than NYS, River Thwake and Kibwezi Bridge sampling stations. 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 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( Figure 6). Higher levels of Cadmium consentrations was found at NYS sampling station, declined at Stony Athi, and Athi river Town stations. Chromium levels increases at Athi River Town with decreasing levels as the river flow progress 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 Quality Pollution of 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** |

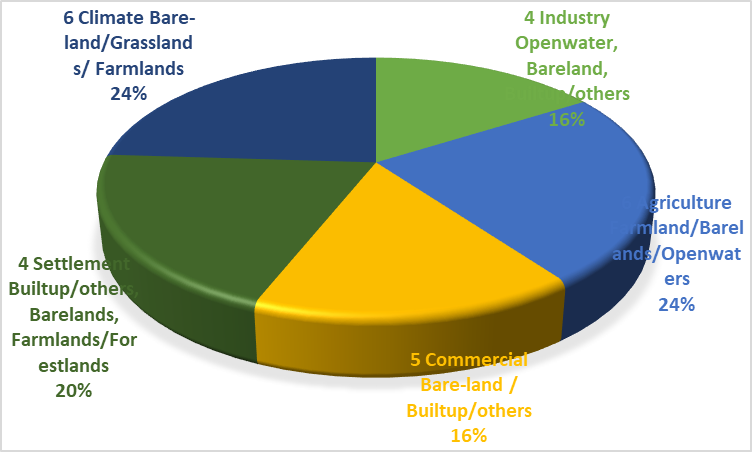
A look at Figure 9, shows that 20 respondents and 5 drivers of change were listed at the Athi River Town (S1) sampling station, 17 respondents and 5 drivers at the Stony Athi (S2) sampling station, 13 respondents and 4 drivers at the NYS (S3) sampling station, 9 respondents and 5 drivers of change at 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 sewages | Open-waters (WWTP) /  barelands, builtup/others |
| 2 | **Settlement:** population/lifestyle, wastewater, washing & bathing, landscape, plants, waste dumpsites. | Built-up/others, barelands, 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 shown 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.

**5 DISCUSSION**

The findings on land use land cover studies revealed that Built-up/Others category had overall increase of 0.29% from 2015 to 2023, highlighting a gradual trend of urbanization and infrastructure development in the region. This trend is consistent with global research on urban sprawl driven by economic growth and population expansion [3]. However, the observation made by [26] indicated an increase in built-up, due to ongoing infrastructure development, with response to population growth and economic demands. Athi basin can only depend in baseflow with changes in flooding during rainfall, which might affect buildup lands near the riparian.

Barelands category indicated substantial reduction from 10.17% in 2015 to 3.11% in 2023, with overall decrease of 7.06%, indicating 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 [31] on land use changes in Mumias District, Kenya, demonstrated a significant decrease in barelands, due to 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 [18]. This findings is essential in preventing land degradation, restoring soil health, and promoting sustainable agricultural productivity [12].

Farmlands category expanded by 3.19% between 2015 and 2020, is an indication of increase in agricultural activities. In 2020, farmlands had a net increase of 0.52% due to temporary agricultural expansion and land abandonment or conversion to other land uses, such as grasslands or reforestation [20]. This finding is consistent with the report by FAO [10], that agriculture influences land use changes in a river basin, highlighting how agricultural land expanded by 3.2% from 2015 to 2020, due to increase in agricultural activities, then declined by 2.5%, leading to a net increase. In addition, Tilman et al. [53], identified a dynamic balance between agricultural expansion and conversion to other land uses, including natural grasslands, due to conservation efforts.

The forestlands category had a constant increase from 6.83% in 2015 to 11.37% in 2023, representing an overall gain of 4.54% for 8 years. This growth suggests successful reforestation and conservation programs in the Country and individual aesthetic or commercial land reforestations as well as natural forest regrowth in the basin. Similar to this finding is a study in Kenya forest service projected an increase in forest from 6.9% in 2015 to 10% in 2022 due to successful reforestation and conservation programs [20]. These positive trends are crucial for mitigating climate change impacts, enhancing biodiversity, and supporting ecosystem services [21].

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. This increase in grasslands indicate 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 are increasing as a result of restoration efforts and sustainable management practices, which suggests a reduction in agricultural pressure [17]. 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. [19] 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. This decline, especially in surface water, can be attributed to urbanization and the effects of climate change. This is evidently supported by the findings made by NASA [35], that 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 attributes to series of droughts, exacerbated by climate change and global warming causing surface water deficits and 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 alarming. This trend could negatively affect groundwater recharge, aquatic habitats, food production, and the overall health of the river basin ecosystem. This phenomenon was observed by Kitheka [23] and Rodell et al. [46], who concluded 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 led to a significant rise in built-up areas, which in turn has increased the concentrations of Cr, Cd, TDS, and EC (Figures 9 & 10). These increases are attributed to storm water 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 sampling stations 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. [58] who found that an increase in industrial and urban expansions induced encroachments and destructions of wetlands and riparian ecosystems as well as 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) (Table 5). This is consistent with research by Huang et al. [16] and Ling et al. [28], highlighting how urbanization increases the levels of organic matter, heavy metals, and pollutants in water bodies. Elevated levels of Cd and Cr in these populated areas also suggest that storm water runoff and industrial operations are contributing factors (Figure 9). 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, before discharging into the Indian Ocean. These findings is similar to international research on urban river pollution, highlighting the impact of untreated wastewater and the damage rapid urbanization causes to river ecosystems[ 42].

The decline in open-water areas from 2015 to 2023 is expected to significantly impact pollutant levels. The reduction in open-water areas leads to increased TDS, BOD, and COD levels, which in turn restricts water diluting capacity, especially during the dry season (Figure 6). A 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. [56] 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. The trend is consistent with the findings by Ling et al. [28], who documented comparable impacts in the Batang Rajang River. Decreased open-water areas make aquatic ecosystems more susceptible to contamination, so specific actions are needed to protect these vital habitats.

In the Bare-land areas, the decrease influences 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 spells (Table 5). Ndugga [36] 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. Similar to these findings, Ling et al. [28] 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 bareland 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.

Farm lands 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. This finding is consistent with Crooks et al. (2021) who concluded that intensive agricultural practices induce stream water quality due to correlation with nutrients (NO3 and PO4). 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 Athi River water is widely used for domestic activities like washing, bathing, and drinking, and 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 engages 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 can disrupt aquatic habitats and degrade water quality, particularly 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.[45] 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. 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. These areas have a crucial role in reducing both organic and inorganic pollution, as evidenced by their negative connection with BOD and TDS. 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. [28]. 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 [7]. 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 filter pollutants and control sediment and nutrient runoff, among other vital ecosystem services, despite their restricted size. 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). These results support research by Omer [42] and Ling et al. [28], which highlight the importance of forest conservation as a tactic or strategy for improving water quality. The findings by Forestry [11] 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 into the dunes for filtered water collection, 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 [39]. 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.[13] 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 Bare-lands, Farmlands, and Grasslands due to urban sprawl and dispersed settlements. Urban expansion driven by settlement growth transforms natural landscapes into built-up areas [55]. Industry affects Built-up/other areas and Open-waters, 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 are recommended to explore on how rainfall variability, temperature changes, and extreme weather events influence land cover transformations, particularly in areas dominated by agriculture and natural vegetation. Secondly, study should be conducted on the impact of urban expansion and infrastructure development near riparian zones flood patterns, water retention, and surface water quality. Focusing on how impermeable surfaces contribute to increased runoff and water pollution of the river basin.

**6 CONCLUSION**

The study on LULC changes in Athi River Basin from 2015 to 2023, including spatial LULC variations and interview survey indicate significant transformations in land use, 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 shows higher concentrations of NO3, PO4, BOD, COD, Cd, TDS, and Cr pollutants attributed to runoff from agriculture, urbanization, open water reduction, and high population. The findings call for an urgent response to mitigate water resources deficits and pollution control in the river basin. It is essential to foster collaboration among stakeholders, including government agencies, local communities, industries, and non-governmental organizations, to develop and implement effective land use management plans. This include climate adaptation strategies to address the impacts of climate variability on land use and water quality. These strategies can include water conservation measures, drought-resistant crop varieties, and flood management plans.

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