# IMPACTS OF HUMAN ACTIVITIES ON WATER QUALITY IN THE UPPER ATHI RIVER CATCHMENT, KENYA

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## DECLARATION

I hereby declare that the work contained in this thesis is my original work and has not been submitted or presented elsewhere for examination, award of a degree or publication. Where other people's work has been used, this has properly been acknowledged.

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# DEDICATION

This thesis is dedicated to my husband, Mr. Justus Waturu, our sons Jonathan and Jacob for their encouragement, patience and the sacrifice they made over the years for my sake.

MAY GOD BLESS YOU

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## ABSTRACT

In the past few decades, the impacts of human activities on water quality (WQ) have been demonstrated to have a strong negative effect on downstream users. In spite of this linkage, little is known about the specific effects on the Upper Athi River Catchment (UARC). The catchment has experienced rapid industrialization coupled with an increased human population that has led to the encroachment of the watershed. This study aimed at: (1) determining the levels/concentrations of physicochemical parameters (pH, Electrical Conductivity (EC), temperature, Total Suspended Solids (TSS), Total Nitrogen (TN), Total Phosphorus (TP), Biological Oxygen Demand (BOD), Chemical Oxygen Demand (COD), Chlorophyll *a* and heavy metals (Iron, Zinc, Lead, Copper, Manganese and Chromium) at different sampling sites in different seasons, (2) assessing Land Use Land Cover Changes (LULCC) in relation to water quality in the UARC using Geographical Information System (GIS) and Remote Sensing (RS) technologies, and (3) generating scenarios to predict future water quality trends by utilizing one-dimensional river and stream water quality (QUAL2Kw) and forecasting models. WQ samples were collected every month from February 2017 to December 2018, and analyses for nutrients and heavy metals were done in the laboratory following standard methods for water and wastewater analysis. WQ data was analysed using principal component analysis (PCA) and further subjected to the Kruskal-Wallis test. Dry and wet seasons data were analysed using ANOVA. Historical Landsat satellite data was acquired for the periods 1990, 2004, 2010, 2014 and 2018 to prepare LULCC maps of the study area. A hybrid classification technique was used to classify LULCC into six categories. The physicochemical parameters showed spatial-temporal variations, with a significant increase in TSS, Turbidity, and BOD recorded during the wet seasons. Nutrient concentrations were higher in stations adjacent to industrial, agricultural, and domestic effluents as compared to those in upstream areas. TP values were higher in two tributaries, Nairobi River at Njiru (0.17 mg/l) and Mathare (0.25 mg/l) than in Kikuyu springs (0.009 mg/l). Multiple regression analysis showed that EC, DO, Zn and Pb were significantly associated with urban areas ($p < 0.009$, $p < 0.042$, $p < 0.031$, and $p < 0.02$, respectively). Correlation results presented strong $R^2$ values between the observed and predicted: temperature: 0.82, electrical conductivity: 0.99, total dissolved solids: 0.94, biochemical oxygen demand: 0.66, chlorophyll a: 0.89, total nitrogen: 0.75, and total phosphorus: 0.94. These results depict the model's reliability in predicting water quality parameters in rivers and streams, even in watersheds with little data availability. There was a strong correlation between the urban area and water quality parameters, with Cr ($r = 0.56$) and Pb ($r = 0.80$) as the most significant parameters. Shrubland was the most dominant land use type (56.5%) in 1990 but declined considerably to (49.16%) in 2018, mainly due to conversion into urban and agricultural land uses, whose increase tripled (from 0.93% to 3.11% and 5.66% to 18.17%, respectively). From the models, it was shown that DO will continue to decline towards the year 2030, indicating increased pollution. In contrast, EC, TSS, BOD, and iron will increase significantly in tandem with the present trends in LULCC. The implication is that pollutants will increase to unsafe levels in the UARC if appropriate watershed management actions are not taken in good time. Significant land cover degradation is expected to occur if no mitigation measures are instituted, creating a threat to biodiversity conservation and the survival of local communities.



**KEYWORDS:** Aquatic ecosystems; Degradation; Prediction; pollutants; Watershed management

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| Acronyms | Full names/meaning | SI Unit |
|---|---|---|
| BOD | Biochemical Oxygen Demand | mg/l |
| Chla | Chlorophyll a | mg/l |
| Cl | Chloride | mg/l |
| Cr | Chromium | mg/l |
| Cu | Copper | mg/l |
| DO | Dissolved Oxygen | mg/l |
| EC | Electrical Conductivity | mg/l |
| Fe | Iron | mg/l |
| Mn | Manganese | mg/l |
| Pb | Lead | mg/l |
| pH | pH | |
| TDS | Total Dissolved Solids | mg/l |
| Temp | Temperature | °C |
| TN | Total Nitrogen | mg/l |
| TP | Total Phosphorous | mg/l |
| TSS | Total Suspended solids | mg/l |
| Turb | Turbidity | mg/l |
| Zn | Zinc | mg/l |
| CDF | Constituency Development Fund | |
| CLUE | Conversion of Land Use and its Effects | |
| CMS | Catchment Management Strategy | |
| ETM | Enhanced Thematic Mapper | |
| EMCA | Environment Management and Coordination Act | |
| FAO | Food and Agriculture Organization | |
| GIS | Geographical Information System | |
| GOK | Government of Kenya | |
| HH | Households | |
| IRBM | Integrated River Basin Management | |
| KEBS | Kenya Bureau of Standards | |
| KFS | Kenya Forest Service | |

| | |
|---|---|
| KNBS | Kenya National Bureau of Statistics |
| LULCC | Land Use Land Cover Changes |
| MSS | Multispectral Scanner |
| NEMA | National Environmental Management Authority |
| RS | Remote Sensing |
| TM | Thematic Mapper |
| USGS | United States Geological Survey |
| UTM | Universal Transverse Mercator |
| WHO | World Health Organization |
| WRA | Water Resources Authority |

## OPERATIONAL DEFINITION OF TERMS

**Water Quality -** Water quality is the chemical, physical, and biological characteristics of water. It is influenced by a number of factors mainly natural and anthropogenic activities.

**Non-point pollution sources** - These refer to diffuse sources of pollution such as: natural leachates from rocks; Agro-chemicals used on farmlands, urban run-off, run-off from roads and farmlands. Sources of pollution from these areas are not easily identified.

**Geographic Information System (GIS) -** is a computer system capable of capturing, storing, analysing, and displaying geographically referenced information; that is, data identified according to location. Practitioners also define a GIS as including the procedures, operating personnel, and spatial data that go into the system.

**Global Positioning System** - is the only fully functional Global Navigation Satellite System (GNSS). The GPS uses a constellation of at least 24 (32 by March 2008) Medium Earth Orbit satellites that transmit precise microwave signals, that enable GPS receivers to determine their location, speed, direction, and time.

**Land cover -** Implies the physical or natural state of the Earth’s surface.

**Land use -** This is the manner in which human beings employ land and its resources.

**Water scarcity -** A country is categorized “water scarce’ if its renewable freshwater potential is less than $1000M^3$ per capita per annum e.g., Kenya is classified as water-scarce country because its natural endowment of renewable freshwater is currently about $647m^3$ per capita per annum.

**The Integrated River Basin Management -** can be defined as a "process of coordinating conservation, management and development of water, land and related resources across sectors within a given river basin, in order to maximize the economic and social benefits derived from water resources in an equitable manner while preserving and, where necessary, restoring freshwater ecosystems." Global Water Partnership (2000).

**Watershed degradation -** is the loss of value over time, including the productive potential of land and water, accompanied by marked changes in the Hydrological behaviour of a river system resulting in inferior quality, quantity and timing of water flow.

**Watershed management -** Watershed management is the process of formulating and carrying out a course of action involving the manipulation of resources in a watershed to provide goods and services without adversely affecting the soil and water base. Usually, watershed management must consider the social, economic and institutional factors operating within and outside the watershed area.

**Water resources -** are sources of water that are useful or potentially useful. Uses of water include agricultural, industrial, household, recreational and environmental activities. The majority of human uses require fresh water.

**Water use -** can mean the amount of water used by a household or a country, or the amount used for a given task or for the production of a given quantity of some product or crop. The term "water footprint" is often used to refer to the amount of water used by an individual, community, business, or nation.

**Remote Sensing -** This is the practice of deriving information about the earth's land and water surfaces using images acquired from an overhead perspective, using electromagnetic radiation in one or more regions of the electromagnetic spectrum, reflected or emitted from the earth's surface ("Sensor systems for environmental monitoring," 1996).

**Climate change** - refers to the change in climate attributed directly/indirectly to human activities which in addition to natural climate variability is observed over comparable period.

**Water scarcity -** the point at which the aggregate impact of all users impinges on the supply or quality of water under prevailing institutional arrangements to the extent that demand by all sectors, including the environment cannot be satisfied fully.

**Non-point source pollution** - Diffuse pollution sources (without a single point of origin or not introduced into a receiving stream from a specific outlet)

**Point source pollution -** represents those activities where wastewater is routed directly into receiving water bodies, for example discharge pipes, where they can be easily measured and controlled

**Water stress -** occurs when the demand for water exceeds the available amount during a certain period or when poor quality restricts its use. Water stress causes deterioration of fresh water resources in terms of quantity (aquifer over-exploitation, dry rivers, etc.)

**pH -** the term pH is used in this report to express the acidity or alkalinity of water.

**Turbidity -** a measure of the cloudiness or murkiness of water due to suspended particles.
**Eutrophication -** an increase in the concentration of chemical nutrients in an ecosystem to an extent it increases the primary productivity of the system

# CHAPTER 1

## 1.0 INTRODUCTION

This chapter presents the background to the study, statement of the problem and study objectives. It also presents significance and scope of the study including theoretical and Conceptual framework. The chapter covers the general review of literature that is relevant in answering the research questions. The review is carried out in a systematic manner with references made to empirical research carried out on the subject matter. Sources of literature include information in research articles, journals, online journals, abstracts, books as well as relevant publications.

### 1.1 Background to the study

Understanding the relationship between Land-Use-Land-Cover-Changes (LULCC) and water quality (WQ) is important for the identification of primary threats to water quality, with anthropogenic activities playing a significant role (Horan et al., 2019). Such human activities are directly reflected in the characteristics of land use (Maloney and Weller, 2011). This is as a result of the growing population which has caused a remarkable increase in demand for the use of natural resources due to processes such as urbanization, agriculture, and industrialization (Kitheka and Mavuti, 2016; Kithiia, 2012).

Globally, this situation is also attributed to the uncontrollable desire of these nations to achieve industrialized status as well as the diversification of national development goals (Devaraju et al., 2015). LULCC can be a major biodiversity threat due to the destruction and isolation of natural vegetation or the fragmentation of natural areas (Muriithi, 2016). LULCC is one of the major anthropogenic-induced activities that alter the hydrological system (Mahmoud and Alazba 2015). Further, it impacts the energy and water balance, thereby directly influencing the climatic conditions. Studies have revealed that LULCC impacts are apparently global, with significant cumulative effects worldwide (Devaraju et al., 2015). Additionally, the intensive and extensive utilization of land resources by humans has resulted in remarkable changes in vegetation cover (Clerici et al., 2019). Moreover, with rapid industrialization coupled with unprecedented population increase, LULCC has been on the rise in many developing nations, especially in the global south (Clerici et al., 2019), Kenya included (Kithiia, 2012; Kitheka and Mavuti, 2016). Such drastic changes have impacted the catchment hydrology in many of these countries (Birhanu et al., 2019; Osei et al., 2019).

Recently, researchers have shown great interest in the impacts of LULCC, resulting in numerous studies using both model simulations and field observations (De Mello et al., 2020; Osei et al., 2019; Zhang et al., 2017). In addition, LULCC-water quality correlation for a given area can be applied to watersheds because they are mainly influenced by land cover, watershed hydrology, climatic conditions, surficial geology and topographic conditions (Zhang et al., 2017). Therefore, the evaluation of the LULCC and water quality relationship may be of great significance since it presents ideas on freshwater protection as well as assisting man in satisfying the increasing demands of clean water for domestic consumption, industrial use, agricultural use, recreational use, and potable water supply (Osei et al., 2019). In such studies, LULCC-water quality correlation data for a given area can be applied to unmonitored watersheds because they are mainly influenced by land cover and land management practices (Zhang et al., 2017; De Mello et al., 2020).

Studies have also revealed that due to rapid land use development, LULCC are resulting in soils becoming impervious, thus leading to a decreased rate of rainfall infiltration and consequently increased surface runoff and stream flows. Both annual and seasonal stream flows have been exacerbated by anthropogenic activities such as urbanization and deforestation, among others (Zhang et al., 2020). In other studies, Prodi et al. (2000) showed that rainfall reduction alone was insufficient to account for the reduced observed inflow. The study also revealed a non-linear relationship between stream flow and temperature.

Furthermore, an increase in temperature of 0.4°C would result in a 45% decline in stream flows (Prodi et al., 2000). Atmospheric pollution can have a significant effect on surface water quality through atmospheric transport and deposition. The risk of this atmospheric deposition is particularly evident for metal pollution (Semerádová et al., 2022). Such global environmental changes and their consequences are largely influenced by the LULCC (Yu et al., 2016). Notably, LULCC modified by humans has adversely caused biodiversity loss, deforestation, flooding, land degradation, and changes in climatic conditions, thereby disrupting ecological balance (Olang et al., 2011).

Other studies revealed the use of remote sensing in the evaluation of LULCC based on temporal and spatial data globally, with results showing that world water consumption is increasing with increasing population and that the increase will continue due to the rapid expansion of domestic, agricultural, and industrial activities (Shiferaw et al., 2021).

The modeling of water quality in rivers and streams has been applied more extensively in developed countries than in developing nations (Bui et al., 2019). In the USA, Hobson (2013) used QUAL2Kw as a decision support tool for Silver Creek Water Shade and found that modeling could be more cost-effective than regular water quality monitoring. For instance, in the Cértima River in Portugal, the Qual2Kw model showed that the river was highly contaminated with high levels of nutrients (Zhang et al., 2012; Song et al., 2020), although neither phosphorous nor nitrogen were limiting the proliferation of algal blooms (Schmidt et al., 2019). QUAL2kw is a one-dimensional model with many applications, especially in river channels with non-uniform but steady flow and a roughly constant pollution loading (Ye et al., 2013; Flynn et al., 2015; Zhang et al., 2015; Zhu et al., 2015; Chowdhury et al., 2018). In simulation, QUAL2kw factors in both the point and non-point pollution sources (Pelletier et al., 2006). The usage of the model has been far and wide, and there have been recent modifications to the model to allow for a more robust simulation of river and stream water quality (Chaudhary et al., 2018; Kalburgi et al., 2015; Zhang et al., 2014).

A general mass balance equation is used to guide the model in the simulation of concentrations of constituents within the water column (Santy et al., 2020). The QUAL2kw model calibration process is geared towards determining model parameter values that best fit the modeled system (Yin and Seo, 2013). Both manual and automatic approaches are used to calibrate the Qual2Kw model. The manual calibration depends on the user's ability, and it’s usually done by varying specific parameters, monitoring the final output, and repeating the process until the user is satisfied with the results (Rafiee et al., 2014; Abidin et al., 2018; Cho and Lee, 2019). On the other hand, automatic calibration applies internal inbuilt algorithms that are based on specific stoichiometry constants and rates (Nagisetty et al., 2019; Zhu et al., 2015). The automatic calibration optimizes the goodness of fit from the results of the model and compares data measured through the in-built algorithm (Hadgu et al., 2014; Tang et al., 2014; Kamal et al., 2020). The in-built algorithm is the weighted average of the normalized root-mean square error (RMSE) of the variations between observed data and water quality parameter model predictions (Chen et al., 2018; Xin et al., 2019).

Forecasting tools have been developed and designed to apply past happenings and present information regarding possible future scenarios of certain parameters (Sharma et al., 2018; Katimon et al., 2018; Abdeveis et al., 2020; Babamiri and Marofi, 2021; Eskafi et al., 2021; Fan et al., 2021). Therefore, the main objective of this study is to evaluate the water quality spatial-temporal distribution in relation to land use and land cover changes in the Upper Athi River catchment.

In Kenya, intensification of croplands, conversion of grasslands to agriculture, conversion of forests to agricultural land and urbanization respectively, have caused immense changes to the natural land cover (Cheruto et al., 2016; Mogaka, 2021). Additionally, Nairobi city and its environs, receives its water supply from the Tana River catchment due to the growing pollution of the Athi catchment water resources (MEMR, 2012). The Upper Athi catchment, including Nairobi receives this water supply through inter-basin water transfer due to uncertainty of pollution status in the basin (Kithiia, 2012; Kitheka and Mavuti, 2016).

The major water uses in Nairobi and its environs include domestic (urban and rural population), irrigation, industries, livestock, and wildlife mainly in Nairobi National park. The per capita water availability for the Athi basin is low at 464 $m^3$ per year (Kibiiy and Kosgei, 2018) compared to the global recommended amount of 1,000 $m^3$ per year. In this regard, Kenya, being a member state of the United Nations, adopted and is implementing the Sustainable Development Goals (SDGs) 2015, which advocate for poverty reduction and protection of the planet so as to ensure the prevalence of peace and prosperity by the year 2030. Specifically, SDG 6 emphasizes sustainable water management and ensuring that clean water is readily available to the populace (Assembly, G., SDG Transform the World, 2015). Further, Kenya, being a member of the UN, came up with Vision 2030 to facilitate the implementation of the SDGs. In an effort to achieve SDG 6, Kenya proposed two (2) multipurpose dams, Thwake at Machakos and Munyu in Thika along the Athi River, in order to increase water availability for its increasing population. Currently, very little knowledge exists on the linkage between LULCC and Water Quality in the Athi River Catchment. Consequently, this research study is timely, and its findings will assist in policy development and management of the catchment by mitigating water pollution in the dams. This is because the LULCC is crucial in the process of runoff formation that affects infiltration, erosion, and evapotranspiration. Furthermore, the LULCC is a major driver of water quality deterioration in water courses and impoundments (Namugize et al., 2018). Notably, a sound understanding of the impacts of LULCC on water quality is fundamental to addressing issues of water pollution at the catchment level. Studies by Kithiia (2010) in the Athi river basin, revealed trends of WQ deterioration as a threat to the natural water resources but did not clearly demonstrate the contribution of land use activities to water pollution.

### 1.1.1 Agro - climatic conditions

The study area has an average temperature of about 18 $^{o}$C in the highlands and 25 $^{o}$C in the lowlands. The amount of precipitation varies according to the altitude. The rainfall seasons are bimodal, with the long rains starting in mid-March to June with a peak in April, while the short rains occur between September and December. The mean annual rainfall ranges from 600 mm in the central part of the area to 1,200 mm in the upper area of the Athi catchment. The Athi River catchment is particularly a water-scarce area with renewable water resources of 464 $m^3$/year/capita (NWMP Vision 2030 of 2012).

### 1.1.2 Geology

The geology of the Upper Athi River Catchment is characterized by volcanic rocks of Nairobi phonolite and Trachyte and other trachytic series, Kapiti Phonolite, including other Athi series (Wekesa, 2018). The lower parts of the study area (towards Wamunyu sampling site, Machakos county), the soils are generally deep sandy alluvium and red sandy soils, in addition to patches of black cotton soils and murram. The soils contain little organic matter and hence have low fertility (Prasol Training and Consulting Ltd., 2012).

### 1.1.3 Topography

The topography of the catchment area varies from the highland in the Aberdare Ranges (around 2,600 m above mean sea level (amsl)) to the coastal area at sea level. Athi Catchment Area (ACA) is divided into three zones: the upper zone of 2,600–1,500 m amsl, the middle zone of 1,500–500 m amsl, and the coastal zone of 500-0 m amsl (WRA, 2013). This study focused on the upper zone.

### 1.1.4 Socio-economic activities

The upper part of the basin in the Kenya Highlands is characterized by high population densities (200–300 persons/km$^2$) and intensive cultivation of land. Major crops grown here include various horticultural crops, tea and coffee. While remnants of once luxurious and expansive forests on hills still remain in the highlands, there has been extensive clearance of forests for agriculture, settlements and industrial activities. The waters of the river have not been harnessed for hydropower and only small-scale irrigation is practiced on its flood plains. However, the construction of a mega dam (Thwake Dam) in the middle upper region of the basin is currently ongoing. The dam will be 77 m high above the lowest elevation of the river bed, with a crest elevation of 912 m above sea level (Prasol Training and Consulting Ltd, 2012). The dam is expected to store water for flood control, irrigation, hydropower generation and urban-rural water supplies (Prasol Training and Consulting Ltd, 2012) and will also have major impacts along the coast (Kitheka, 2013, 2014).

## 1.2. Statement of the problem

Globally, and specifically in Africa streams and rivers are recipient of effluent disposed from the sewerage treatment plants in towns and cities. This contaminated effluent subsequently flows downstream. Athi River, the second longest river in Kenya is located in Upper Athi river and receives it waters from several other small streams in the watershed. The river and the streams in the watershed provides water for drinking, fishing, and irrigation among others. The river and its tributaries flow through national parks, major towns, industrial, residential and agricultural areas. The wastewater generated by the Nairobi city and nearby towns and residential areas contaminates the upper Athi River catchment and associated streams ((Kithiia, 2021). For instance, Nairobi River, the main tributary of Athi River traverses the city of Nairobi thus heavily impacted by pollution from both domestic and industrial effluents. Notably, the combined waters of the different streams in the Upper Athi River catchment are extensively and intensively utilized by over 4 million people for drinking, and irrigation downstream.

The lasting nature coupled with the long-term toxic effects of heavy metals such as cadmium (Cd), chromium (Cr), Copper (Cu), lead (Pb), manganese (Mn), and zinc (Zn), resulting from consuming flora and fauna harvested from polluted streams and rivers has raised serious environmental and scientific concerns (Muiruri et al., 2013). Soils and rocks weathering amongst other human activities are additional factors contributing to the occurance of heavy metals in water, thus creating health risks to the watershed communities depending on the water for their livelihoods. Previous studies conducted in Upper Athi River indicated that the water streams and rivers in this catchment do not meet the WHO threshold for domestic and irrigation usage, thus the water is not portable and poses serious health risks to the resident using the river water as their primary livelihood source (Kithiia, 2021).

In similar studies, Kitheka and Mavuti (2016) and Kithiia (2021) attributed water quality degradation to land use changes as a result of increased industrial and agricultural activities and population growth but did not demonstrate the contribution of land use activities to water pollution. In spite of all these studies, there has not been adequate data to link LULCC to water quality to depict seasonal patterns or forecast trends in the Athi River catchment.

The Upper Athi River catchment houses Nairobi metropolitan area and its environs, and the population is about 9.0 million people, which is approximately 25% of Kenya's population (KNBS, 2009). Pollution of the river is on the rise and has negatively impacted the downstream communities for whom the river is a lifeline (Kithiia, 2021). The catchment has experienced rapid industrialization that has led to encroachment of wetlands, river riparian areas, and forests to make way for agriculture and settlements, most of which are informal and lack proper sanitation. This has a negative effect on water quality, which if unchecked, will affect human health, fish, livestock, and crop production. Therefore, the current study assessed the effects of LULCC on water quality to provides valuable insights into the broader field of watershed management by suggesting proper mitigation steps and enhance policy development as well as facilitate localized water monitoring programs on clean water supplies. Such measures will safeguard the health of the riparian communities, protect aquatic life and the use of water for various purposes

## 1.3 Objective of the study

The purpose of this research study is to investigate the impacts of land-use-land-cover changes on the spatial-temporal water quality in the Upper Athi River Catchment.

### 1.3.1 Specific Objectives

1. To determine levels of selected physicochemical parameters in water at different sampling sites in different seasons.

2. To assess the land use land cover changes in relation to water quality in the Upper Athi River Catchment (UARC).

3. To generate scenarios to predict future water quality trends by the year 2030 by utilizing QUAL2Kw and forecasting models.

### 1.3.2 Research Questions

1. What are the levels of the selected physicochemical parameters at different sampling sites in different seasons?

2. What are the impacts of land use land cover changes on water quality in the Upper Athi River Catchment (UARC)?

3. What are the scenarios to predict future water quality trends up to the year 2030 using QUAL2Kw and forecasting models?

## 1.4 Significance of the study

Land-use and land-cover changes in the Upper Athi River catchment are taking place at an extremely rapid pace, and the direction of change is not clear (Katana et al., 2013). With increased developments coupled with a rapidly growing population, water resources have become an important commodity that every sector is competing for, consequently resulting in ecological changes in the Upper Athi catchment.

In general, the pollution in the Upper Athi River catchment emanates from agricultural activities, industrial waste, and municipal effluent (from old, dilapidated, and overwhelmed sewer lines and sewerage treatment works in the catchment, whose initial design capacity was to cater for a small population). For example, the Dandora wastewater treatment plant at Ruai was designed for a capacity of 80,000 $m^3$/day in 1980, when the Nairobi city population was

863,000 (KNBS, 1979). In 1994, the capacity was expanded to 120,000 $m^3$/day (Sewe, 2013) and has remained so, despite the Nairobi population growing to approximately 4 million (KNBS, 2019).

The demand for water for various uses within the Upper Athi River catchment is high, but due to pollution, the water remains unsafe for domestic use. As a result, Nairobi city and its environs (towns within the catchment) are being supplied with water through inter-basin water transfer from the Tana River catchment. The major water uses in the catchment include domestic (urban and rural population), irrigation, industries, livestock, and wildlife. The per capita water use for the Athi basin is low at 464 $m^3$ per year compared to the global recommended amount of 1,000 $m^3$ (Katana et al., 2013) a reflection of the status of water use in most parts of Kenya.

The Sustainable Development Goals (SDGs) adopted by United Nations member states in 2015 envision the availability and sustainable management of water and sanitation (UN-Water 2021). In an effort to achieve SDGs 3 (Good health and well-being), 6 (Clean water and sanitation), 11 (Sustainable cities and communities) and 15 (Life on land), Machakos County Integrated Development Plan (MCIDP) 2018-2022, and Vision 2030, Kenya uproposed two (2) multipurpose dams, Thwake at Machakos and Munyu in Thika, which are along the Athi River, in order to increase water availability for its increasing population. Clean water is a right of every human being, and hence, the Athi River and its tributaries need protection to ensure the achievement of this right. This research study (carried out between February 2017 to December 2018) was therefore timely as it contributed to expanding our understanding of the changes in the Athi River ecosystem and propose mitigation measures that can help achieve sustainable utilization of the resource.

## 1.5 Scope of the study

The study was limited to the various human activities and land cover contributing to the deterioration of the Upper Athi River Catchment. This research study focused on pollutant levels in the catchment area in order to capture various activities from different industrial, economic, and agricultural activities taking place in the catchment. The study involved sampling and laboratory analyses of water samples from eleven (11) existing stations and seven (7) other sampling points selected at strategic locations (points) of the river and its tributaries. An assessment of land use and land cover practices and their impact on water quality was carried out. The study used Landsat images and river discharge data. The discharge measurements were sourced from WRA, Kenya. However, a number of constraints were encountered during the fieldwork and data collection stages of the research study. Most of the regular gauge stations in the Upper Athi catchment had short periods of hydrological records. Thus, to address the challenge, there was an extension of time allocated for fieldwork as well as in-situ data collection.

The parameters analysed consisted of those associated with surface water and wastewater quality, such as pH, conductivity, temperature, dissolved oxygen and turbidity, $BOD_5$, COD, total nitrogen (NO3-, NO2-, and NH4+), total phosphorus (inorganic and organic phosphates), chlorophyll A, heavy metals (Fe, Mn, Zn, Pb, Cu, and Cr), and total suspended solids (TSS).

## 1.6 Conceptual Framework

This study was conceptualized based on the Drivers-Pressures-State-Impacts-Responses (DPSIR) framework (Widinoyo, 2022). According to the DPSIR framework there is a chain of causal links starting with ‘driving forces’ (human activities such as land use land cover changes) through ‘pressures’ (waste such effluents) to ‘states’ (physical, chemical and biological) and ‘impacts’ on ecosystems, human health and functions, eventually leading to political ‘responses’ (prioritisation, target setting, indicators). As a result of pressures, the ‘state’ of the environment is affected; that is, the quality of the various environmental compartments (water and soil) in relation to the functions that these compartments fulfil. The ‘state of the environment’ is thus the combination of the physical, chemical and biological conditions. **State affects** water quality (rivers, lakes, seas, coastal zones, groundwater), Soil quality (national, local, natural areas, agricultural areas), hence impacting the Ecosystems (biodiversity, vegetation, soil organisms, water organisms) and Humans (health). On the other hand, a **‘response’** by society or policy makers is the result of an undesired impact and can affect any part of the chain between driving forces and impacts. An example of a response related to driving forces is a policy to change mode of transportation, e.g from private (cars) to public (trains), while an example of a response related to pressures is a regulation concerning Levels of Phosphorus, Nitrogen, Pb, Cu, Zn among others in drinking water. DPSIR show clearly the link between LULCC and the state of water quality (Obubu et al., 2022; Widinoyo, 2022) as illustrated in Figure 1. In Kenya, the DPSIR framework was adopted by Atkins et al., (2011), on simulation and scenario analysis of water resources management using WEAP model. In this study, the drivers are human activities on (land-use-land-cover-changes); pressures include physical and chemical pollutants impacting on environment; states include water quality and pollutant levels; and responses include management decision to mitigate on pollution.

The state of water is determined by the pressures exerted by human activities on land use and land cover, as illustrated in Figure 1.1. Many of the pressures and the underlying driving forces are common to all or a number of the issues relating to water quality.

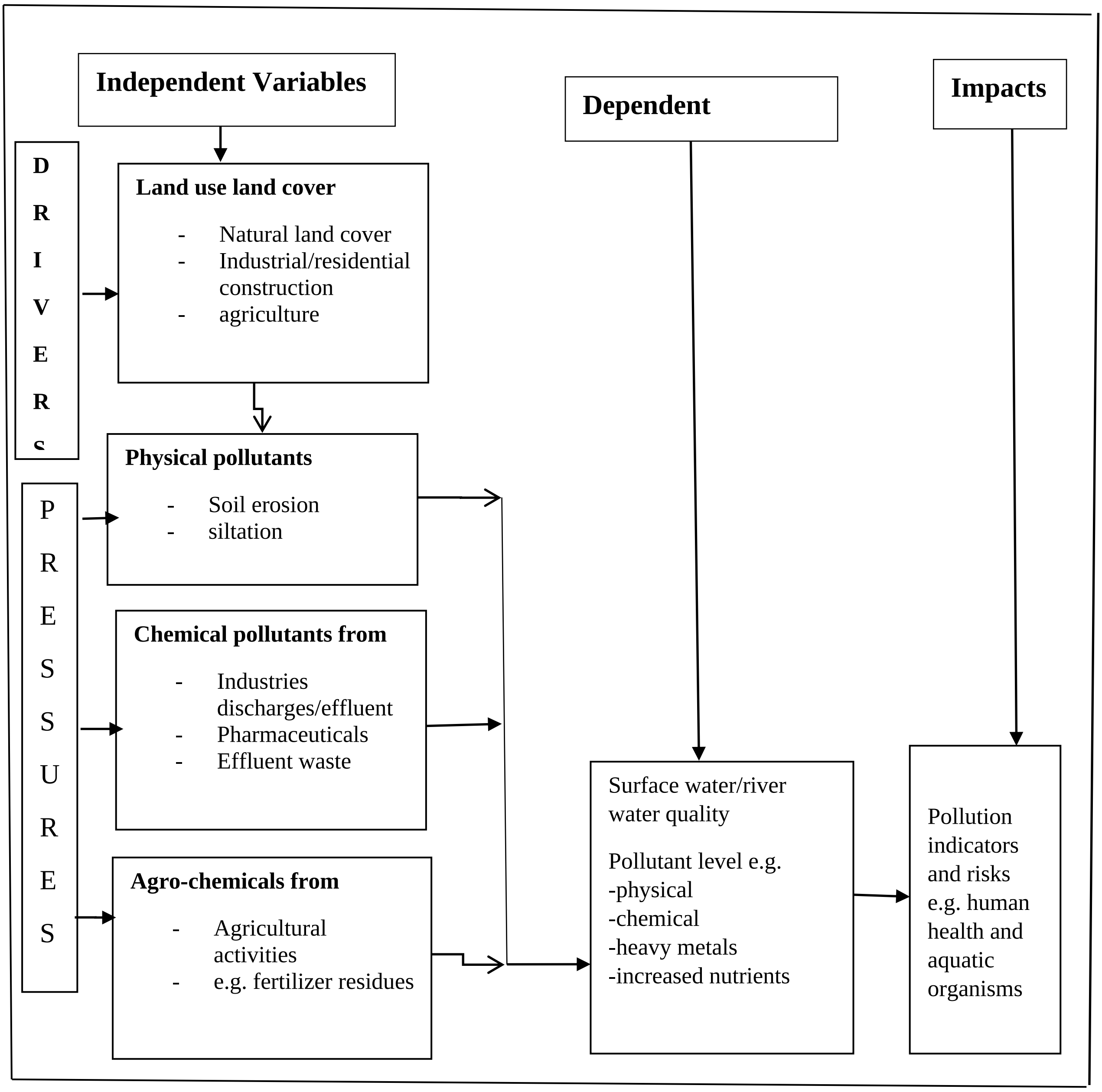



**Figure 1.1. Conceptual framework model applied for the study of the impacts of anthropogenic activities on water quality in the Upper Athi River Catchment.**

# CHAPTER 2

# 2.0 LITERATURE REVIEW

This chapter deals with the review of water quality degradation and physicochemical characteristics in the study area, remote sensing and GIS, and water quality modelling. Sources of literature include information in research articles in journals, online journals, abstracts, books as well as relevant publications.

## 2.1 Water quality degradation

Globally, aquatic ecosystems such as lakes, dams, streams, and rivers are sources of livelihood for humans in developing nations, especially in the global south. In the past several decades, these aquatic ecosystems have been under threat of degradation arising from agricultural runoff, domestic wastes, municipal effluents, and industrial discharges at the catchment (Hu and Cheng, 2013; Chowdhary et al., 2020). Studies have revealed that anthropogenic activities, urbanization, and industrial activities have resulted in the enormous production of waste at the catchment, which eventually finds its way into water bodies such as streams and rivers (Ullah et al., 2013; Mushtaq et al., 2020). The chemistry of water is an extensive subject since water is the universal solvent and many chemical compounds are dissolved in it at naturally occurring temperatures in streams and rivers. Some of the physicochemical parameters influencing water chemistry include water temperature, turbidity, electrical conductivity (EC), biological oxygen demand (BOD), chemical oxygen demand (COD), pH, and heavy metal residues from industries and mining activities (Pobi et al., 2019).

In the watershed, there is municipal wastewater discharge that can be considered point-source pollution since the origin can be traced to a specific source. Such point-source pollution is considered to be relatively easy to regulate and monitor, and often treatment can be used to control point-source pollution since the source can be easily identified (Pobi et al., 2019; Zhu et al., 2020). On the contrary, non-point pollution sources in the catchment usually emanate from extensive land areas and are transported downstream of streams and rivers. The effect of municipal sewage disposal is felt far and wide, not only in the water catchment, since the rivers and streams traverse long distances downstream (Xue et al., 2022). Studies conducted in the recent past have demonstrated that the municipal wastewater discharged into streams and rivers may contain harmful microbes such as fungi, bacteria, parasites, and viruses (Zhang et al., 2020).

Heavy metals are elements whose density is greater than 5.5/cm$^3$, for example, Mn, Pb, Zn, Cr, Cu, and Fe (Lewis and Evans, 2018). These metals are integral components of aquatic life and aquatic ecosystems. Studies have revealed that some of these elements are essential, without which a number of biochemical processes in all living organisms would cease to take place (Vardhan et al., 2019). However, when the concentrations of the elements exceed the normal levels, they become toxic to organisms and may result in attrition (Vardhan et al., 2019). Despite the advances made in the management of environmental wastes, heavy metals such as Mn, Pb, Zn, Cr, and Cu still remain hazardous to aquatic biota and humankind (Carolin et al., 2017). The essential heavy metals for aquatic life include Fe, Pb, Zn, and Cu and are required in small concentrations for the activity of enzymes (Carolin et al., 2017), but metals such as lead and chromium may exhibit extreme toxicity even at low concentrations under certain conditions (Okoro *et al.*, 2012). However, they can be altered from more toxic complexes to less toxic forms that are more stable (Carolin et al., 2017).

Atmospheric deposition has been recognized as a significant source of pollution in surface water although it is often underestimated. Atmospheric deposition occurs through various pathways, including rainfall and dry deposition. Pollutants deposited from the atmosphere include particulate matter, heavy metals, organic compounds and microbial pathogens. Semalulu et al. (2005) undertook atmospheric deposition studies from Kakira, Uganda which revealed that in warm tropical environments, sulphate reducing bacteria, varying redox conditions, anoxic conditions, solar radiation and several other factors play a key role in surface water pollution. According to recent studies, heavy metal discharge into streams and rivers has the potential to change both aquatic ecosystems and species diversity (Statzner and Beche, 2010; Kahlon et al., 2018). Additionally, aquatic life forms such as shellfish are able to accumulate heavy metals at concentrations that may be many times greater than the levels in the sediments and water columns.

Some studies have revealed that heavy metal elements in minute quantities consumed in food may be detrimental to health (Bosch et al., 2016; Kumar et al., 2019). For example, they are able to cause metabolic disturbances if they exceed the permissible levels. However, the deficiency of certain heavy metals such as Cr, Zn, and Fe can also have an adverse effect on health, and therefore their consumption through uptake of water should be within limits allowable by the WHO. Reports show that many communities are exposed to heavy metal ingestion, and their adverse impact on biotic communities usually reduces diversity, mostly due to species elimination or a reduction in the number of intolerant species within a community (Gall et al., 2015; Kahlon et al., 2018). Recent studies have also revealed that trace metal concentrations may considerably vary in aquatic organisms depending on the presence of agonists and antagonists in the diet, the geographical region, the environment, and the extent of environmental pollution. Additionally, biotic communities are usually subject to contamination when they indirectly or directly consume water resources laced with trace elements (Gall et al., 2015).

## 2.2 Physical and chemical parameters

Physicochemical variables of water quality consist of water temperature (Temp.), electrical conductivity (EC), total suspended solids (TSS), pH, dissolved oxygen (DO), turbidity, and total dissolved solids (TDS), among others. These physical parameters can be measured in the field, that is, in-situ, or in a laboratory. The evaluation of the basic water chemistry is done using water quality parameters, and this helps in determining if the water meets the minimum threshold for chemical and bacterial content. It’s known that water has two crucial dimensions that are connected: quantity and quality. Water quantity is concerned with the amount, while quality deals with aesthetic (that is, smell and appearance), chemical, physical, and biological characteristics. These water quality dimensions are essential for the maintenance of a healthy aquatic environment.

The Athi River catchment experiences Seasonal variability that greatly influences water quality, whereby distinct dry and wet patterns are observed. During different seasons changes in rainfall patterns, temperature, and evapotranspiration rates alters water availability, river discharge, and water quality. Studies have reported high concentrations of pollutants such as nutrients (nitrogen and phosphorus) and heavy metals during the dry season. Wet seasons result in high river discharges and eventual pollutants dilution (Njuguna et al., 2017; Yang et al., 2013). However, surface run-off, erosion and transport of top soils and organic matter may lead to poor clarity, including high pollutant loads. Solar radiation and temperature fluctuations gives rise to change in dissolved oxygen and pH.

The water quantity has been established to support varied and rich aquatic flora and fauna and equally protect public health since water is essential to human life and the health of the environment (Reid et al., 2019). For example, the Athi River at certain times of the year is unable to support aquatic and human life. Upstream tributaries like Nairobi, Ngong, and

Mathare Rivers develop a black color while downstream of the river they turn green (Kitheka et al., 2022). This is because the water quality in Upper Athi is influenced to a large extent by partially treated or untreated effluents from industries and informal settlements that lack proper sanitation facilities, while downstream algal blooms develop due to increased pollution and gentle flow rates. Some of the water quality parameters and their characteristics are described in the subsequent paragraphs.

As a standard physical characteristic, temperature affects both the biological and chemical characteristics of the water. The measurement of water temperature is essential for evaluating its effects on changes in aquatic organisms (Abidi et al., 2022). This is because temperature influences the rate of chemical reactions, interactions of pathogens with aquatic organisms, the metabolic rates of organisms, the photosynthetic rate of both macrophytes and algae, as well as parasitic development (Abidi et al., 2022). Studies have shown that temperature is crucial in all aquatic ecosystems since it results in mortality and also influences dissolved oxygen solubility as well as other materials present in the water column (Olden and Naiman, 2010).

The electrical conductivity of water generally measures the ability with which current passes through a water column (Rhoades, 1996). High electrical conductivity infers the occurrence of dissolved inorganic solids that permit the transmission of electrical charge. Among the dissolved substances that conduct electrical charge are heavy metals. Studies have demonstrated that the specific conductance of water is influenced by both anthropogenic and natural factors in the catchment (Greig et al., 2010). Consequently, electrical conductivity determination assists in the estimation of the electrolyte concentration, which may make the water unsuitable for both human and wildlife consumption.

At the watershed, human activities have been known to influence the surface water conductance the most as compared to natural causes. Moreover, the inorganic pollutants entering streams and rivers through surface runoffs usually lower or raise the surface water conductivity (Greig et al., 2010). The organic compounds that lower electrical conductivity include oil because it lacks the ability to transmit electrical charge. Catchment basins with a high proportion of impervious surfaces, like in urban areas, usually cause huge runoffs that contain oils that have the effect of lowering the electrical conductivity of the streams and river water in the catchment. Other studies have shown that the residential and agricultural land uses in the catchment are likely to raise the electrical conductivity of streams and river waters (Zhang et al., 2020).

Turbidity can be defined as the amount or quantity of suspended solids in stream and river waters, such as microbes, algae, and soil particles (Yang et al., 2020). It can also be described as the measure of the cloudiness of a water body. Turbid water has both organic and inorganic particles. These suspended solids often enter streams and rivers through non-point pollution sources such as urban runoff and soil erosion, as well as other processes like algal growth or eutrophication (Yang et al., 2020). Studies have shown that high levels of turbidity in surface waters are attributed to high proportions of impervious surfaces existing in catchments, resulting in sediment loading from erosion and subsequent runoff (Voli et al., 2013). The high quantity of soil in the surface water in streams and rivers usually blocks the sunlight and prevents it from reaching the benthic zones of the aforementioned water bodies.

Therefore, turbid water results in floating and suspended particles absorbing sun rays, thus heating the water and causing the water temperature to rise (Voli et al., 2013). It is well known that turbidity may result from heavy rains, surface runoff and flooding, bank erosion, boats or animals disturbing the stream and riverbeds, storm waters from urban areas, people, or anthropogenic activities that cause watershed disturbance. According to the United States Environmental and Protection Agency (USEPA), turbidity measures the light transparency in the water bodies and is thus used as an index of water quality (Wilson et al., 2018). Moreover, turbidity is likely to be influenced by the variation in the colored dissolved substance and suspended particulate matter concentrations, including phytoplankton and other sediments. The aforementioned variables may be influenced by changes in oceanographic, meteorological, and hydrological phenomena (Wilson et al., 2018). The waters that are turbid generally increase light attenuation, which as a result, causes a reduction in the quantity of available light reaching the benthic aquatic organisms. Other studies have revealed that the turbidity arising from phytoplankton blooms or eutrophication may result in hypoxia events or harmful red tides, which consequently deprive the benthic flora and fauna of dissolved oxygen, thus resulting in the massive death of the local aquatic organisms (Stanton and Taylor, 2012). Such kinds of turbidity phenomena are usually closely monitored by the local environmental authorities, who normally give directives on management actions, typically in response to such events.

Total suspended solids (TSS) are primarily the most pronounced extraneous matter that is transported by the flowing water along the river channel (Stagge et al., 2012). The type and amount of TSS depend on the flow velocity and the water discharge. Additionally, TSS as pollutants in stream and river water are derived from inorganic and organic sources, usually from catchment activities (Stagge et al., 2012). The composition of TSS varies, that is, from organic to inorganic mineral particles usually transported along the river from the nearby watershed. Just like turbidity, TSS is closely associated with land erosion at the catchment as well as erosion activities in the river bed. TSS is a key measure of erosion activities in the river catchment and is also closely connected to the transportation of nutrients, especially phosphorus, heavy metals, and an array of both agricultural and industrial chemicals (Wang et al., 2018; Obodai et al., 2023). For example, previous studies have demonstrated that the sediment load of Sondu-Miriu, a river impacted by agricultural activities at the watershed, is about 150 t/km, while 423 t/km was reported for the Nyando river, which is impacted by agrochemicals from the nearby sugar farms and sugar processing industries (Abong'o et al., 2018).

Biochemical Oxygen Demand (BOD) typically measures the quantity of oxygen consumed by aquatic microorganisms as they biodegrade organic materials in aquatic ecosystems. Studies have established that BOD directly influences the quantity of dissolved oxygen (DO) in waterbodies (Bhateria and Jain, 2016). Principally, the higher the rate of DO depletion, the higher the BOD in the given stream or river. Additionally, studies have revealed that high BOD measurement is an indicator of high organic matter concentration, especially from wastewater discharges into streams and rivers. Therefore, high BOD infers an unhealthy stream or river, hence harmful to aquatic flora and fauna since the organisms suffer from stress and suffocation, with the ultimate consequence of attrition (Bhateria and Jain, 2016). BOD is a key parameter for water quality since it has a massive impact on both aquatic flora and fauna that rely on DO for survival. It directly measures the quantity of organic matter in stream and river water, and it is often considered a water quality test that is almost a standard measure for wastewater.

Water pollution in streams and rivers is mainly due to domestic waste, industrial discharge, and municipal waste disposal. Usually, wastewater pollution is associated with organic pollution. Organic pollution is mainly the disposal of the biodegradable organic matter into streams and rivers, resulting in the consumption of DO when such organic matter degrades, which, as has been mentioned earlier, leads to a decline in DO concentrations in the stream and river waters. Studies have revealed that the biogenic litter (e.g., sewage, vegetation, paper etc.) degradation immensely contributes to reduced DO concentrations in the recipient streams and rivers (Chan et al., 2022). Extremely low DO concentrations have been established to be detrimental to the aquatic flora and fauna and also affect the dissolution of minerals and inorganic minerals. However, studies have also revealed that minerals and metals adsorbed onto benthic sediments in streams and rivers are usually dissociated under anoxic or low oxygen conditions, thereby dissolving back into the water column with serious implications for aquatic flora and fauna (Chan et al., 2022). Increasing BOD in streams and rivers is an indicator that there is increased loading of organic matter, and this may be due to the influx of raw sewage into such streams and rivers. These observations are supported by a previous study finding by Antao et al. (2007) who revealed that the high BOD levels in Ruiru River could be associated to the high content of organic matter discharged into the river. However, some studies have demonstrated that the buffer zones or vegetative strips have low nutrient loading into stream waters from the agricultural land use, even though fecal coliform counts may not be reduced.

pH is defined as a measure of the basic or acidic status of the stream or river water. Normally, the pH of naturally occurring water in streams and rivers ranges between 6.5 and 8.2, with certain exceptions where it can be extremely low or high in certain waterbodies (Bills et al., 2003). For example, a water quality monitoring of the River Ruguti in Meru South revealed that the pH of the water samples ranged between 6.89 and 7.85 (Ombaka and Gichumbi, 2012), thus falling within the threshold range from 6.55 to 8.50 set by the World Health Organization (WHO). Just like other water quality variables, studies have also shown that stream water pH has a great impact on aquatic flora and fauna. Additionally, the pH of stream or river water is crucial in controlling the concentrations of dissolved anions and cations (Boyd et al., 2016; Favas et al., 2016). Further, a previous study revealed that pH values tend to be higher in the dry season than the wet season due to the increased photosynthetic activities of the cyanobacterial blooms as well as other algae that cause the precipitation of bicarbonates and carbonates in the River Ruguti (Ombaka and Gichumbi, 2012).

COD measures the oxidation of the organic matter of a water sample that, in most cases, is prone to oxidation by a chemical oxidant that is considered strong in terms of strength (Cardona et al., 2016). Among the strong oxidants used in COD tests is the dichromate ion, often with unique chemical properties. As aforementioned, both inorganic and organic substances in stream and river waters are subject to oxidation (Geerdink et al., 2017). However, in most scenarios, organic matter predominates and is thus of greater interest among studies. The sample oxidation extent may be affected by sample COD concentration, digestion time, and reagent strength. Notably, as a defined test, COD is usually used as a measure of pollutants in natural water and in wastewater from industrial and municipal discharges.

### 2.2.1 Heavy metals (Iron, Manganese, Zinc, Copper, Chromium and Lead)

Heavy metals like zinc, lead, chromium, copper, Manganese etc. are inorganic contaminants. They are naturally found in earth’s crust and are also present in sediments resulting in contamination aquatic life (Jamal et al.,2013). The metals are toxic but are only present in very small amounts in most natural waters. They find their way into our environment through anthropogenic activities and geological cycles (Kumar et al., 2019). In agriculture, chemical fertilizers are the main source of heavy metals. Excess application of fertilizers in the cultivation process increases the residues of these metal ions in the soil, which bioaccumulate and eventually, the toxic metals reach water bodies through surface runoff and leach into groundwater. Natural sources of metals emanate from weathering or from volcanic activities and eventually find their way into the rivers and streams.

Chromium (Cr) is considered an essential mineral element for both plants and animals. Additionally, it is considered one of the heavy metals that are pollutants in stream and river water (Li and Zhang, 2010). $Cr^{4+}$ is the most common Chromium species occurring in natural stream and river waters. In the aquatic ecosystem, the distribution of compounds whose contents contain Cr3+ and $Cr^{4+}$ often depends on the redox potential kinetics, the presence of reducing or oxidizing compounds, the total chromium concentration, pH, and the formation of $Cr^{3+}$ complexes or insoluble $Cr^{3+}$. Studies by WHO (2003) revealed that $Cr^{4+}$ salts are more soluble than Cr3+ salts, thereby making $Cr^{4}$ relatively mobile. On the other hand, $Cr^{3+}$ species are the most predominant forms of chromium in stream and river waters, especially at a low pH range of between 5 and 7, often in the presence of organic substances that are readily reducible (Rakhunde et al., 2012). Various studies have demonstrated that the nature and behavior of the different Cr species found in aquatic ecosystems are different from those in wastewater, a fact attributed to the altered physicochemical states of industrial and municipal effluents (Li and Zhang, 2010; Rakhunde et al., 2012).

The thermodynamic calculations revealed that $Cr^{3+}$ ions in aqueous solution occur as hydroxo-species, including $Cr^{+}$, Cr(OH)2+, Cr(OH)4-, $Cr(OH)_3$, $Cr_2(OH)_2^{4+}$, and Cr3(OH)45+, as well as a mixture of ligand complexes such as $Cr(SO_4)^{+}$ and $Cr(OH)Cl^{+}$. Usually, the dominant at pH 5 is $Cr(OH)^{2+,}$ while at pH 8, Cr(OH) 3 prevails (Namieśnik and Rabajczyk, 2010). However, the free Cr cations, polynuclear cationic species, chloro species, and sulfate complexes are often ignored since their contribution to surface water pollution under typical pH conditions is minimal. $Cr^{4+}$ can occur in aqueous solutions ordinarily as chromate, chromic acid, dichromate, hydrogen dichromate, and hydrogen chromate. $CrO_4^{2-}$ and $HCrO_4^{-}$ are frequently found in stream and river waters when chromium concentrations are lower than 5 μg/L (Namieśnik and Rabajczyk, 2010). Further, the hydrogen chromate ion predominates at pH<6, while the chromate ion is predominant at pH>7.

Iron (Fe) has been documented as an essential mineral for both humans and animals' nutrition. Despite its widespread as well as harmful effects, many countries are yet to adopt a numeric chronic Fe standard for the protection of aquatic flora and fauna (Burton et al., 2014). Currently, the USEPA chronic Fe threshold is 1000 µg/L for conservation and protection of aquatic ecosystems. In streams and rivers, Fe occurs in two main oxidation states, namely, the oxidized ferric ion ($Fe^{3+}$) and the reduced ferrous ion ($Fe^{2+}$) (Burton et al., 2014). In oxygenated stream and river waters, soluble $Fe^{2+}$ is oxidized to $Fe^{3+}$ ions. However, in circumneutral stream waters with a pH of about 6.5, ferric ions remain insoluble and quickly precipitate as oxyhydroxides and hydroxides. Even though Fe speciation is usually complex, Fe precipitates are often the predominant type in stream waters that support aquatic flora and fauna. Therefore, Fe precipitates are considered the most relevant species of iron when developing the threshold for protection of streams and rivers as well as the aquatic life in such water bodies.

Lead (Pb) naturally exists in the earth's crust and is generally considered toxic. In the water catchment, there are different sources of lead, including but not limited to erosion, industrial and municipal discharges, and metallic corrosion (Borah et al., 2020). Pb in stream and river water pollution is a major environmental concern, especially when wastewater treatment procedures are compromised, thereby resulting in elevated Pb levels that are detrimental to both human and aquatic life. Since Pb is non-biodegradable, it bioaccumulates and biomagnifies in the food chain and food webs and finally enters the bloodstream of humans and animals. It bioaccumulates in soft tissues like the brain, liver, nervous system, and kidneys (Bosch et al., 2016). The key sources of Pb in aquatic ecosystems include volcanicity and rock weathering; and human activities, which occur due to the mobilization of lead impurities originating from raw materials and finished products containing traces of lead. For instance, fossil fuels, mining and extraction of other minerals, as well as recycling processes.

Anthropogenic releases result from Pb being used intentionally in many manufacturing products and the subsequent incineration or disposal of lead-containing products (UNEP, 2010). Regardless of the pathway, Pb has been found to be carcinogenic in many studies conducted previously.

Manganese (Mn) is among the heavy metals whose uncontrolled discharge into aquatic environments is a matter of concern because of its toxic nature (Chowdhary et al., 2020). Even though Mn is an essential element for different biochemical and physiological activities in aquatic flora and fauna, its high concentration poses a health risk and may be harmful to aquatic ecosystems. Just like Pb, Mn is widely distributed in the mantle and earth's crust and is also present in the water as well as in the atmosphere as particulates. In terms of proportion, it is the most abundant heavy metal after iron and titanium. Due to its electronic configuration, Mn can be present in many oxidation states ranging from 0 to +7. Historically, the high concentrations of Mn in stream and river waters may have been linked to mining effluents and industrial discharges. However, metallic plumbing products such as water storage tanks, wells, and water pumps may contribute to Mn contamination (Chowdhary et al., 2020; Mahmood et al., 2012). Today, many nations globally have developed regulations and water monitoring frameworks that present the definition of acceptable levels of Mn in drinking waters of 0.3 mg/L as stipulated by the USEPA. Aquatic ecosystem pollution by Mn is a problem that is becoming a global concern because of the rapid increase in demand for this precious mineral, which consequently finds its way into streams and rivers, thus causing pollution.

In general, there are several regulatory bodies for water resources globally, particularly in regions that are directly affected by agricultural and industrial activities. This is because Mn pollutants in streams and rivers may become an ecological problem and a public health concern since most sewage treatment plants are inefficient in the removal of Mn from the wastewater. Many studies have revealed that Mn has serious pathological impacts in animal models and humans, especially under prolonged exposure at high concentrations (Pratush et al., 2018; Ahamad et al., 2020). However, few studies have documented the risks that a population exposed to Mn is exposed to, and very little is known when it comes to the ecological effects on aquatic life.

Zinc (Zn) has been revealed to be distributed widely throughout natural aquatic ecosystems such as streams and rivers. Some studies have demonstrated that zinc is an important trace element for both aquatic flora and fauna (Fallah et al., 2011). The implication is that when the amount of Zn exceeds certain levels, it may have a negative impact on organisms. According to the United States of America, the EPA threshold for Zn to protect and conserve aquatic flora and fauna is 120 µg/L for both short-term and long-term exposure concentrations. Studies have also revealed that aquatic organisms are generally more sensitive to Zn concentrations in stream and river waters than humans taking the same water for consumption (Fallah et al., 2011; Rakib et al., 2022).

Copper (Cu) is used for making anti-fouling paint for water vessels like boats and ships, thus demonstrating that it is highly toxic and harmful to aquatic flora and fauna (Nwuzor et al., 2021). Additionally, many studies have revealed that Cu is one of the most toxic heavy metals to aquatic life and the entire aquatic ecosystem. Cu has been used as an algaecide since it inhibits algal growth and thus can be of great danger when large quantities are discharged into streams and rivers (Zhou et al., 2017). This is because algae are found at the base of many food chains; thus, algae generally influence the quantity of food available for aquatic fauna such as macroinvertebrates, shellfish, reptiles, zooplankton, amphibians, and mammals, amongst others, in aquatic ecosystems (Zhou et al., 2017). Moreover, aquatic macroinvertebrates such as certain species of mayflies and stoneflies cannot tolerate water that is highly polluted with heavy metals such as Cu. Such species will disappear and be replaced by other tolerant macroinvertebrate species. Consequently, a change in macroinvertebrate community composition frequently affects the composition of aquatic vertebrates such as finfish, amphibians, reptiles, and mammals. Therefore, the high toxicity of Cu to algae can result in ripple effects in the entire aquatic ecosystem, and it also shows that changing one section of an ecosystem usually affects the entire ecosystem (Zhou et al., 2017).

### 2.2.2 Chlorophyll *a*, Total Nitrogen (TP) and Total Phosphorous (TP)

Chlorophyll a (Chl a) is the green photosynthetic pigment present in plants, including algae, cyanobacteria, and macrophytes (Waters et al., 2015). The quantity of Chl found in streams and rivers usually depends on nutrient content, wind, water temperature, and sunlight. Anthropogenic practices such as sewage discharges and fertilizer use in stream catchments often increase the quantity of nutrients, especially phosphorus and nitrogen. Excessive input of nutrients has the effect of facilitating massive algal growth or eutrophication beyond levels considered to be healthy for aquatic flora and fauna (Adams et al., 2020). Finfish and shellfish, among others, may die due to the decreased levels of dissolved oxygen caused by eutrophication, and equally, the macrophyte population may decline as a result of the low levels of DO. Additionally, the blue-green algae, especially the cyanobacteria, may dominate when nutrient levels increase, thus producing harmful toxins that may cause death to other aquatic life (Adams et al., 2020).

Farmland fertilizers and washing detergents are composed of P-compounds. Such fertilizers and washing detergents are washed into streams and rivers through runoff. Sewage and industrial wastes also contain high concentrations of P compounds (Chowdhary et al., 2020).

The P compounds may result in a secondary problem in streams and rivers where the growth of algae is limited by P. In such a scenario, the influx of P compounds has the ripple effect of stimulating algal growth and therefore facilitates the process of eutrophication (Chowdhary et al., 2020). Notably, human activities are the main sources of P, which, as aforementioned, is generated through the application of pesticides, cleaning using soaps and detergents, and the use of fertilizers. The excessive presence of P in stream and river waters may cause aquatic macrophytes and algae to grow rapidly, thereby chocking the river and stream channels (Karunanithi et al., 2015). Njuguna et al. (2017) found that the Nairobi River average TP concentration was 1.5ml/L and 2 ml/L in the rainy and dry seasons, respectively. Fresh water TP concentrations above 0.02 ml/L accelerate eutrophication (Njuguna et al., 2017).

Nitrogen (N) is considered an essential element for the growth of plants since it is a constituent of nucleic acids and proteins. To improve agricultural crop yield, the application of fertilizer is mandatory with N. The agricultural fertilizers form the main source of N. The fertilizers can be organic farmyard manure in regions with a high density of animals or commercial fertilizer (Strady et al., 2021). Total nitrogen (TN) consists of dissolved inorganic compounds such as ammonia, nitrites, and nitrates, as well as organic nitrogen. TN ends up in aquatic ecosystems through mainly agricultural activities. Excess TN in stream and river waters may result in eutrophication since it stimulates the massive growth of macrophytes and algae. Subsequently, stream water clarity is reduced, benthic zones of the stream are depleted of DO, and consequently, shellfish and finfish may die (Strady et al., 2021).

Additionally, the high concentration of TN has been revealed to be toxic to humankind. The concentration of $NO_3^{-1}$ above 10 mg/l in drinking water is generally harmful, especially to unborn babies, and may result in blue baby syndrome (Jagessar, 2013), whereas the concentration of $NO_2$ above 4 mg/l is toxic to sensitive aquatic fish such as rainbow trout (Lahnsteiner, 2008). Even though few studies have documented TN levels in the Upper Athi River catchment, a study by Njuguna et al. (2017) showed that at the Fourteen Falls sampling site, which was predominantly covered with water hyacinth (*Eichhornia crassipes),* recorded an average $NO_3^{-1}$ level of 104 μg/L, in the rainy season, compared to the next sampling site, upstream of the river, which had $NO_3^{-1}$ level of 2382 μg/L.

## 2.3 Remote Sensing and GIS

Generally, a Geographical Information System (GIS) provides an environment to acquire, store, process, and map spatial datasets (Cheruiyot et al., 2019). Many GIS tools are today available for specialized purposes in data management. Remote sensing data and GIS are increasingly becoming important tools in hydrology and land use and land cover (LULCC) analysis. This is due to the fact that most of the data required for hydrological and LULCC analysis can easily be obtained from remotely sensed images. Remote sensing has the capability to acquire spectral signatures instantaneously over large areas. The signatures allow for the extraction of information pertaining to land use and land cover, emissivity, surface temperature, and energy flux (Cheruiyot et al., 2019). LULCC can be analyzed over a period of time using Landsat Multi Scanner (MSS) data and Landsat Thematic Mapper (TM) data using image classification techniques (Cheruiyot et al., 2019). Using independent validation data, an error matrix (also known as a confusion matrix) is calculated to determine the accuracy of the classification and to identify where misclassification occurs. In studying LULCC, Geographical Information Systems (GIS) and remote sensing techniques are important tools in monitoring and assessing their dynamics. This is determined by the production of geospatial components for land features and natural resources based on time-series imagery. Variation in the temporal distribution of LULCC practices helps in the monitoring and assessment of environmental degradation (Veldkamp and Kok, 2002).

### 2.3.1 Image classification

The selection of the image classification scheme is to ensure that it represents the features as the true ground brightness value of each pixel. Visual and statistical examination of the images is used to assess the contamination of the scenes by factors such as clouds and other atmospheric conditions (Chasia et al., 2021). Reducing and eliminating these factors can be costly in terms of time and money and, therefore, can result in the removal of useful image information. Some of the preferred selection classifications include per-pixel and object-based classifications (Chasia et al., 2021).

### 2.3.2 Supervised Classification

A supervised classification procedure classifies an image based on a pre-defined land cover type. This involves identifying and delineating regions in the satellite image to be used as training sites (Chasia et al., 2021). The sites should have the same spectral information as the land cover types to be used to calculate the classification algorithm. This uses multivariate statistics of the training areas to assign a specific code to every pixel in the image. Some of the techniques used in supervised classification include the selection of training areas, the selection of feature space, the classification algorithm, and the parallel-piped classifier (Chasia et al., 2021). The parallel-piped classifier was widely involved in this study.

### 2.3.3 Pre-processing

In order to analyze remotely sensed images, the different images representing different bands must be stacked. This allows for different combinations of red, green, and blue (RGB) to be shown in the view (Chasia et al., 2021). Landsat images from TM and ETM+ are in 8 bands.

Layer stacking was performed to combine all the image bands, minus the thermal bands. The study area spanned several image files. Image mosaicking, which involved the combination of the two TMs and ETM+, was performed to create one large file for each study period (1990 and 2018).

An Arcview shapefile for the watershed, geo-referenced to the same coordinate system as the mosaiced image, was used to get a subset of the images for the catchment. Sub-setting not only eliminates the extraneous data in the file, but it also speeds up processing due to the smaller amount of data to process, which is important when dealing with multiband data (Chasia et al., 2021). The extracted subset was used in the classification procedures for the images. Unsupervised classification followed by supervised classification was used.

### 2. 4 Modelling Water Quality

The Water Quality Models are the key tools to test the impact of various actions on land use (Liu et al., 2021). A water body needs the appropriate type of model. For this research study, the prediction of water quality trends was undertaken in two phases. The longitudinal water quality profile was carried out using QUAL2Kw model, while the second phase of predicting future water quality trends was performed using the SPSS forecasting tool.

QUAL2Kw was developed by Park and Lee (2002). It is a one-dimensional steady state model which includes the simulation of water quality interactions such as conversion of algal deaths to BOD, denitrification process and DO change caused by plants. The QUAL2K model can simulate up to 16 water quality determinants along a river and its tributaries (Liu, et al., 2021). The model is freely available and can be downloaded from http:www.ecy.wa.gov/. It’s useful even when water quality data availability is limited.

There are tools that have been developed and designed to apply past happenings and present information regarding possible future scenarios of water quality parameters. One of the most applied techniques is forecasting. Water quality future trends forecasts refer to the ability to look into the behavior of certain water quality parameters in the future. The generation of future water quality trends not only gives a look into possible future happenings but also plays a key role in management, decision-making, and planning. However, developing a forecasting decision support system is usually non-trivial as there are several uncertainties affecting the selected parameters (Liu et al., 2021). There are numerous forecasting techniques that vary from domain to domain. However, resource management deals with time series data, and in that case, the study scope is limited to time series forecasting (Liu et al., 2021).

**2.5 Research gaps**

Seasonal variations play a key role in water quality in both natural and anthropogenic affected environments (Khatri and Tyagi, 2015). During different seasons changes in rainfall patterns, temperature, and evapotranspiration rates alters water availability, river discharge, and water quality. Globally, different studies have reported high concentrations of pollutants such as nutrients (nitrogen and phosphorus), and heavy metals during the dry season (Yang et al., 2017). However, in the Upper Athi River few studies such as Adongo et al. (2022) studied the seasonal variation in physicochemical characteristics of groundwater, a case study of Kamiti-Marengeta Sub-catchment in Kiambu. Notably, Adongo et al. (2022) did not study the surface waters. Ngatia et al. (2023) studied the effects of anthropogenic activities on water quality within Ngong River, but not the entire Upper Athi River watershed. Apparently, there is no known study that has investigated the water quality of streams in the entire Upper Athi River. Therefore, the present study objective addressed this gap and generated data for the entire Upper Athi River Catchment.

Several research studies have been undertaken in Athi River and its tributaries, Ndarugu and Nairobi River system in relation to water quality. A research study by Wambugu (2018) in Ruiru and Ndarugu rivers found out that LULCC was mainly due to increasing population pressure, and this would continue with the unprecedented urban development, affecting water quality parameters. Munyao, (2018) demonstrated that water pollution from industries and sewerage upstream the Athi River had a negative effect on riparian community downstream in Makueni county. Kienja (2017) showed that water quality of Nairobi River, one of the streams in the Upper Athi River catchment, was being degraded as a result of uncontrolled development arising from informal settlement. All the aforementioned studies were undertaken in individual streams or smaller catchment areas that could not adequately represent the bigger picture of the Upper Athi River catchment degradation. Other studies such as Kitheka et al. (2022) studied sediments transport in relation to LULCC but not water quality in relation to LULCC. Hence, this research study aimed to address the gap by assessing the land use land cover changes in relation to water quality in the larger Upper Athi River Catchment.

The modeling of water quality in rivers and streams has been applied more extensively in developed countries than in developing nations (Bui et al., 2019). In the USA, Hobson (2013) used QUAL2Kw as a Decision Support Tool for Silver Creek Watershed and found that modeling could be more cost-effective than the regular water quality monitoring. For instance, in Cértima River in Portugal, Qual2Kw model showed that the river was highly contaminated with high levels of nutrients (Song et al., 2020; Zhang et al., 2012). QUAL2kw is a one-dimensional model with many applications, especially in river channels with non-uniform but steady flow with a roughly constant pollution loading (Chowdhury et al., 2018; Flynn et al., 2015; Ye et al., 2013; Zhang et al., 2015; Zhu et al., 2015). In simulation, QUAL2kw factors in both the point and non-point pollution sources (Pelletier et al., 2006). Hadgu et al.

(2014) undertook a study on effect of untreated industrial, domestic and agricultural waste of point source and non-point discharges from coffee and tea factories in Ndarugu River, a tributary of Athi River, using QUAL2Kw model and found out that the model reflected the field data quite well. This was a smaller river watershed, and hence could not be a representative of the large Upper Athi River watershed. Therefore, the present study embarked on modelling water quality in the main Athi River channel to assess water quality conditions and causes of degradation. Additionally, forecasting will help in predicting how surface waters will respond in future to the land use changes in the Upper Athi River Catchment.

# CHAPTER 3
# 3.0 VARIATION OF PHYSICOCHEMICAL PARAMETERS IN THE UPPER ATHI RIVER CATCHMENT IN KENYA

This chapter deals with the results for physicochemical parameters, seasonal variations in water quality and their corresponding discussion, conclusion and recommendations.

## 3.1 Introduction

Aquatic ecosystem such as rivers, dams, and lakes provide livelihoods for the natural population in both developing and developed countries. In the recent past, they have been subjected to various forms of degradation due to pollution arising from domestic wastes, industrial effluents, agricultural runoffs, and bad fishing practices (Bağdatlı and Belliturk, 2016). According to Okoro et al. (2012), industrialization and human activities have partially or totally turned the aquatic environment into dumping sites for waste materials. As a result, such pollution has led to numerous adverse influences on water resources.

Water in the natural environment contains many dissolved substances and non-dissolved particulate matter. Dissolved salts and minerals are necessary components of good-quality water as they help maintain the health and vitality of the organisms that rely on this ecosystem service (El-Said et al., 2021). Water quality is used to evaluate basic water chemistry and to determine whether the water meets the minimum criteria for bacterial and chemical content. Safe drinking water is essential for maintaining public health; hence, every effort should be made to achieve the highest quality drinking water possible. Hence, protection of water sources and rivers from contamination is the first step in providing clean drinking water.

Water quality degradation makes water harmful to human beings, unfit for industrial use, and adversely affects aquatic plants and animals. The freshwater ecosystems are vulnerable to human impacts and are likely to be influenced by catchment activities (Kamba et al., 2016).

This is because terrestrial ecosystems have linkages with aquatic ecosystems. Contamination of aquatic ecosystems with a wide range of pollutants has become a matter of concern over the past few decades (Gangloff et al., 2016).

In East Africa, water resources have experienced profound ecological changes, including phytoplankton primary production (Whitehead et al., 2009), for instance in Lake Victoria. The water resource has undergone eutrophication as a result of pollution from rapid population growth and increased industrial and food production (Helmer et al., 2022). Lake Victoria Environmental Management Programme (LVEMP) data demonstrate a high level of variability in physicochemical parameters. These variations occur at both temporal and spatial scales (Balaka and Chagoma, 2022). In this regard, there is no comprehensive data that could be relied on to generate scenarios to predict future water quality trends in the Upper Athi River basin. Moreover, LVEMP covers a large area, with a great variation in land use ranging from agriculture (sugar belt, maize, coffee, fish farming, and tea zones), and climatic conditions are very different. The Upper Athi river catchment covers a smaller area and is highly urbanized, and the environmental pollution requires urgent research to come up with a model to generate timely data at a low cost to reclaim the water resource.

Hamid et al. (2020) affirms that one of the most significant determinants of water quality is land use and land cover. Land use and land management practices affect the quantity and quality of runoff water, which in turn affects the water budget, water chemistry, and biodiversity of aquatic organisms in receiving waters. Doe et al. (2022) on "The influence of land-use patterns on water quality in a river watershed system" asserted that the land use within the watershed has great impacts on the water quality of the river.

The water quality of rivers may be altered due to changes in the land cover patterns within the watershed due to an increase in the types and intensity of human activities. Changes in land cover and land management practices have been regarded as the key influencing factors behind the alteration of the hydrological system, which leads to a change in runoff and water quality (La Mela et al., 2016). The quality of water essentially determines the extent to which it can be used for various purposes. The examination of the physical, chemical, and biological characteristics of any water resource is an important undertaking, as this enables the determination of the chemical, physical, and biological constituents in water and the determination of the extent to which a particular water resource can be utilized for a variety of purposes. The quality of any body of surface or ground water is a function of either or both natural influences and human activities.

In Kenya, land use changes on various catchments and water towers have been increasingly characterized by human settlement, deforestation, wetland reclamation, and unsustainable agricultural activities (Aura et al., 2011). Kenya's environment has suffered from the impacts of human activities and land degradation. Deforestation, soil erosion, and water pollution are some of the challenges the nation needs to address in order to achieve $SDG_6$ and Goal 15 of the SDGs as asserted by UNCSD (2012). La Mela et al. (2016) found out that landscape properties such as riparian zone condition, channel slope and aspect, local geology, vegetation and hydrology, all affect the structure and function of aquatic ecosystems. While appreciating the contribution of urban and peri-urban agriculture to financial, food, and nutritional security, particularly for the urban poor, ways should be sought to educate both producers and consumers of the hazards and risks of agricultural waste without compromising the benefits derived (MEMR, 2012).

Catchment degradation is a major problem that is undermining the limited sustainable water resource base in the country. Catchment degradation results in increased runoff, flash flooding, reduced infiltration, erosion, and siltation. The main causes of catchment degradation are poor farming methods, population pressure, and deforestation. To support the social pillar of Kenya's Vision 2030, Kenya aims to provide its citizens with a clean, secure, and sustainable environment by the year 2030 (MEMR, 2012). To achieve this, the nation has set goals such as increasing forest cover from less than three percent (3%) of its land base at present to four percent (4%) by 2030 and reducing by half all environmental-related diseases at the same time (MEMR, 2012).

Safe drinking water is essential for maintaining public health; hence, every effort should be made to achieve the highest quality drinking water possible. Protection of water sources and rivers from contamination is the first step in providing clean drinking water. This research study focused on assessing pollutant levels in the Upper Athi River catchment area by analyzing various water quality physical-chemical parameters that are influenced as a result of different industrial, economic, and agricultural activities taking place in the catchment. The data will enable policymakers to make decisions on water quality management and the implementation of mitigation activities.

## 3.2 Methodology

### 3.2.1 Study Area

The study was carried out in the Upper Athi River Catchment (UARC) which lies between latitudes $0^0$ 45‘S and $1^0$47‘S and Longitudes $36^0$29‘E and $37^0$53‘E. The area covers the entire Nairobi County and extends to the peripheral parts of Kiambu, Kajiado and Machakos counties (Figure 3.1). In Kenya, the Athi river drainage basin is considered the fourth largest drainage system with a total surface area of 69,930 $km^2$ (Kitheka, 2019). However, the upper Athi River where this study was done has a surface area of about 6754 $km^2$ which is equivalent to about 9.7% of the total basin area (GIS & Survey of Kenya, 2016).

### 3.2.2 Drainage

The Athi River originates from the Central Kenya highlands, especially the Ngong Hills, Kikuyu Escarpment, and southern parts of the Aberdares ranges. The upper section of the Athi River basin in the Kenya Highlands is densely populated, with approximately 200–300 persons per $km^2$, with intensive crop cultivation dominating the area (Prasol Training and Consulting Ltd., 2012). Major crops cultivated here include various horticultural crops, coffee, and tea (Prasol Training and Consulting Ltd., 2012). The main tributaries of the Upper Athi River include the Nairobi River (Mathare, Ruiruaka, and Ngong), Komo, Mbagathi, Ndarugu, Riara, and Ruiru rivers (Figure. 3.1), which traverse densely populated areas within the Nairobi metropolitan area with varied anthropogenic activities such as commercial, industrial, informal settlements, agriculture, deforestation, solid waste disposal, wetland, and riparian encroachment (Kitheka et al., 2022).

Nairobi River originates from Ondiri/Kikuyu swamps and Kikuyu protected springs by Nairobi City Water and Sewerage Company. The river traverses through the Nairobi City Central Business District (CBD). Downstream from the CBD, it receives pollutants from informal settlements, including surface run-off from the CBD. The Dandora dumping site is located on the banks of the Nairobi River at Dandora Estate, where the river receives leachate and other forms associated with solid waste. Studies have confirmed the presence of dangerous elements such as lead, mercury, cadmium, and PCBs, which are seriously hazardous for humans (Bini and Wahsha, 2014). Mathare, Ngong, and Ruiruaka join the Nairobi River downstream of the dumping site. The Mathare and Ruiruaka Rivers traverse Mathare slums that have no proper sanitation, bringing along pollution loads. The main head waters of the Ngong River are the Ngong Hills and Dagoretti Forest, then the river traverses through Kibra informal settlements and the Nairobi industrial area, where it receives raw or untreated wastewater from dilapidated sewer lines. Dandora Wastewater Treatment Plant discharges final effluent into the Nairobi River before the river joins the main Athi River. Ruiru, Komo and Ndarugu are tributaries of the Athi River. The rivers originate from Gatamayu Forest, at the southern most tip of the Aberdare Ranges. The Ruiru River traverses Ruiru town and, hence, is subjected to industrial pollutants and surface run-off from the town during rains. The land uses for the sub-catchments are industries and agriculture (tea, coffee, and subsistence crops). Komo stream is a recipient of final effluent from the Thika Wastewater Treatment Plant and joins the Athi River before Fourteen Falls.

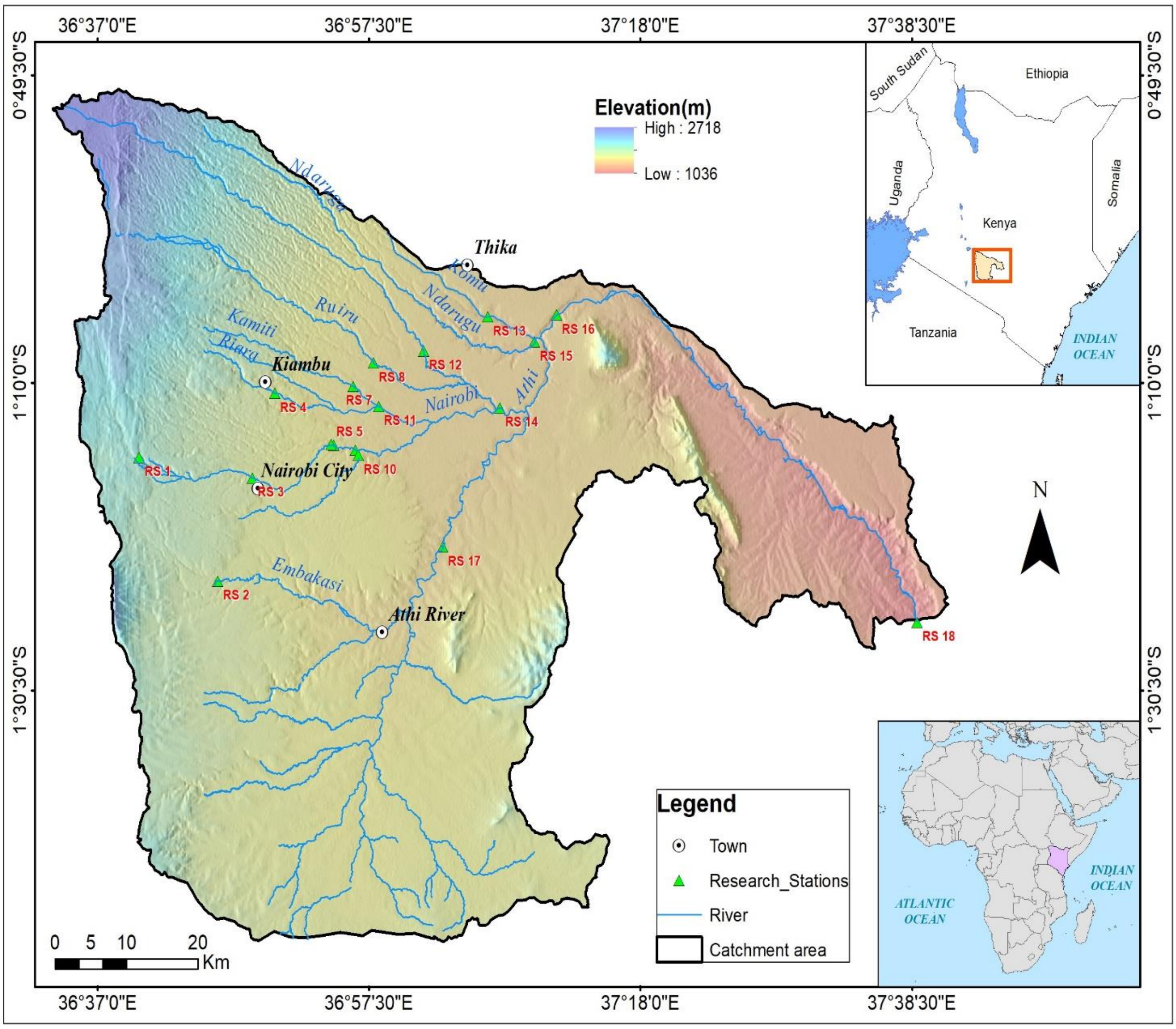



**Figure 3.1 Map showing the Upper Athi River Catchment with Research stations (sampling sites) indicated by RS codes and red triangles symbols, river network and the legend (inset).**

**Table 3.1 The codes, names and coordinates for sampling sites**

| Code | Name of sampling site | Coordinates for sampling site | |
|---|---|---|---|
| | | **Longitude** | **Latitude** |
| RS1 | Kikuyu Springs | 36.407 | -1.1456 |
| RS2 | Mbagathi | 36.627778 | -1.2833 |
| RS3 | Nairobi River at museum | 36.81230 | -1.2745 |
| RS4 | Riara River | 36.584175 | -1.2723 |
| RS5 | Ruiruaka River | 36.534320 | -1.1430 |
| RS6 | Mathare River | 36.5347 | -1.1437 |
| RS7 | Kiu River | 36.920l30 | -1.1196 |
| RS8 | Ruiru River | 36.963170 | -1.1426 |
| RS9 | Nairobi River at Njiru | 36.562450 | -1.1435 |
| RS10 | Ngong River at Njiru | 36.564530 | -1.1455 |
| RS11 | Kamiti River | 36.579810 | -1.1157 |
| RS12 | Thiririka River | 37.007430 | -1.0679 |
| RS13 | Komo River | 37.07325 | -1.0596 |
| RS14 | Nairobi River at Ruai | 37.013860 | -1.1330 |
| RS15 | Ndarugu River | 37.161111 | -1.1306 |
| RS16 | Athi River at Fourteen | 37.147610 | -1.0481 |
| RS17 | Athi River EPZA WWTP | 37.05415 | -1.3456 |
| RS18 | Athi River at Wamunyu | 37.645450 | -1.4107 |

### 3.2.2. Materials and Methods

The study investigated levels of Physicochemical parameters (pH, Electrical Conductivity (EC), Temperature, BOD and COD, Total Suspended Solids (TSS), Total Nitrogen, Total Phosphorus), Chlorophyll *a* concentration and heavy metals (Iron, Zinc, Lead, Copper, Manganese and Chromium) in water samples from eighteen (18) sampling sites, eleven (11) existing stations and seven (7) other research stations selected at strategic locations (sites) of Athi River and its tributaries, using appropriate laboratory instruments.

Sampling was done once a month from the 18 Research stations (sampling sites) (Figure 3.1) located along the Athi River and its tributaries from February 2017 to December 2018. The coordinates of the sampling sites were recorded using Global Positioning System (GPS). These sites were chosen to represent different sub-catchments that drain into the Athi River in order to understand the influence of LULCC on water quality.

### 3.2.3 In-Situ field measurements

The measurements of water temperature, pH, dissolved oxygen (DO), and electrical conductivity (EC) were undertaken in-situ in the field using a portable multi-parameter meter (Model: H1 9828 HANNA instruments) supplied with a multi-sensor probe. The electrical conductivity and pH probes were first calibrated against standard solutions each day before sampling commenced, while the dissolved oxygen probe was calibrated using ambient air. The measurements were taken by immersing the probe into the river water to a depth of about 0.3 m, and the reading was allowed to stabilize. Then pH value of the water was then read and recorded. Similarly, temperature, dissolved oxygen, and electrical conductivity were also measured.

Sampling and sample analyses was carried out according to standard protocols (APHA, 2012). Sampling period was between 7:30am to 1:00pm to avoid heat of the day that would cause variation of sample status. During sampling, the time of sampling, date and weather conditions were noted, including whether the weather was sunny, cloudy or windy. Water samples were collected using 1000 ml plastic bottles for laboratory analyses i.e Biological Oxygen Demand (BOD), Chlorophyll *a* (Chl *a*), Total Suspended Solids (TSS), Total Nitrogen (TN), and Total Phosphorous (TP). River discharge data was obtained from the Water Resources Management Authority (WRA) of Kenya.

TDS was calculated from the following formula;

$$TDS = (EC\ Value \times 0.62)$$

Where EC = Electrical Conductivity

Turbidity was also measured in-situ by use of a Turbidity meter (Model: H1 93703) and the value was recorded in NTU units.

### 3.2.4 Laboratory Analyses

#### 3.2.4.1 Analysis of Heavy Metals by Atomic Absorption Spectrophotometer (AAS)

Heavy metals analysis was carried out using AAS, Shimadzu GFA-7000 located at WRA Central Water Testing Laboratories. The instrument is well suited for metal analysis because of its ability to detect small quantities (detection limit of 20µl, injection Pb modifier) of substances readily and accurately.

#### 3.2.4.2 Total Suspended Solids (TSS)

Total Suspended Solids (TSS) was determined by the gravimetric method where filtering with GF/A filter paper was employed. A well-mixed sample was filtered through a weighted standard glass filter paper. The residue retained on the filter paper was dried at temperatures between 103$^oC$ to 105$^oC$) to a constant weight. The increase in weight of the filter paper represented the Total Suspended Solids (APHA, 2012).

The filter paper was weighed to an accuracy of 0.1 mg and placed in the Buchner funnel. A sufficient volume of the sample was filtered. Thereafter the funnel and filter were washed with a little distilled water. The funnel was washed and washings passed through the filter paper, then the filter paper was transferred to the drying oven for 30 minutes at 105°C. Finally, the filter paper was removed from the oven and transferred with a clean tweezer to a desiccator for 5min to dry completely and the filter paper weighed to an accuracy of 0.l mg.

The TSS was calculated using the equation below:

$$\text{Total Suspended Solids in mg/l} = \frac{(f - i)\ \text{mg} \times 1000}{S}$$

Where: f =Final weight of filter paper

i =Initial weight of filter

S=Volume of sample

#### 3.2.4.3 Biochemical Oxygen Demand, $BOD_5$

A given volume of sample was transferred to an Oxitop bottle with a magnetic stirrer. Colour and smell judgment or conductivity of a sample was used to judge how much of the sample was needed for a given sample, that is, if sample was very thick with strong smell, 43.5 mls was used. For samples with less smell and not very thick, other values given on the oxitop box were used as shown in the Dilution Factor table below.

| Sample Volume | Dilution Factor |
|---|---|
| 432 | 1 |
| 365 | 2 |
| 250 | 5 |
| 164 | 10 |
| 97 | 20 |
| 43.5 | 50 |

Potassium Hydroxide (KOH) pellet was put in the breather of the bottle and corked using the Oxitop and the Oxitop adjusted to zero. The Oxitop bottle was placed in the Oxitop box for 5 days at 20$^{o}$C, after which the result was read.

**Calculation:** $BOD_5$ = Meter Reading x Dilution factor.

#### 3.2.4.4 Chemical Oxygen Demand (COD)

Digestion vessel with holes sized for close fit of culture tubes was used for sample digestion. The Culture tubes were arranged in test tube rack for the different samples and 2 more were added for a blank and a standard. 1.5ml Potassium Dichromate was added into the small tubes. Distilled water (2.5 ml) was added into the test tubes for standard and blank and separately kept.

Depending on the strength of pollution, between 1.5ml and 0.001ml of sample was placed in the test tubes. 1.5ml for less polluted samples and 0.001ml for highly polluted samples. Personal judgment and experience is used to decide on the amount of sample taken for analyses based on the colour of the sample, the conductivity and the smell of the sample. Then, the sample was topped up to 2.5ml with distilled water.

NB: Whatever amount of sample is taken its topped up with distilled water to make 2.5ml.

3.5ml of the conc. Sulphuric acid was measured and added to the standard. A lot of care was taken when doing this to avoid burning oneself with splashing acid. This was immediately sealed. The Standard is never put in the digester. 3.5ml of the sulphuric acid with silver Sulphate was measured and added to the blank and all the samples that were prepared. They were sealed and placed in a digester for 2 hours at 148°C. The standard was left in the rack. After 2 hours digestion, cooling was done. Finally, titration was carried out with Ferrous Ammonium Sulphate (FAS) using Ferroin indicator. All results were recorded.

**Calculation**

$$\text{Molarity of FAS solution} = \text{Volume } 0.0167\ K_2Cr_2O_7 = \frac{\text{Solution titrated, ml} \times 0.1}{\text{Volume of FAS used in titration (ml)}}$$

$$\text{Hence, to calculate the COD level in mg } O_2/l = \frac{(A-B) \times M \times 8000}{\text{Volume of sample in mls}}$$

Where: A = ml FAS used for blank

B = ml FAS used for sample and M = molarity of FAS

### 3.2.4.5 Determination of Total Nitrogen

Nitrate -Nitrogen was determined by the cadmium reduction method. In this method, nitrate ($NO_3^-$) is reduced almost quantitatively to nitrite ($NO_2^-$) in the presence of cadmium (Cd).

The $NO_2$ – produced thus, is determined by diazotizing with sulphanilamide and coupling with N-(1- naphthyl)-ethylenediamine dihydrochloride to form a highly coloured azo dye that is measured calorimetrically. Analysis was carried out within 24 hours. All the reagents used were of analytical grade and distilled water was used in the preparation of standards and reagents; Samples were filtered through 0.45µm pore size 47mm diameter membrane filter paper (Whatman) to remove suspended matter. The pH adjustment to about 9 was done using HCL.

To 25.0 ml of sample, 75 ml of Ammonium Chloride- EDTA solution was added and mixed. This mixture was then poured into the column and sample collected. The first 25 ml was discarded and the rest of the sample collected (approximately 70 ml) in the original sample flask. 2 ml Colour reagent was added in 50 ml of the reduced sample and allowed 10minutes for colour to develop. The absorbance was measured within 2 hours at 540nm against a reagent blank. The reduction of the Standards was carried out exactly as described for the samples. At least one nitrite standard was compared to a reduced nitrate standard at the same concentration to verify the efficiency of the reduction column. A UV-Visible Spectrophotometer (Shimadzu UV, Visible UVmini-1240) was used to read the absorbance. A standard curve was obtained by plotting absorbance of standards against $NO_3$–-N concentration. Sample concentrations were computed directly from the standard curve obtained and the results reported as milligrams oxidized Nitrogen per Liter (the sum of $NO_3$-N plus $NO_2$-N).

### 3.2.4.6 Determination of Total Phosphorus

Ascorbic acid method was used to determine phosphates (Orthophosphate-Phosphorus). An amount of 50ml of thoroughly mixed sample was measured and taken through the persulfate digestion process to a volume of 10ml. Standard solutions in the ranges of, (0.0, 0.2, 0.4, 0.6, 0.8, 1.0 mg/l) were also prepared the same way. After cooling, 8 ml of combined reagent was added. A UV-Visible spectrophotometer (Shimadzu UV-Visible mini-1240) was then used to obtain the absorbance of the prepared samples and the standard solutions at 880nm. A curve of absorbance verses concentration was plotted and the sample concentrations obtained directly from the curve.

#### 3.2.4.7 Chlorophyll *a* determination

Analysis of the photosynthetic chlorophyll pigment present in aquatic algae is an important biological measurement which is commonly used to assess the total biomass of algae present in water samples. For this study, one Liter (1L) of sample was taken with a grab sampler from the Research station and covered with Aluminium foil to stop any light penetration and prevent further photosynthesis.

**Procedure**

Water Samples for chlorophyll analyses were collected from the same sites and at the same time as other parameter measurements, using a standard water sampling technique (grab sampler). Initial Volume of water was recorded. Cells were separated from the water by filtration. Filtration was continuous, not to allow the filter to dry during filtration of a single sample. At the end of the filtration 0.2 ml of $MgCO_3$ suspension was added to the final few millilitres of water in the filter cup. The filter paper was placed in the tissue-grinder, 2-3 ml of 90% acetone added, then ground until the filter fibres were separated. The acetone and ground filter were poured into a centrifuge tube; grinding tube rinsed with another 2 ml of 90% acetone and added to the centrifuge tube. The total volume in the centrifuge tube was made to 10ml with 90% acetone. A top was placed on tube, labelled and stored in darkness at $4^oC$ for 10-12 hrs. Closed tubes were placed in a centrifuge for 15minutes at 3,000 rev/min to clarify samples; clear supernatant was decanted into clean centrifuge tubes and the volume recorded. A cuvette was filled with 90% acetone (Blank). Absorbance recorded from the spectrophotometer at 750nm and 663nm.  This blank was zeroed.

Sample was placed in the cuvette, absorbance recorded at 750nm and 663nm (750a – 663a). Two drops of 1 mol $l^{-1}$ HCl was added to sample in 1cm cuvette. This was agitated gently for a minute and absorbance recorded at 750nm and 665nm (750b and 665b).

The procedure was repeated for all samples.

**Calculation**

(i) Absorbance: 663a – 750a = corrected 663a

Absorbance: 665b – 750b = corrected 665b

(ii) Corrected absorbance 663a and 665b was used to calculate:

$$\text{Chlorophyll } a = \frac{26.73(663a - 665b) \times Ve}{Vs \times L} \text{ mg m}^{-3}$$

$$\text{Phaeophytin } a = \frac{26.73(1.7(665b) - 663a) \times Ve}{Vs \times L} \text{ mg m}^{-3}$$

Where: $V_e$ = Volume of acetone extract (Liters)

$V_s$ = Vol. of Water Sample ($m^3$)

L = Path length of cuvette (cm)

Chlorophyll *a* concentration was recorded. The ratio of chlorophyll *a* to phaeophytin *a* gives indication of the effectiveness of sample preservation, as well as of the condition of the algal population.

### 3.2.5 Data Analysis

For data analysis, R software a free software for environment data statistical computing and graphics was used. It compiles and runs on a wide variety of UNIX platforms, Windows and MacOS. In the present study, R software was downloaded and different packages such as vegan package provides for descriptive community ecology (Okansen et al., 2019). During the study period, the water quality parameters were compared between the dry and wet seasons using a one-way repeated measures analysis of variance (RM ANOVA) for DO, pH, TDS, BOD, Zn, Mn, Cr, Pb, TN, and Chl *a*. The nonparametric Friedman repeated measures ANOVA on ranks was used for data that did not pass the tests for normality and equal variance, these are (EC, Turbidity, Cl-, TSS, COD, TP, Fe, and Cu). The relationship between different variables was tested using the nonparametric Spearman rank order correlation. The data was analysed using Sigma plot version 14.

## 3.3 Results

### 3.3.1 Physicochemical parameters

In general, most physicochemical concentrations increased in sampling stations located adjacent to industrial, agricultural and domestic effluents compared to Kikuyu springs (the control station) upstream of the study area (Fig. 3.2-3.5). Higher TP concentration was recorded in the Nairobi River at Ruai ranging between 0.016-3.48 mg/l, and lower at Kikuyu springs, ranging between 0.001-0.021 mg/l (Fig. 3.4c). For TN, the highest concentrations were recorded at Wamunyu, ranging between 0.002-6.283 mg/l, and the lowest concentrations were recorded at Komo River, ranging from 0.000-0.229 mg/l (Fig. 3.4b).

In addition, sampling stations along the Athi River exhibited a decrease in the TN mean value downstream from Mbagathi to EPZA and 14 Falls but increased at Wamunyu station. In contrast, stations located along Nairobi River showed an increase in both TN and TP concentrations downstream from Museum to Dandora WWTP (Ruai). Interestingly, TN was observed to be higher in Kikuyu springs than in other stations, such as Dandora WWTP (Ruai). For TSS, the concentration varied widely along Nairobi River, at Njiru, 140-2760 mg/l; Mathare station, ranging from 40-2885 mg/l; while at Athi River, the concentrations were much lower ranging from 30-96.67 mg/l (Fig. 3.4d). Similarly, peaks of turbidity were recorded at Thiririka and at 14 falls (Fig.3.4e). The COD along Ngong River at Njiru sampling station ranged from 180-1701mg/l and BOD ranged from 28.8-301 mg/l (3.3 a, d). The DO value recorded along the Nairobi River at Museum, ranged from 4.8-11 mg/l and at Kikuyu springs (control station), DO ranged from 5.5-7.1 mg/l which was relatively higher compared to other sampling stations (Fig. 3.2e).

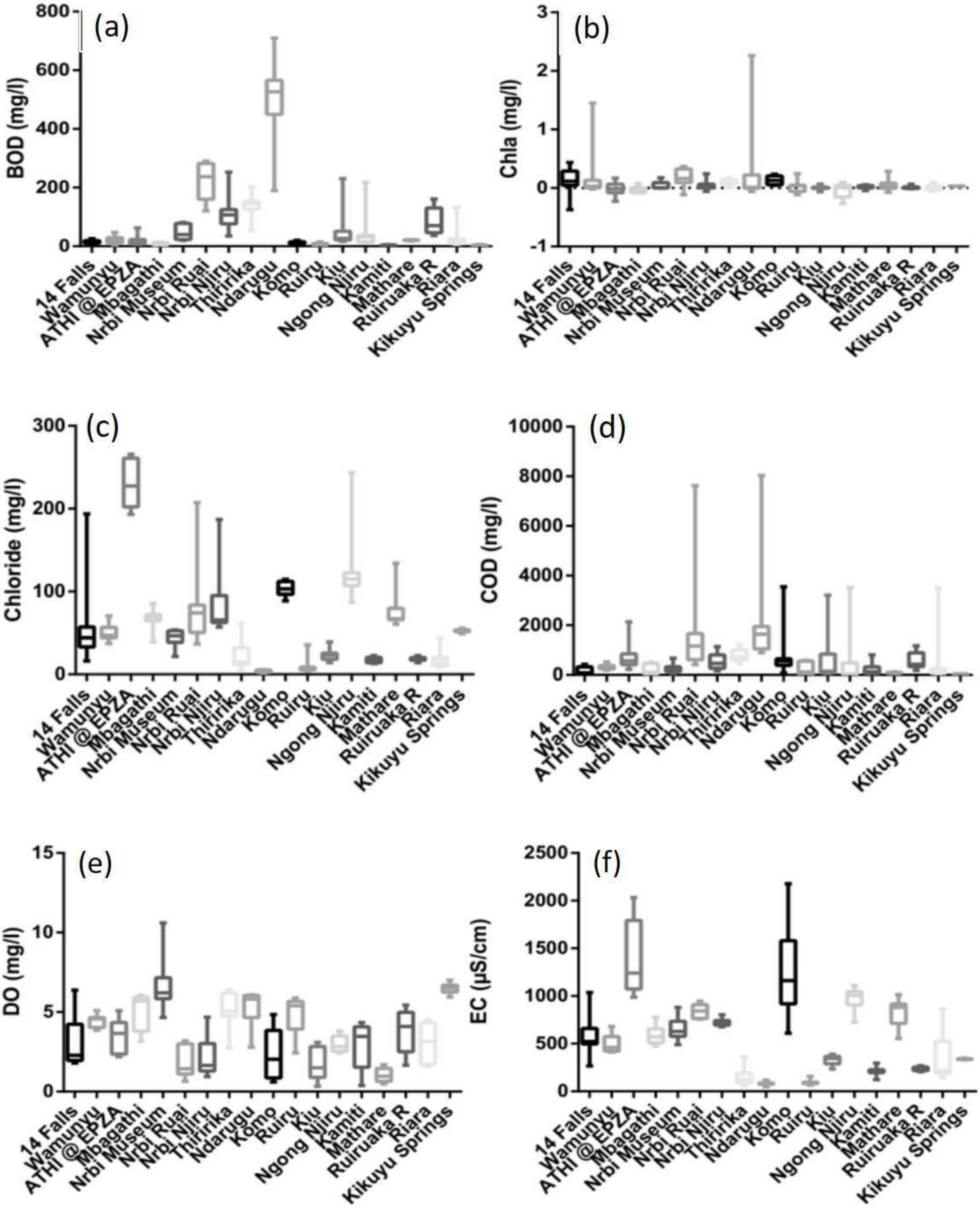



**Figure 3.2 Boxplots showing variation in physicochemical parameters (a)BOD, (b) Chla, c) Cl-, (d) COD, (e) DO, (f) EC in sampling sites.**

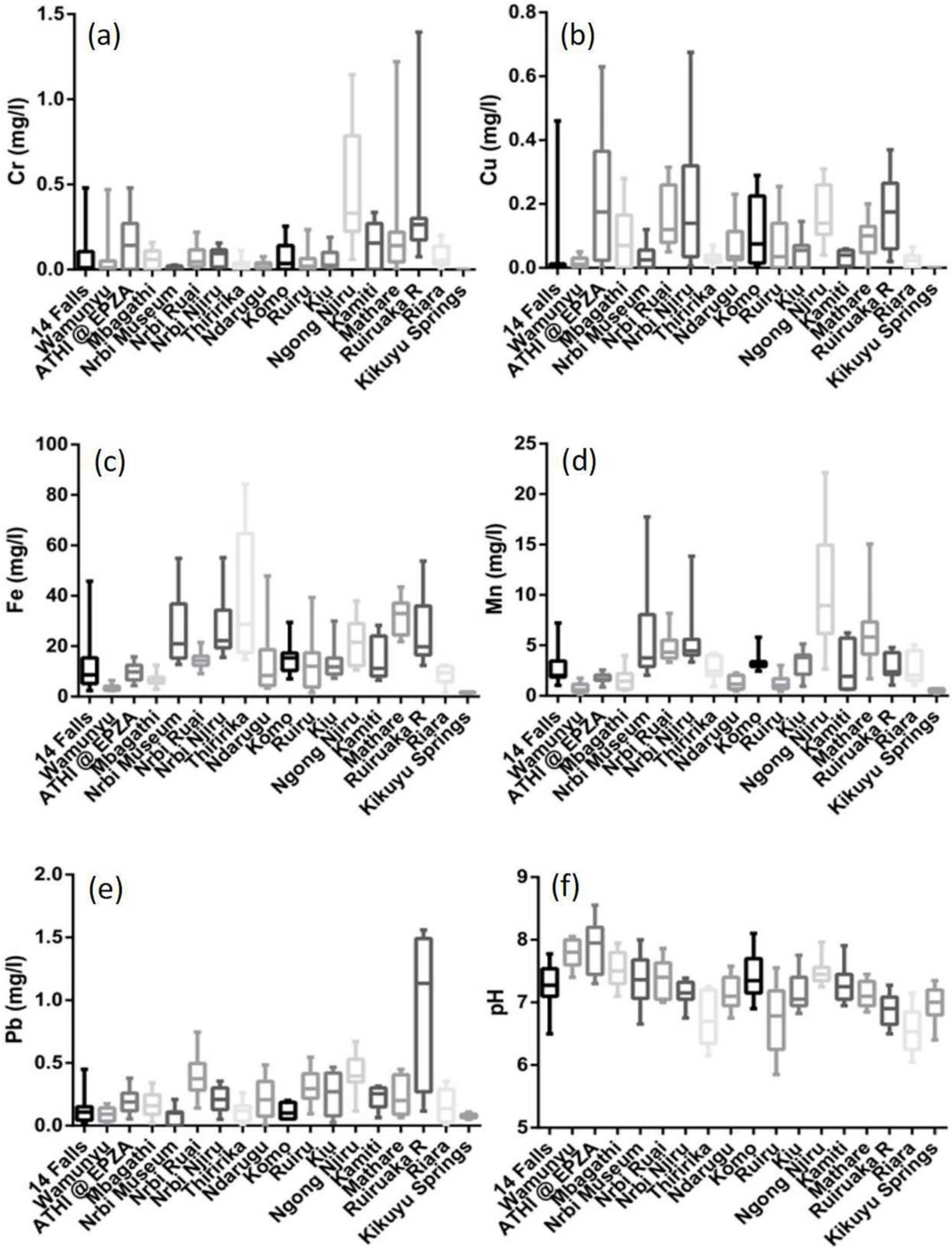



**Figure 3.3 Boxplots showing variation in physicochemical parameters (a) Cr, (b) Cu, (c) Fe, (d) Mn, (e) Pb, and (f) pH in sampling sites.**

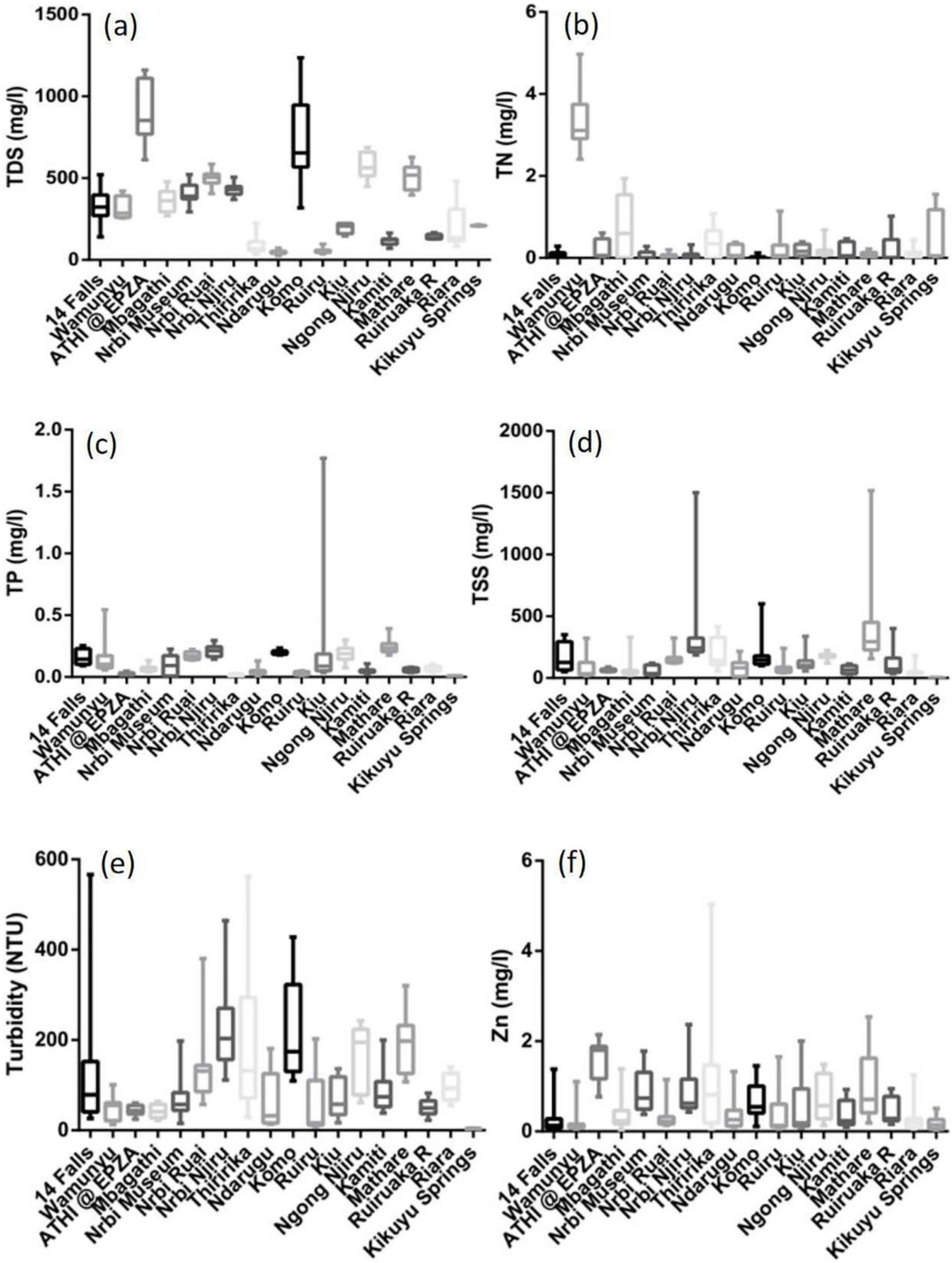



**Figure 3.4 Boxplots showing variation in physicochemical parameters (a) TDS, (b) TN, (c) TP, (d) TSS, (e) turbidity, and (f) Zn in sampling sites.**

On average, sampling station along Nairobi River (d/s Dandora WWTP at Ruai) recorded the highest chlorophyll *a* concentration when compared to stations along Athi River, except for Wamunyu station, which recorded higher chlorophyll a concentration. Additionally, at some sampling stations along Athi River, Mbagathi and EPZA (WWTP), chlorophyll *a* value were below detection limits (Fig. 3.2b). For heavy metals (Cr, Fe, Pb, Mn, and Zn), high concentrations were recorded in pollution impacted areas compared to the control station (Kikuyu springs).

**Table 3.2 Mean values for some physico-chemical water quality parameters (EC, Turbidity, TDS, TSS) at sampling sites for 1999-2002 (Kithiia 2010) and 2017-2018 (This study).**

| River & Sampling Site | EC (uS/cm) | | Turbidity (mg/l) | | TDS (mg/l) | | TSS (mg/l) | |
|---|---|---|---|---|---|---|---|---|
| | 1999-2002 | 2017-2018 | 1999-2002 | 2017-2018 | 1999-2002 | 2017-2018 | 1999-2002 | 2017-2018 |
| Nairobi R. at Museum | 398 | 672 | 69 | 71 | 244 | 451 | 129 | 61 |
| Nairobi R. at Njiru | 510 | 718 | 68 | 218 | 311 | 436 | 199 | 362 |
| Ngong.R at Njiru | 612 | 940 | 71 | 167 | 174 | 608 | 180 | 180 |
| Mathare River | 527 | 841 | 85 | 195 | 350 | 519 | 251 | 435 |

EC= electrical conductivity, TDS=total dissolved solids, TSS= total suspended solids. Nrb R= Nairobi River, Ngong R=Ngong River.

**Table 3.3 Mean concentrations of metal ions at various sampling points for 1999-2002 (Kithiia 2010) and 2017-2018 (This study).**

| River & Sampling Site | Pb (mg/l) | | Zn (mg/l) | | Cu(mg/l) | | Fe (mg/l) | | Cl- (mg/l) | |
|---|---|---|---|---|---|---|---|---|---|---|
| | 1999-2002 | 2017-2018 | 1999-2002 | 2017-2018 | 1999-2002 | 2017-2018 | 1999-2002 | 2017-2018 | 1999-2002 | 2017-2018 |
| Nairobi R. at Museum | 0.02 | 0.13 | <0.01 | 0.95 | 0.01 | 0.05 | 0.7 | 25 | 56 | 45 |
| Nairobi R. at Njiru | 0.04 | 0.22 | 0.02 | 0.96 | 0.18 | 0.22 | 1.4 | 26.9 | 40 | 82 |
| Ngong R. at Njiru | 0.07 | 0.42 | 0.02 | 0.72 | 0.15 | 0.2 | 1.3 | 22 | 46 | 121 |
| Mathare River | <0.01 | 0.22 | <0.01 | 1.1 | 0.01 | 0.12 | 0.4 | 32 | 40 | 76 |
| Athi R. at 14 falls | <0.01 | 0.13 | <0.01 | 0.23 | <0.01 | 0.1 | 0.3 | 11.9 | 8 | 54 |

### 3.3.2. Seasonal variation in water quality parameters

In general, there was seasonal variation in the concentrations of water quality parameters recorded in the Upper Athi River Catchment during the study period. On average, the concentrations of the majority of parameters, including EC, turbidity, TDS, TSS, COD, and BOD, were higher during the wet season, except for pH, which recorded a higher value during the dry period (Table 3.4). Turbidity, TSS and COD increased significantly during the wet seasons when compared to the dry spells (turbidity, $p = 0.006$; TSS, $p = 0.039$; COD, $p = 0.029$, Friedman Repeated Measures ANOVA on ranks, Table 3.4). The EC was significantly positively related to turbidity during dry period (Spearman Rank Order Correlation, $r = 0.726$, $p = 0.003$) and wet seasons ($r = 0.874$, $n = 12$, $p < 0.001$). Similarly, a significant positive relationship was observed between EC vs. TSS during dry spell ($r = 0.958$, $p < 0.001$) and wet spell ($r = 0.93$, $p < 0.001$); while EC vs. TDS during dry seasons ($r = 0.972$, $p < 0.001$) and wet seasons ($r = 0.993$, $p < 0.001$); and EC vs. Cl- during dry seasons ($r = 0.958$, $p < 0.001$) and wet seasons ($r = 0.979$, $p < 0.001$) (Fig 3.5). For other parameters such as TN, TP, and Chl *a*, only a slight variation in their average concentrations between the wet and dry seasons was observed during the study period (Table 3.4).

In addition, seasonal variation in water quality parameters at different sampling stations was observed. The Mathare site (RS6) and Nairobi River at Njiru (RS9) recorded higher TSS, ranging from 40-2885 mg/l and 140-2760 mg/l during the wet season compared to the dry season, which ranged from 130-600 mg/l and 178-360 mg/l respectively (Tables 3.5 and 3.7). In contrast, variations in TSS concentrations were not recorded at the Kikuyu springs (RS1), which ranged from 1-6 mg/l in both seasons (Tables 3.5 and 3.7).

For metals, the mean concentrations for Fe and Zn were higher during the wet season compared to the dry period. On the contrary, other metals, including Cu, Cr, Mn, and Pb, recorded higher concentrations during the dry season. However, there was no significant difference in concentrations between the dry and wet seasons during the study period (Table 3.4).

Similarly, seasonal variations in metal ion concentrations were recorded at different sampling stations. Cu and Cr in Ngong River at Njiru (RS10) increased significantly, ranging from 0-0.31 mg/l and 0-0.12 mg/l during the wet season to 0.05-0.32 mg/l and 0.11-1.48 mg/l during the dry season, respectively (Tables 3.6 and 3.8). For Pb, minimal variation was recorded at this station during the wet (0.07-0.71 mg/l) and dry seasons (0.09-0.71 mg/l). A general increase in Chloride was recorded from 63-171 mg/l during the dry season to 39-345 mg/l during the wet season. In contrast, Cu and Cr were not detected at Kikuyu springs (Control station) in both dry and wet seasons (Tables 3.6 and 3.8).

Comparison of water quality parameters and some metals (min.-mean±SE-max.) during the wet season (months of March, April, May, October, November, and December, n=12) in 2017-2018 vs. the dry season (months of January, February, June, July, August, September, and n=12) in 2017-2018. One-way Repeated Measures (RM) ANOVA test at p (0.05) significance level (DO, pH, TDS, BOD, Zn, Mn, Cr, Pb, TN, and Chl *a*), and The Friedman Repeated Measures ANOVA on ranks (EC, Turbidity, Cl-, TSS, COD, TP, Fe, and Cu).

## Table 3.4 Comparison of water quality parameters and some metals

| Parameter | Wet season | Dry season | *p* -value |
|---|---|---|---|
| Electrical Conductivity (uS/cm) | 374.28-(571.61 ± 39.74)-827.22 | 387.74-(556.41 ± 32.71)-741.14 | 0.146 |
| Dissolved Oxygen (mg/l) | 2.28-(3.77 ± 0.36)-6.03 | 2.65-(3.61 ± 0.27)-5.16 | 0.624 |
| pH | 6.69-(7.23 ± 0.08)-7.80 | 6.81-(7.27 ± 0.08)- 7.65 | 0.554 |
| Temperature (℃) | 20.49-(22.29 ± 0.29)-24.58 | 19.39-(21.89 ± 0.39)-23.60 | 0.774 |
| Turbidity (NTU) | 75.07-(117.60 ± 9.92)-183.48 | 50.11-(88.40 ± 9.40)-163.92 | 0.006 |
| Chloride, Cl- (mg/l) | 41.44-(61.63 ± 6.53)-126.31 | 41.56-(57.58 ± 3.16)-70.67 | 0.74 |
| Total Dissolved Solids, TDS (mg/l) | 234.11-(346.22 ± 24.63)-488.07 | 244.62-(339.23 ± 20.07)-448.12 | 0.774 |
| Total Suspended Solids,TSS (mg/l) | 782.33-(155.38 ± 34.81)-524.79 | 79.00-(126.58 ± 17.22)-263.40 | 0.039 |
| Biological Oxygen Demand, BOD (mg/l) | 26.16-(74.71 ± 7.30)-106.81 | 27.21-(65.54 ± 6.14)-91.97 | 0.029 |
| Chemical Oxygen Demand, COD (mg/l) | 158.26-(600.92 ± 212.09)-2708.93 | 84.53-(369.74 ± 48.78)-634.79 | 1.000 |
| Total Nitrogen,TN (mg/l) | 0.01-(0.36 ± 0.07)-0.79 | 0.08-(0.34 ± 0.05)-0.57 | 0.853 |
| Total Phosphorus,TP (mg/l) | 0.06-(0.11 ± 0.02)-0.32 | 0.06-(0.11 ± 0.01)-0.21 | 0.388 |
| Chlorophyll a, Chl *a* (mg/l) | 0.00-(0.06 ± 0.02)-0.29 | 0.00-(0.06 ± 0.02)-0.17 | 0.910 |
| Metals | | | |
| Iron, Fe (mg/l) | 6.80-(17.62 ± 2.44)-31.71 | 4.84-(15.99 ± 1.83)-23.06 | 0.388 |
| Zinc, Zn (mg/l) | 0.18-(0.81 ± 0.23)-2.42 | 0.09-(0.53 ± 0.15)-2.00 | 0.229 |
| Manganese,Mn (mg/l) | 1.13-(3.38 ± 0.58)-8.44 | 1.39-(3.43 ± 0.45)-6.85 | 0.928 |
| Copper,Cu (mg/l) | 0.00-(0.08 ± 0.03)-0.25 | 0.02-(0.10 ± 0.01)-0.19 | 0.146 |
| Cromium, Cr (mg/l) | 0.00-(0.11 ± 0.03)-0.33 | 0.03-(0.12 ± 0.02)-0.23 | 0.696 |
| Lead, Pb (mg/l) | 0.03-(0.23 ± 0.04)-0.48 | 0.13-(0.26 ± 0.03)-0.43 | 0.344 |

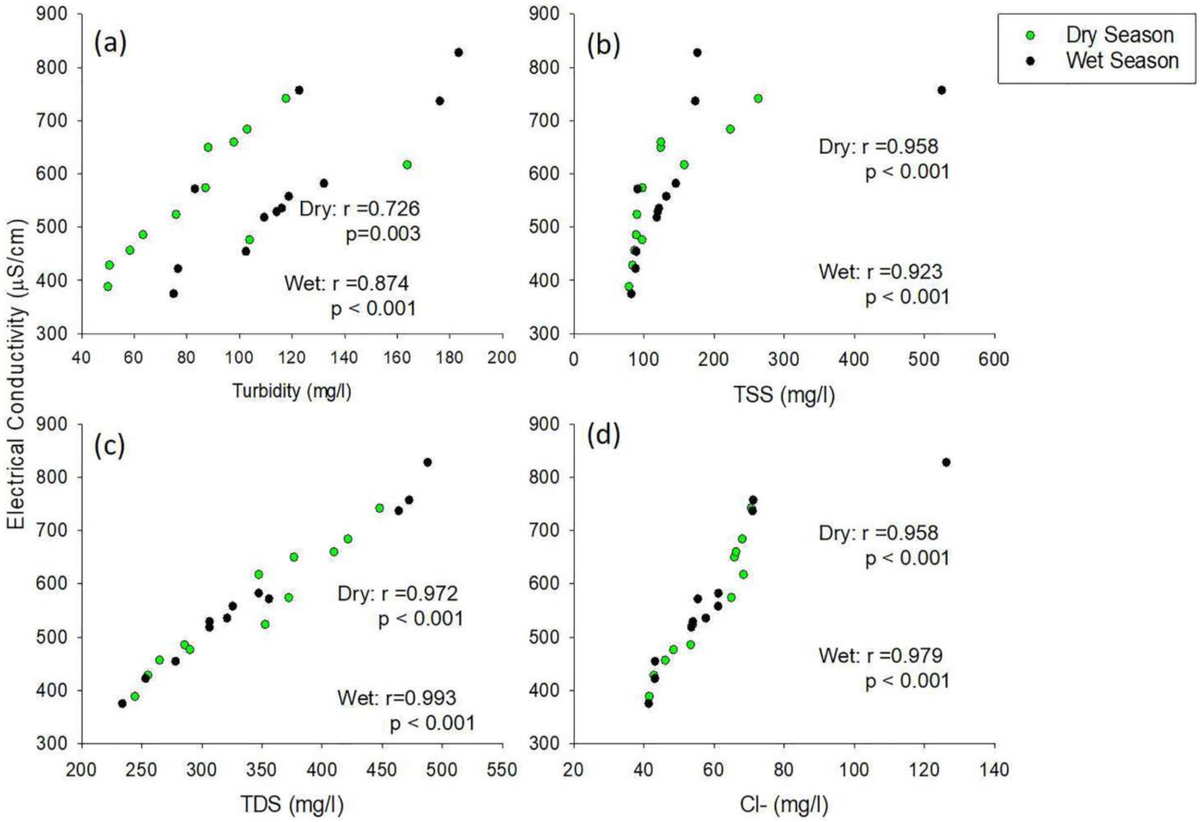



**Figure 3.5 Positive relationships between electrical conductivity (uS/cm) and (a) turbidity (mg/l), (b) TSS (mg/l), (c) TDS (mg/l), and (d) Cl-(mg/l) during the dry season (indicated in green circles) and wet season (indicated in black circles).**

**Table 3.5 Physicochemical parameters (range, min.-max.) at different sampling sites during the wet seasons (months of March, April, May, October, November, and December).**

| Sampling Site | EC (uS/cm) | DO (mg/l) | pH | Temp. (℃) | Turbi. (NTU) | TDS (mg/l) | TSS (mg/l) | BOD (mg/l) | COD (mg/l) |
|---|---|---|---|---|---|---|---|---|---|
| RS1 | 324-355 | 6.1-6.9 | 6.1-7.7 | 20.4-23.8 | 0-6 | 162-220 | 1-6 | 1.0-8.0 | 1.8-18 |
| RS2 | 369-960 | 1.2-7.3 | 7.2-8.6 | 17.7-25.4 | 16.3-99 | 228.8-595 | 12- 80 | 1.0-25 | 20.4-6 |
| RS3 | 463-805 | 2.76-8 | 6.3-8.13 | 19.9-25.1 | 11.2-224 | 389-518 | 18-200 | 12-130 | 46-984 |
| RS4 | 106-916 | 0.32-6.94 | 6-7.5 | 18.01-22.5 | 24.8-158 | 70-567.9 | 15-85 | 3.0-40 | 14.8-1 |
| RS5 | 198-290 | 0.4-7.1 | 6.3-7.6 | 18.3-21.8 | 26-131 | 102-180 | 8-333 | 3.0-17.0 | 12-97 |
| RS6 | 97-1058 | 0-2.1 | 6.5-7.6 | 14.1-25.5 | 72-382 | 249-656 | 130-600 | 5-921 | 613-26 |
| RS7 | 207-411 | 0-5 | 6.1-7.7 | 19.7-22.2 | 15.2-162 | 128-255 | 40-333 | 1.5-7.3 | 11-21 |
| RS8 | 50-117 | 1.1-7.7 | 5.6-7.6 | 19.2-25.4 | 6-392 | 31.2-72.5 | 6.7-340 | 3.0-60 | 1-40 |
| RS9 | 512-880 | 0-5.9 | 6.8-7.8 | 21.3-24.8 | 76-554 | 317.4-545 | 178-360 | 27-300 | 456-17 |
| RS10 | 563-1277 | 1.3-5.8 | 6.9-8.2 | 22.3-26.8 | 41-372 | 349-792 | 100-252 | 29-227 | 302-14 |
| RS11 | 153-281 | 0.42-7.5 | 6.7-7.9 | 18.3-22.6 | 28-159 | 80-174 | 20-180 | 2.0-17 | 7-216 |
| RS12 | 53-276 | 0.69-6.7 | 5.1-7.5 | 19.6-22.9 | 21-667 | 33-171 | 10-550 | 0-6 | 1-15 |
| RS13 | 228-2472 | 0-5.1 | 6.2-8.4 | 20.5-25.5 | 87-606 | 141-1533 | 86-268 | 4-224 | 113-14 |
| RS14 | 530-1094 | 2.2-4.3 | 7.8-8.02 | 23.9-24.7 | 33-632 | 328-678 | 60-210 | 97-170 | 22-200 |
| RS15 | 42-87 | 1.1-7.6 | 5.7-7.8 | 19-22.4 | 14-345 | 25-60 | 6-220 | 0-4 | 3-25 |
| RS16 | 135- | 1.5-5.7 | 6.1-7.9 | 20.8-25.5 | 34-534 | 94-700.6 | 40-500 | 4-112 | 50-350 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1130 | | | | | | | | |
| RS17 | 834-2415 | 1.48-6.6 | 7-8.7 | 20-25.4 | 24-74 | 667-1497 | 42-94 | 8-61 | 54-532 |
| RS18 | 172-920 | 1.75-6.9 | 7.2-8.4 | 21.9-24.9 | 26-175 | 107-570 | 20-610 | 2-22 | 37-812 |

RS1= Kikuyu springs, RS2= Mbagathi R., RS3= Nairobi R. at Museum, RS4=Riara R., RS5=Ruiruaka R., RS6= Mathare R., RS7= Kiu R., RS8=Ruiru R., RS9= Nairobi R. at Njiru, RS10= Ngong R. at Njiru, RS11=Kamiti R., RS12= Thiririka R., RS13= Komo R., RS14= Ruai R., RS15= Ndarugu R., RS16= Athi River at 14 falls, RS17= Athi River EPZA, and RS18= Athi River at Wamuyu.

**Table 3.6 Metal concentrations range from min. to max. at different sampling sites in the Upper Athi River Catchment during the wet season.**

| Sampling Site | Fe (mg/l) | Zn (mg/l) | Mn (mg/l) | Cu (mg/l) | Cr (mg/l) | Pb (mg/l) | Cl- (mg/l) |
|---|---|---|---|---|---|---|---|
| RS1 | 1.02-2.11 | 0.01-0.89 | 0.11-1.18 | nd | nd | 0.01-0.15 | 49-58 |
| RS2 | 2.7-10.6 | 0.05-2.68 | 0.18-3.01 | 0-0.51 | 0-0.22 | 0-0.27 | 36-94 |
| RS3 | 11.3-47.4 | 0.31-3.13 | 1.31-4.78 | 0-0.11 | 0-0.04 | 0-0.3 | 23-76 |
| RS4 | 1.1-22.1 | 0.02-2.49 | 0.7-8.4 | 0-0.1 | 0-0.3 | 0-0.45 | 5.0-70.0 |
| RS5 | 4.7-76.4 | 0.12-1.78 | 0.34-4.98 | 0-0.4 | 0-2.79 | 0.01-2.77 | 14-24 |
| RS6 | 13.3-46.4 | 0.2-4.9 | 2.1-7.9 | 0-0.2 | 0-0.23 | 0.01-0.58 | 59-200 |
| RS7 | 3.7-55.6 | 0.01-3.97 | 0.05-4.68 | 0-0.13 | 0-0.2 | 0-0.84 | 13-35 |
| RS8 | 1.3-77.1 | 0.01-3.26 | 0-3.9 | 0-0.5 | 0-0.45 | 0-0.61 | 2-15.2 |
| RS9 | 10.27-42.83 | 0.24-3.95 | 2.2-6.43 | 0-0.73 | 0-0.21 | 0.03-0.51 | 43-303 |
| RS10 | 8.2-38.2 | 0.14-2.82 | 3.1-23.9 | 0-0.31 | 0-1.2 | 0.07-0.71 | 39-345 |
| RS11 | 19.8-30.3 | 0-0.36 | 0-12.5 | 0-0.07 | 0-0.4 | 0-0.4 | 8.0-25.0 |
| RS12 | 2.3-166.3 | 0.02-10.05 | 0.13-8.31 | 0-0.12 | 0-0.08 | 0-0.17 | 3 - 56 |
| RS13 | 1.67-43.2 | 0.03-2.8 | 0.79-5.22 | 0-0.48 | 0-0.27 | 0-0.2 | 53-171 |
| RS14 | 18.51-20.59 | 0.56-2.09 | 4.11-5.84 | 0-0.5 | 0-0.43 | 0.1-1.32 | 69-357.5 |
| RS15 | 2.3-62.1 | 0.02-2.62 | 0.21-4.25 | 0-0.23 | 0-0.13 | 0-0.76 | 1 - 7 |
| RS16 | 2.16-86.7 | 0.02-2.74 | 0.32-9.92 | 0-0.02 | 0-0.023 | 0.01-0.7 | 14-360 |
| RS17 | 0.3-28.74 | 0.07-3.54 | 0.79-3.3 | 0-1.1 | 0-0.91 | 0.04-0.27 | 159-277 |
| RS18 | 0.1-5.6 | 0.03-1.1 | 0.02-2.13 | 0-0.06 | 0-0.043 | 0.012-0.3 | 15-95 |

Nd= not detected

**Table 3.7 Physicochemical parameters (range, min.-max.) at different sampling sites during the dry seasons (months of January, February, June, July, August, and September).**

| Sampling Site | EC (uS/cm) | DO (mg/l) | pH | Temp. (°C) | Turbi. (NTU) | TDS (mg/l) | TSS (mg/l) | BOD (mg/l) |
|---|---|---|---|---|---|---|---|---|
| RS1 | 322-355 | 5.5-7.1 | 6.1-7.9 | 20.9-24.1 | 0-6.0 | 204-220 | 1.0-6.0 | 0-5.0 |
| RS2 | 368-976 | 4.02-7.17 | 7-7.9 | 16.9-25.9 | 17.4-70 | 228-650 | 5-600 | 4.0- 30 |
| RS3 | 422-916.9 | 4.5-11 | 6.8-8.5 | 20.5-24.7 | 10-112 | 446-568.5 | 10-200 | 20-130 |
| RS4 | 127-916 | 0.4-6.9 | 6.0-7.4 | 16.2-22.5 | 29-138 | 68-568 | 17-350 | 3-250 |
| RS5 | 181-294 | 2.5-7.3 | 6.3-7.3 | 17.0-22.5 | 20-78 | 112-182 | 11-640 | 4.0-30.0 |
| RS6 | 688-1034 | 0.4-2.5 | 6.3-7.8 | 19.4-25.5 | 57-276 | 427-665 | 40-2885 | 23-923 |
| RS7 | 259-1046 | 0.1-4.5 | 6.8-7.9 | 18.8-25.7 | 16-174 | 523-649 | 35-600 | 1.9-6.8 |
| RS8 | 67.9-171.9 | 3.12-8.09 | 5.9-7.9 | 16.2-29.1 | 4.9-39.24 | 40-106.6 | 7.5-151.37 | 3.0-69 |
| RS9 | 534-894 | 0.9-6.72 | 6.6-7.8 | 20.3-26.2 | 52-313 | 331.5-626 | 140-2760 | 50-374 |
| RS10 | 540-1259 | 1.5-5.4 | 7-7.9 | 22-26.5 | 49-378 | 334-781 | 120-250 | 28.8-301 |
| RS11 | 153-281 | 0.42-7.50 | 6.7-7.9 | 18.3-22.6 | 28-159 | 80-174 | 20-180 | 2.0-17 |
| RS12 | 70-645 | 2.7-7.39 | 5.6-7.3 | 16.8-28.7 | 9.6-1107 | 43.4-399.9 | 15-800 | 1 - 7 |
| RS13 | 396-2440 | 0-7 | 6.2-8.4 | 20.1-31.6 | 64-394 | 246-1512.8 | 57-1100 | 2-136 |
| RS14 | 606-993 | 0.2-4.01 | 6.7-8.3 | 21.4-24.6 | 30.36-257 | 306-673 | 56-480 | 50-418 |
| RS15 | 67.7-159.9 | 4.12-7.9 | 6-7.9 | 17.4-29.7 | 10.0-58 | 33-99 | 6-420 | 0 - 3 |
| RS16 | 244-1138 | 1.5-7.7 | 6.5-7.8 | 18.4-26.4 | 17-131 | 548.7-705.6 | 20-552 | 2.0-29 |
| RS17 | 734-1883 | 1.3-8.69 | 7.1-8.7 | 18.2-25.4 | 13.6-57.11 | 455-1167 | 30-96.7 | 1 - 69 |
| RS18 | 277-646 | 2.1-7.62 | 7.2-8.5 | 21.5-24.2 | 10.11-62 | 171.7-400.52 | 15-141 | 1.0-24 |

**Table 3.8 Metal concentrations, range from min.-max. of different sampling sites in the Upper Athi River Catchment during the dry season.**

| Sampling Site | Fe (mg/l) | Zn (mg/l) | Mn (mg/l) | Cu (mg/l) | Cr (mg/l) | Pb (mg/l) | Cl- (mg/l) |
|---|---|---|---|---|---|---|---|
| RS1 | 0.98-2.21 | 0.02-0.75 | 0.08-1.18 | nd | nd | 0.01-0.19 | 46-61 |
| RS2 | 1.9-17.7 | 0-0.35 | 0.29-7.35 | 0-0.28 | 0-0.18 | 0.03-0.35 | 7 - 87 |
| RS3 | 11.3-62.4 | 0.31-2.31 | 2.68-21.7 | 0-0.13 | 0-0.05 | 0-0.3 | 11 - 74 |
| RS4 | 0.01-21.50 | 0.02-0.46 | 0.86-9.33 | 0-0.05 | 0-0.2 | 0.05-0.48 | 11.0-27.0 |
| RS5 | 0.25-50.28 | 0.03-0.52 | 0.63-8.94 | 0-0.62 | 0.01-0.63 | 0.1-2.9 | 11.0-27.0 |
| RS6 | 14.8-56.7 | 0.17-2.36 | 0.6-25.5 | 0.01-0.25 | 0.05-2.39 | 0.03-0.69 | 63-97 |
| RS7 | 2.9-21.4 | 0.01-0.5 | 1.12-7.24 | 0.01-0.28 | 0.001-0.31 | 0.01--0.81 | 16-57 |
| RS8 | 0.96-49.6 | 0.01-0.24 | 0.17-5.72 | 0-0.4 | 0-0.2 | 0.02-0.57 | 2.0-67 |
| RS9 | 10.45-95.6 | 0.12-1.91 | 2.25-24.6 | 0.03-1.24 | 0.02-0.25 | 0.11-0.46 | 51-117 |
| RS10 | 0.36-38.43 | 0.1-1.4 | 0.04-33.3 | 0.05-0.32 | 0.11-1.48 | 0.09-0.71 | 63-171 |
| RS11 | 19.8-30.3 | 0-0.36 | 0-12.5 | 0-0.07 | 0-0.4 | 0-0.4 | 8.0-25.0 |
| RS12 | 2.4-127.1 | 0.04-1.8 | 0.44-7.72 | 0-0.07 | 0-0.21 | 0-0.37 | 5-117 |
| RS13 | 2 to 57 | 0.04-2.8 | 1.01-10.6 | 0.01-0.25 | 0-0.28 | 0.02-0.27 | 71-146 |
| RS14 | 2.32-26.85 | 0.06-0.38 | 0.71-10.23 | 0-0.32 | 0-0.14 | 0.09-1.12 | 22-101 |
| RS15 | 3.2-87.4 | 0-0.48 | 0.08-3.85 | 0-0.23 | 0-0.15 | 0-0.91 | 2 - 7 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| RS16 | 2.16-29.76 | 0.01-0.37 | 0.61-13.13 | 0-0.9 | 0-0.95 | 0.02-0.23 | 22-97 |
| RS17 | 0.91-29.16 | 0.04-3.72 | 0.32-3.64 | 0.01-0.66 | 0.001-0.36 | 0.13-0.43 | 141-281 |
| RS18 | 0.33-6.49 | 0.002-0.19 | 0.02-2.08 | 0-0.09 | 0-0.91 | 0.01-0.22 | 0-89 |

Nd= not detected

## 3.4 DISCUSSION

### 3.4.1 Water quality variation in the Upper Athi River Catchment

This study revealed that there is variability in water quality parameters at different sampling stations. This could be attributed to anthropogenic activities which include industrial, agricultural, and urban settlements (Kithiia, 1992, 2007, 2010). These study findings are consistent with previous studies in the catchment by Kithiia and Mutua (2006). The authors indicated that water sampling stations along the rivers close to the urban areas were highly polluted when compared to those far away from urban areas due to dilution effects (Kithiia and Mutua, 2006). In addition, this could also be attributed to the effect of self-purification of the river resulting from the dissolution of atmospheric oxygen, the deposition of sediments, and the inflow of less polluted tributaries into the main river (Kithiia, 2007).

The comparison of the study findings to previous studies conducted in 1999-2002 by Kithiia (2010) revealed that there was an increase in the mean concentration of electrical conductivity, turbidity and total dissolved solids by two folds at Mathare River and Nairobi River at Njiru sampling stations as well as Ngong River at Njiru (Table 3.4). Equally, the total suspended solids also doubled at Mathare and Nairobi River at Njiru in the past two decades (Table 3.4), which could be linked to the type and intensity of land uses (Kithiia, 2007).

Notably, sampling stations at Mathare River, the Nairobi River at Njiru, Komo River and Ngong River had high mean concentration for TSS of 435 mg/l, 362 mg/l, 222 mg/l, and 180 mg/l respectively. It was observed that erratic variation of TSS occurred at Mathare River in August of both years, which recorded high mean level of 2885 mg/l (Figure 3.4d). The abrupt increase was as a result of the heavy rains experienced in that month. This could be due to the high population upstream of the station, with informal settlements constructed along the river riparian area.

According to NEMA (2016) and WHO (2006) guidelines, the allowable TSS limit is 30 mg/l. In reference to the guidelines, the TSS mean values at the majority of research stations were above the required standards. Similarly, there was an increase in BOD levels along Nairobi River from Museum station, downstream to Nairobi River at Njiru with mean BOD of 175.7 $mgO_2/l$ (Figures 3.2a & d) as the river traversed through densely populated residential areas, which could have contributed to the high levels of organic pollution and thus, the high BOD levels. Station d/s Dandora WWTP (Ruai), BOD concentration dropped to 120.4 mg/l, and this could be due to dilution by final effluent from the Dandora WWTP.

The study also revealed an increase in levels of heavy metals during the study period (Table 3.3). High heavy metals mean concentration were recorded at Ngong River (Njiru station) for (Mn-10.24 mg/l, Cr-0.46 mg/l, Pb-0.42 mg/l, and Cu-0.18 mg/l). This could be attributed to inflows of industrial effluents as the Ngong River traverses Nairobi City industrial area. Similarly, there were high heavy metals mean concentration for Mn-5.73 mg/l and Cu-0.20 mg/l along Nairobi River at Njiru and high Mn-5.0 mg/l and Pb-0.42 at Nairobi River d/s Dandora WWTP (Ruai). Sampling station at Athi River d/s Export Processing Zone WWTP had high mean concentration for Cu (0.22 mg/l) and Cr (0.16 mg/l). This could be attributed to industrial effluent from EPZ, especially from industries such as the Athi River and Alpharama tanneries.

Additionally, this study compares very well with previous study by Kithia (2007) who revealed an increase in concentration of heavy metals (Pb, Zn, Cu, and Fe) over years in Nairobi River (a tributary of Athi) and its system (Table 3.3). The increase in the levels of heavy metals in Athi River and its Nairobi River system (Mathare and Ngong) and Komo

Rivers could be to a greater extent, attributed to effluents coming from industries (Kithiia 2010). The recorded Lead concentration (Table 3.3) in the rivers mentioned above, was higher than the 0.1 mg/l World Health Organization and Kenya Bureau of Standards guidelines. This is in consistent with a previous study by Kithiia (1992), who reported higher levels of lead concentration in Nairobi River. These findings are in line with previous studies by Kinyua and Pacini (1991) and Njuguna et al. (2017). In general, the increasing pollution levels and water quality deterioration could be attributed to increased land-use activities and population growth within the urban area and the Upper Athi catchment that lacks proper sanitation (Kithiia, 2007; Ngatia et al., 2023).

### 3.4.2 Seasonal Variation of water quality

The study findings in UARC revealed seasonal variability of water quality parameters in different sampling stations (Tables 3.4–3.8). This corresponds very well with previous studies undertaken in Athi River and tributaries by (Kithiia, 2010; Ngatia et al., 2023), who recorded high physical chemical parameters in wet season compared to dry spell. Generally, surface runoff, and its erosive action, is attributed to an increase in turbidity and TSS, resulting from materials carried from both agricultural and urban land use areas during the wet season (Kithiia, 2010).

On the contrary, electrical conductivity showed a decline during the wet season which could be attributed to the dilution effect (Kithiia, 2010). During dry season, the river experiences low flows with relatively high proportion of pollutants associated with wastewater discharges, characterized by high electrical conductivity levels (Kithiia, 2006; Kithiia and Mutua, 2006). Furthermore, the increasing electrical conductivity might also be attributed to the inflow of groundwater from the adjacent aquifer into the river channel during the dry season in the Athi River (Kumarswamy, 1991; Kitheka, 2017).

Study by Ngoye and Machiwa (2004), recorded higher conductivity values at sampling sites close to residential areas. Therefore, the high conductivity values at EPZA could be attributed to wastewater inflows from residential areas, EPZ industries, and municipal effluent discharged into the Athi River. Generally, an increase in turbidity, TDS, TSS, BOD and COD during the wet season was revealed when compared to the dry season (Table 3.3). This is attributed to the overall effect of increasing discharge during the wet season, resulting in an increase in the pollutants concentration, thus degrading the water quality (Kithiia, 2010).

Measured levels of DO were higher in the wet season than in the dry season that ranged between 2.28-6.03mg/l and 2.65-5.16mg/l respectively (Table 3.4). This is because wet season leads to increased turbulence in water which contributes to accumulation of DO in water. This trend has similarly been reported by other studies (e.g. Inthasaro and Wu, 2016). Other factors that could result in variation in DO levels may include oxygen depletion resulting from eutrophication of water resources that receives excessive amounts of nutrients. Such nutrients could be associated with wastewater from industrial, urban and agricultural land uses (Inthasaro and Wu (2016). The minimum dissolved oxygen level required for survival of fish and aquatic live is 4.0mg/l (Stoklosa et al., 2018).

The heavy metal concentrations increased significantly at the Mbagathi site (RS2) in both wet and dry seasons (Tables 3.2-3.6), when compared to previous findings by Mwangi (2013) who found that Pb (0.004-0.047 mg/l), Mn (0.187-1.048 mg/l), Zn (0.002-0.695 mg/l), and Cr (0-0.068 mg/l). This could be as a result of high levels of pollutants emanating from residential area, natural weathering of the volcanic rock dominant in the area and soils from agricultural fields (especially irrigation farms) carried to the river by surface run-off upstream of the sampling site. This corresponds very well with the study undertaken by Li and Bai

(2021), who observed that Built-up (urban) area and agricultural lands produced much higher inorganic pollution on surface water in Ohio watersheds than other land surfaces.

### 3.5. Conclusion and Recommendations

The study findings reveal a continuous deterioration of water quality attributed to an increase in human activities in the Upper Athi River Catchment. The high concentration of heavy metals observed specifically Pb, Mn, Zn and Cr is a health risk to the riparian community as well as to the ecosystem. Nairobi City is supplied with water through inter-basin water transfer from the Tana River catchment. However, the provision of this vital resource to the riparian community is likely to be compromised. Therefore, there is need to enforce water quality regulations to ensure wastewater discharged from industries and wastewater treatment plants meet the water quality standard guidelines set by KEBS/WHO, 2005.

In addition, there is need to employ an integrated approach to the management of water resources, including soil conservation and management, forest conservation and reafforestation, protection of water catchment areas and river riparian zones, and prohibition of dumping waste into rivers.

## CHAPTER 4
## 4.0 IMPACTS OF LAND-USE-LAND-COVER-CHANGES ON WATER QUALITY IN THE UPPER ATHI RIVER CATCHMENT IN KENYA

This chapter deals with the results for land use land cover changes (LULCC) in relation to water quality and their corresponding discussion, conclusion and recommendations.

### 4.1 Introduction

Water quality degradation is one of the global challenges in both developing and developed countries (Biswas and Tortajada, 2019; Tan et al., 2021). World-wide, surface water resources are increasingly facing threats of water pollution, particularly in streams and rivers (Loi et al., 2022). The water quality of streams and rivers in watersheds is crucial for various uses such as agricultural practices, domestic consumption, and industrial uses (Berhe, 2020), as well as for the prevention of waterborne diseases (Nabeela et al., 2014). The water quality and the quantity of aquatic resources are influenced by both anthropogenic and natural activities (Aghakouchak et al., 2021), which may affect their value for human consumption. Additionally, there is an increasing trend of exploitation and development of unconventional water resources at the watersheds, such as agricultural, rural, and industrial effluents used to compensate for water scarcity required for irrigation, leading to increased soil pollution at the catchment (Ramesh and Ostad-Ali-Askari, 2023).

Recent scientific investigations have demonstrated that anthropogenic and natural activities have greatly influenced land use and land cover changes (LULCC), which in turn have affected the ecosystem services of the vegetation provided at the catchment (Makwinja et al., 2021; Belay et al., 2022; Ge et al., 2022). Human activities, for example, urbanization, deforestation, and agricultural practices, have been established as the key drivers of LULCC, which immensely impact the water quality of aquatic ecosystems through increased nutrient levels such as TN and TP (Hassan et al., 2016; Pullanikkatil et al., 2016; Zhang et al., 2017).

The LULCC within a catchment has enormous influence on both the water quantity and quality of streams and rivers (Namugize et al., 2018; Tahiru et al., 2020). However, there is limited information on the linkage between LULCC and the water quality of streams and rivers in the catchment. The identification of such a relationship is important for sustainable management of stream water quality, particularly in the reduction of pollutant influx into the water bodies (Wang et al., 2023).

In the developing nations within Sub-Saharan Africa, water for agricultural, industrial, and domestic uses is drawn mostly from streams and rivers. This is because a huge proportion of the rural poor in Sub-Saharan Africa heavily rely on natural resources extracted from the catchment areas, such as timber or cultivating the watersheds for subsistence farming (Rebelo et al., 2010). Approximately 28% of the 925 million people living in Sub-Saharan Africa inhabit degraded catchments (Le et al., 2014; UN, 2014). Moreover, the grasslands, with a proportion of 40% of the total land area, experienced severe degradation in 2014 (Le et al., 2014; UN, 2014). Other reports show that an estimated 12% of cropland and 26% of forestlands were degraded (Nkonya et al., 2011; UN, 2014). The degradation of the vegetation, especially at the catchment, due to LULCC has definitely had a negative impact on stream and river water quality in the region.

Improvement of stream and river water quality is critical in Sub-Saharan Africa so as to maintain a healthy and safe environment for humans as well as the functioning of ecosystems, especially with the unprecedented demand for freshwater by the increasing human population. Kenya has abundant surface water resources; among them is the Upper Athi River catchment (Kitheka et al., 2022; Waturu et al., 2022). This catchment serves as a key source of freshwater for industrial, agricultural, and domestic uses. Despite the importance of the catchment to social and economic development in the country, the water resources in the catchment suffer degradation due to LULCC brought about by anthropogenic activities (Kitheka, 2019; Kitheka et al., 2022). Furthermore, the livelihood of more than 50% of the local population depends either directly or indirectly on agricultural activities mainly located adjacent to or within the catchment (Waturu et al., 2022). This has further aggravated LULCC alterations that may have a negative impact on the catchment (Kitheka, 2019; Kitheka et al., 2022). The land cultivation methods in the catchment are unsustainable and often lead to frequent soil erosion and sedimentation, resulting in the deterioration of stream and river water quality (Kitheka, 2019; Ostad-Ali-Askari et al., 2017).

The Upper Athi River catchment is one of the critical watersheds in Kenya that has been documented to experience severe land deterioration caused by LULCC (Kitheka et al., 2022; Muriithi, 2016). Although some previous studies have pointed at water quality degradation in this catchment, none of the studies, to the best of our knowledge, have examined the variations in the water quality in recent years in relation to LULCC using GIS (geographic information system) and remote sensing. GIS, coupled with remote sensing techniques, are robust and effective tools that can investigate numerous environmental degradation issues, such as the determination of water availability and water quality assessment at both the local and regional scales (Thakur et al., 2017). The present study evaluated the water quality spatial-temporal variation in relation to LULCC in the Upper Athi River Catchment (UARC) using geographic information system (GIS) and remote sensing (RS) technologies. The findings provide key information for stakeholders and policymakers at UARC at all levels for them to make informed decisions on how to manage the water resources within the catchment.

## 4.2 Methodology

### 4.2.1 Study Area

The Athi River (also known as Galana and Sabaki in the lower coastal reaches of Kenya) is the second longest river in Kenya after the Tana River. The main tributaries of the Upper Athi River are the Nairobi River system (Ngong, Mathare and Ruiruaka), Ndarugu, Ruiru and Komo. Tsavo River joins Athi in the lower reaches (Fig. 4.1) The Nairobi River system traverses the city Central Business District, which is a highly economic zone. The areas drained by the tributaries are densely populated (Waturu et al., 2023). Note: Detailed description of the study area is in chapter 3.

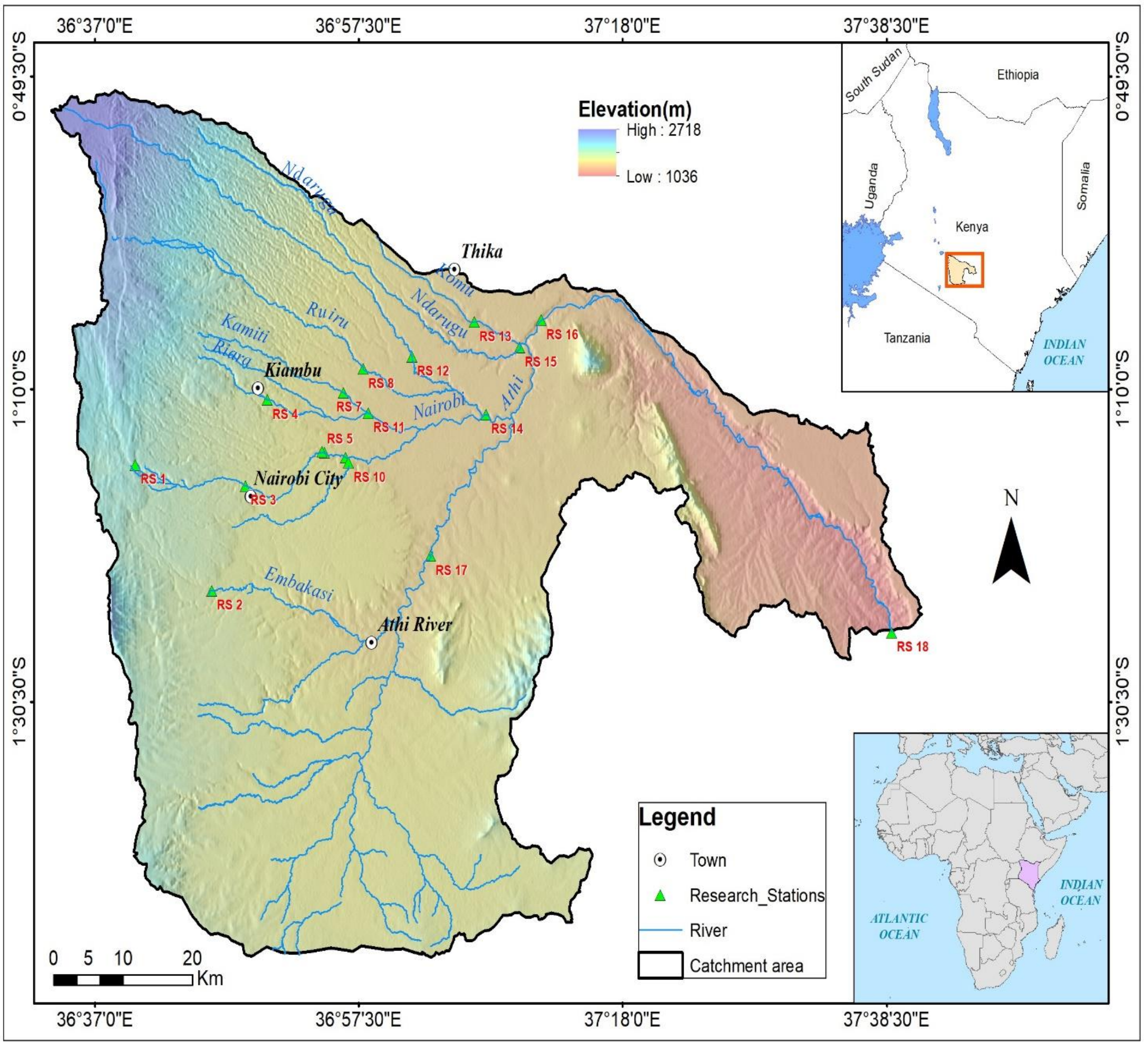



**Figure 4.1 Study area showing 18 sampling sites in the Upper Athi River Catchment, Kenya.**

Note: The key features of the rivers' research stations (sampling sites) and drainage area have been described in more detail in Chapter 3.

#### 4.2.2 Satellite data sources

For purposes of preparing the LULCC map of the study area for the different years, Landsat satellite data was acquired from the United States Geological Survey (USGS) for the periods 1990, 2004, 2010, 2014, and 2018 (Table 4.1). This was captured as Specific Objective 2. Images captured during the wet seasons (March, April, and May), which coincide with the period when human activities are at their peak in the study area, were selected in order to relate them to water quality analysis data. In addition, images with a cloud cover of less than 10% were preferred in order to extract maximum information (Chasia et al., 2021).

**Table 4.1 Satellite data sources and properties**

| Year | Source of data | Sensor | Resolution |
| --- | --- | --- | --- |
| 01-06-1990 | Landsat 4 USGS (https://earthexplorer.usgs.gov/) | Multispectral Scanner (MSS) | 60m |
| 26-04-2004 | Landsat 5 USGS “ | Enhanced Thematic Mapper Plus (ETM+) | 60m |
| 11-06-2010 | Landsat 7 USGS “ | ETM+ | 30m & 15m Panchromatic |
| 29-04-2014 | Landsat 8 USGS (https://earthexplorer.usgs.gov/) | Operational Land Imager (OLI) | “ |
| 14-04-2018 | Landsat 8 USGS “ | “ | “ |

#### 4.2.3 Water quality variables

Sampling for water quality analyses was done every month from February 2017 to December 2018 on eighteen stations, which included eleven pre-determined water quality stations and seven others selected within the study area, as reported in Chapter 3. These sites were chosen to represent different sub-catchments that drain into the Athi River in order to understand the influence of natural and human activities in the area (Figure 4.1). The water quality parameters selected included pH, Electrical Conductivity (EC), Temperature, Total Dissolved

Solids (TDS), Total Suspended Solids (TSS), Chlorides ($Cl^-$), Total Phosphorous and Nitrogen, Chlorophyll *a* (Chl *a*) concentration, as well as selected heavy metals (Iron, Manganese, Zinc, Lead, Copper, and Chromium). All water quality variables were analyzed following standard protocols (ISO/IEC 17025, 2005).

### 4.2.4 Historical data collection

Geo-information analysis was carried out by use of topo sheets (1:50,000) and land cover maps from Survey of Kenya. LULCC analysis for the study was performed using Landsat satellite data (Fig. 4.1 and 4.2). The images analyzed represented the periods 1990, 2004, 2010, 2014, and 2018 (Fig. 4.1 and 4.2). Water quality data (e.g., Cu, Pb, Zn, BOD, COD, TN, TP) for 2010 and 2014 as well as river discharge data for the study area were obtained from the Water Resources Authority (WRA), Kenya (Appendix VII), while data for 1990 and 2004 was sourced from the Ministry of Water and Irrigation, Kenya.

### 4.2.5 Data Analyses

#### 4.2.5.1 LULCC classification

The research identified six dominant LULCC classes presumed to have the greatest influence on the water quality in the area. These are Agricultural land (both irrigated and rain-fed arable land, cropland, farming fields), Forest, Built-up areas (residential, industrial, commercial and institutional), Open water (rivers, dams, marshy areas), Shrub-land (includes grassland) and Bare land. This followed a comprehensive field sampling survey conducted in the years 2017 and 2018, targeting the selected LULC classes.

A hybrid classification technique was chosen in order to improve the accuracy of the classification results (Chasia et al., 2021). Clusters of pixels for 20 classes were initially generated in the QGIS Semi-Automatic Classification Plugin (SCP Version 7.10.10) by applying different band combinations, such as 7, 6, 2; 5, 4, 3; 7, 6, 4; and 6, 5, 2, for extracting bare land, vegetation (forest), built-up (urban area), and agriculture, respectively, using the iterative self-organizing data analysis (ISODATA) unsupervised classification technique (Lillesand et al., 2015). Thereafter, training areas were selected for the six selected land cover classes using clusters obtained from the unsupervised classification, together with field data. A signature file was then generated with training samples for each land use/cover class, and a land use map was generated using the Maximum Likelihood classification algorithm.

#### 4.2.5.2 Water quality data analysis

Prior to data analyses, all the physicochemical variables, except pH were transformed (i.e., arcsine-square root for proportional data and $\log_{10}$ for continuous data) to normalize the data. To reduce redundancy, Variance Inflation Factor (VIF) was done using R (v.3.6.0, R Development Core Team, 2019) package *usdm* (Oksanen et al., 2019), and the highly collinear variables were excluded from the two datasets of physicochemical variables (that is, 2017 and 2018). Principal Component Analysis (PCA) was carried out using R (v.3.6.0, R Development Core Team, 2019) package *vegan* (Oksanen et al., 2019) to determine the most important physicochemical variables. The differences in the important physicochemical variables in the research stations, retrieved from the PCA results, were examined by the Kruskal-Wallis test ($P < 0.05$), a non-parametric test used for the comparison of two or more independent variables (Hollander et al., 2013).

#### 4.2.5.3 LULCC relationship with water quality parameters

The relationship between LULCC and WQ was determined by using Pearson correlation test to measure the strength and direction of how the two variables relate. This is a linear correlation coefficient, abbreviated as r, is the test statistic and the value can be any number between –1 and +1; and it has no units of measure. The correlation can be perfect, of high degree or moderate**:** Perfect: Values near ±1 indicate a perfect correlation, where one variable increase (or decrease) is mirrored by the other. High degree: Values between ±0.50 and ±1suggest a strong correlation. Moderate degree: Values between ±0.30 and ±0.49 indicates a moderate correlation.

To determine the relationship between LULCC ($Km^2$) data with water quality parameters, the multiple regression analysis (MRA) was employed using SPSS software (Kafle, 2019). MRA as a statistical tool for objective optimization, enabled the assessment of the relationship between LULCC data as dependent variables (as indicated in Table 4.2), and water quality parameters as predictor variables. The generated MRA estimates included $R^2$ coefficients that were used to compute the amount of variance in the LULCC that was accounted for by the variation in each of the water quality parameter at $P < 0.05$.

## 4.3 Results

### 4.3.1 LULCC classification

The classified LULCC map for the periods 1990, 2004, 2010, 2014, and 2018 showed that the main land uses were typically six: open water, built-up area (Urban land use), forest, shrubland, agriculture, and bare land (Figure 4.2). The percentage change between the years for a specific land use type was calculated. The most dominant feature was shrubland with an area of 3818.4 $km^2$ (56.5%) in 1990 but decreased to 3320.1 $km^2$ (49.16%) in 2018 mainly due to conversion into urban and agricultural land uses (Figure. 4.2 and Appendix IX)). Forest cover decreased from 1099.2 $km^2$ (16.27 %) in 1990 to 971.01$km^2$ (14.38 %) in 2018. However, the Agricultural area increased from 382.2 $km^2$ (5.66%) in 1990 to 1227 $km^2$ (18.17%) in 2018. A similar trend of increase was observed in urban land use which increased from (63 $km^2$) 0.93% in 1990 to a maximum of 3.11% (210.2 $km^2$) in 2018. Open water generally decreased from (139.6 $km^2$) 2.07% in 1990 to (101.37 $km^2$) 1.5% in 2014 but slightly increased to (109.9 $km^2$) 1.63% of the study area in 2018.

Overall percentage of LULCC from 1990 to 2018, revealed that Shrubland decreased from 3818.4 $km^2$ (1990) to 3320.1 $km^2$ (2018) with a decrease of -13.05%, mainly due to conversion into built-up areas and agricultural land uses (Figure 4.2 and Table 4.2). Forest cover had a decreased from 1099.2 $km^2$ (1990) to 971.01 $km^2$ (2018), a decrease of -11.66%, while bareland decrease was -30.25% (1313.04 $km^2$ to 915 $km^2$ in 1990 and 2018 respectively). However, the agricultural area increased from 382.2 $km^2$ (1990) to 1227 $km^2$ (2018) with an increase of 221.01%. A similar trend of increase was observed in built-up areas, which increased from 63 $km^2$ (1990) to a maximum of 210.2 $km^2$ (2018), indicating 233.76% increase (Figure 4.2 and Table 4.2). Open water generally decreased from 139.6 $km^2$ (1990) to 109.9 $km^2$ (2018), a decrease of -21.28% from 1990 to 2018.

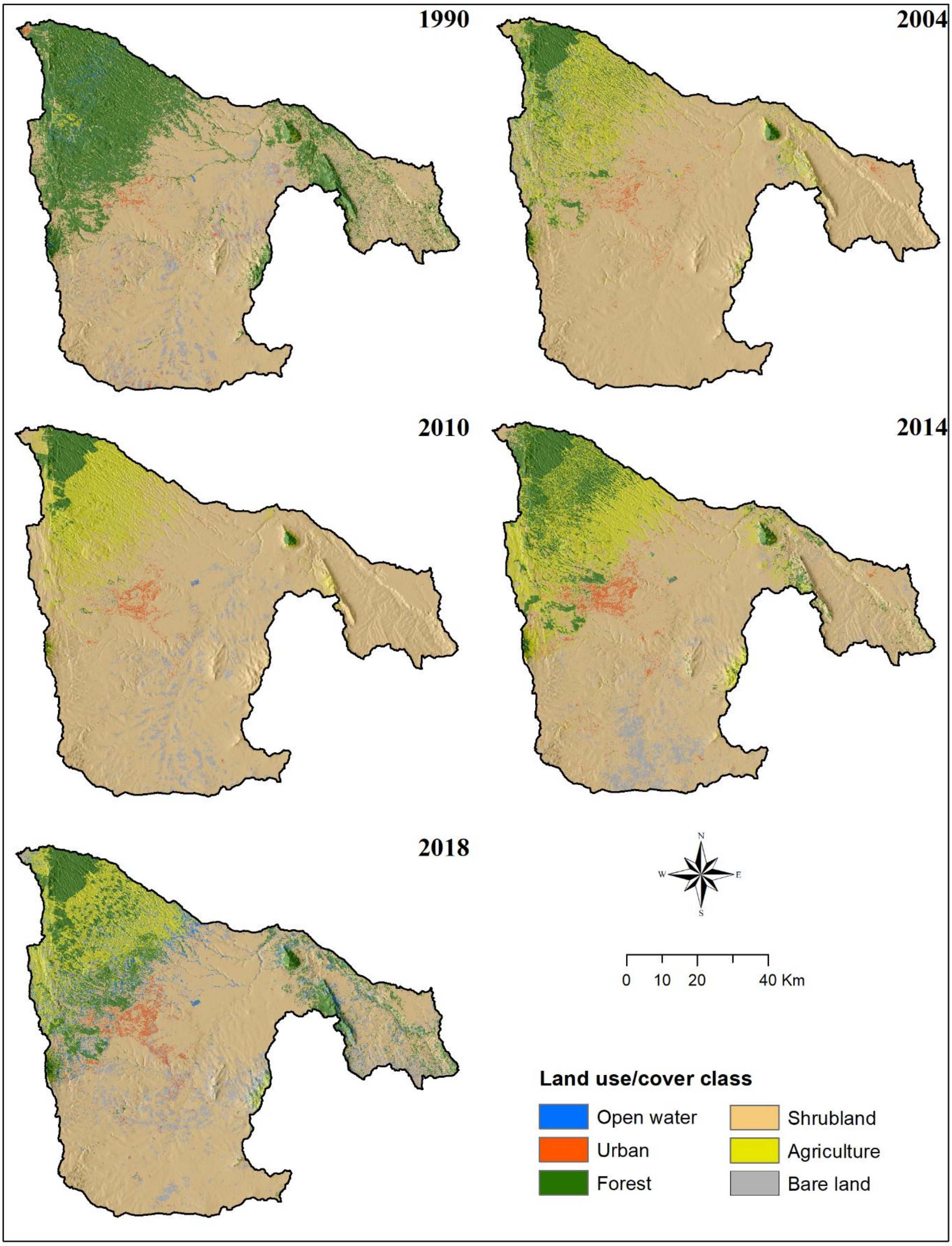



**Figure 4.2 Land use Land cover changes for the periods 1990, 2004, 2010, 2014, and 2018 in the Upper Athi River Catchment area.**

**Table 4.2 Land Use Land Cover Classes in Upper Athi Catchment (Km$^2$).**

| LAND USE CLASS | 1990 | 2004 | 2010 | 2014 | 2018 | % change 1990-2018 |
|---|---|---|---|---|---|---|
| Bare land | 1313.04 | 878.16 | 738.76 | 735.25 | 915.87 | -30.25 |
| Agriculture | 382.17 | 1301.37 | 627.93 | 1571.61 | 1227.01 | **221.06** |
| Shrubland | 3818.39 | 3026.38 | 3860.86 | 3418.23 | 3320.12 | -13.05 |
| Open Water | 139.58 | 369.16 | 107.43 | 101.37 | 109.88 | -21.28 |
| Forest | 1099.21 | 1074.66 | 1310.58 | 806.87 | 971.01 | -11.66 |
| Built-up (urban land) | 62.97 | 104.33 | 108.5 | 120.73 | 210.17 | **233.76** |
| TOTAL | 6754.06 | 6754.06 | 6754.06 | 6754.06 | 6754.06 | |

### 4.3.2 Water quality spatial-temporal patterns (2017-2018)

The physicochemical variables showed spatial-temporal distribution patterns during the study periods from February 2017 to December 2018 (Figures 4.3-4.7, Appendix III). For example, TP was generally higher in year 2017 with less rainfall compared to 2018. In year 2017 the rivers had TP concentration of: at Mbagathi (RS2)-0.1mg/l, Ndarugu (RS15)-0.05 mg/l, Athi at 14falls (RS16)-0.17 mg/l and Kiu (RS7)-0.51 mg/l. In 2018 the rivers Mbagathi (RS2), Ndarugu (RS15), Athi at 14Falls (RS16) and Kiu (RS7), TP concentration was (0.04 mg/l, 0.03 mg/l, 0.16 mg/l, and 0.05 mg/l respectively (Appendix III).

Most research stations along the Athi river experienced high TSS in 2018 that increased downstream but decreased as river velocity reduced. In 2018 TSS level was: Mbagathi-122.38 mg/l, Athi River at 14Falls-206.67 mg/l and Athi at Wamunyu-136.42 mg/l. In 2017 the same stations had the same decreasing trend downstream for TSS level: Mbagthi-48.91, Athi at 14Falls-162.18 and at Wamunyu-30.73 mg/l (Appendix III). Stations along Nairobi River, also had a decrease in TSS downstream in 2018: Njiru-485.33 mg/l and Nairobi d/s Dandora WWTP-134.22 mg/l. In 2017, the same stations recorded TSS of: Njiru-227.82 mg/l and Nairobi d/s Dandora WWTP-176.82 mg/l. Nairobi River tributaries like Mathare and Ngong, TSS level were 562.4mg/l and 164.56 mg/l respectively in 2018, and recorded lower levels of 296.0 mg/l and 197.82 mg/l in 2017. Rivers in the out skirts of Nairobi city like Ruiru River had TSS level of 91.91 mg/l (2018) when discharge was high and 69 mg/l (2017) when there was low discharge and a similar scenario observed at Ndarugu, a tributary of Athi River, TSS level was 119.53 mg/l (2018) and 35.62 mg/l (2017). Komo River (RS13), TSS was 323.17 mg/l (2018) and 113.18 mg/l (2017) (Appendix III and VII). Additionally, heavy metals (Cr, Fe, Pb, and Mn) were generally higher in 2018 than in 2017. Stations that recorded high metal concentration in 2018 were: 14falls (RS 16), Cr-0.09mg/l, Fe-19.19 mg/l, Pb-0.13 mg/l and Mn-4.53 mg/l (2018); Athi river d/s EPZA WWTP (RS17), Cr-0.24 mg/l, Fe-16.97 mg/l, Pb-0.19 mg/l and Mn-1.94 (2018); Komo River (RS13), Cr-0.07 mg/l, Fe-29.53 mg/l, Pb-0.13 and Mn-5.39; Nairobi River d/s Dandora WWTP (RS14) Cr-0.09 mg/l, Fe-17.91 mg/l and Mn-5.16 mg/l; Ngong River (RS10), Mn-13.82 mg/l and Pb-0.41 mg/l. The high metal concentration could have been as a result of surface runoff from highly polluted areas such as urban and agricultural lands during heavy rains in 2018 (Appendix III and X).

In 2017 research stations had lower heavy metal concentration. At 14falls (RS16), Cr-0.04 mg/l, Fe-4.05 mg/l, Pb-0.12 mg/l and mn-1.05 mg/l; Athi d/s EPZA WWTP (RS17), Cr-0.07 mg/l, Fe-4.12 mg/l, Mn-1.72 mg/l and Pb-0.19 mg/l; Komo (RS13), Cr-0.05 mg/l, Fe-3.50 mg/l, Mn-1.24 mg/l and Pb-0.10 mg/l; Nairobi River (RS14), Cr-0.05 mg/l, Fe-10.93 mg/l, Pb-0.50 mg/l and Mn-4.82 mg/l (Appendix III and X).

There were fluctuations observed in a few research stations that had high mean concentration of pollutants in year 2017 that had less rainfall. These are Mbagathi River (RS2) whose Mn mean concentration was 1.95 mg/l while Pb was 0.18 mg/l; Ngong River (RS10) had Cr concentration of 0.72 mg/l and Fe was 25.55 mg/l (Appendix III and X), a trend attributed to the fact that the stations receive irregular effluent discharges from industries, institutions and irrigated agricultural farms.

The Principal Component Analysis (PCA) process resulted in 9 major constraints, that is, Chl *a*, Cr, DO, Pb, pH, TDS, TN, TP, and TSS (Figure. 4.8), with two axes explaining a total of 54.11% contribution to pollution from these physicochemical parameters to environmental variation in 2017. In contrast, the PCA process resulted in 11 major constraints, that is, Chl *a*, Cl, Cr, Cu, DO, Fe, Mn, Pb, pH, Temp, and TN, with two axes explaining a total of 50.02% of the contribution to pollution of these physicochemical parameters to environmental variation in 2018 (Fig. 4.8). Furthermore, the nine (9) physicochemical parameters were significantly different (Kruskal-Wallis test, $p < 0.05$) in 2017, and the eleven (11) physicochemical parameters were significant (Kruskal-Wallis test, $p < 0.05$) in 2018. Interestingly, Chl *a*, DO, Pb, and TN were significantly different in both 2017 and 2018 (Table 4.3).

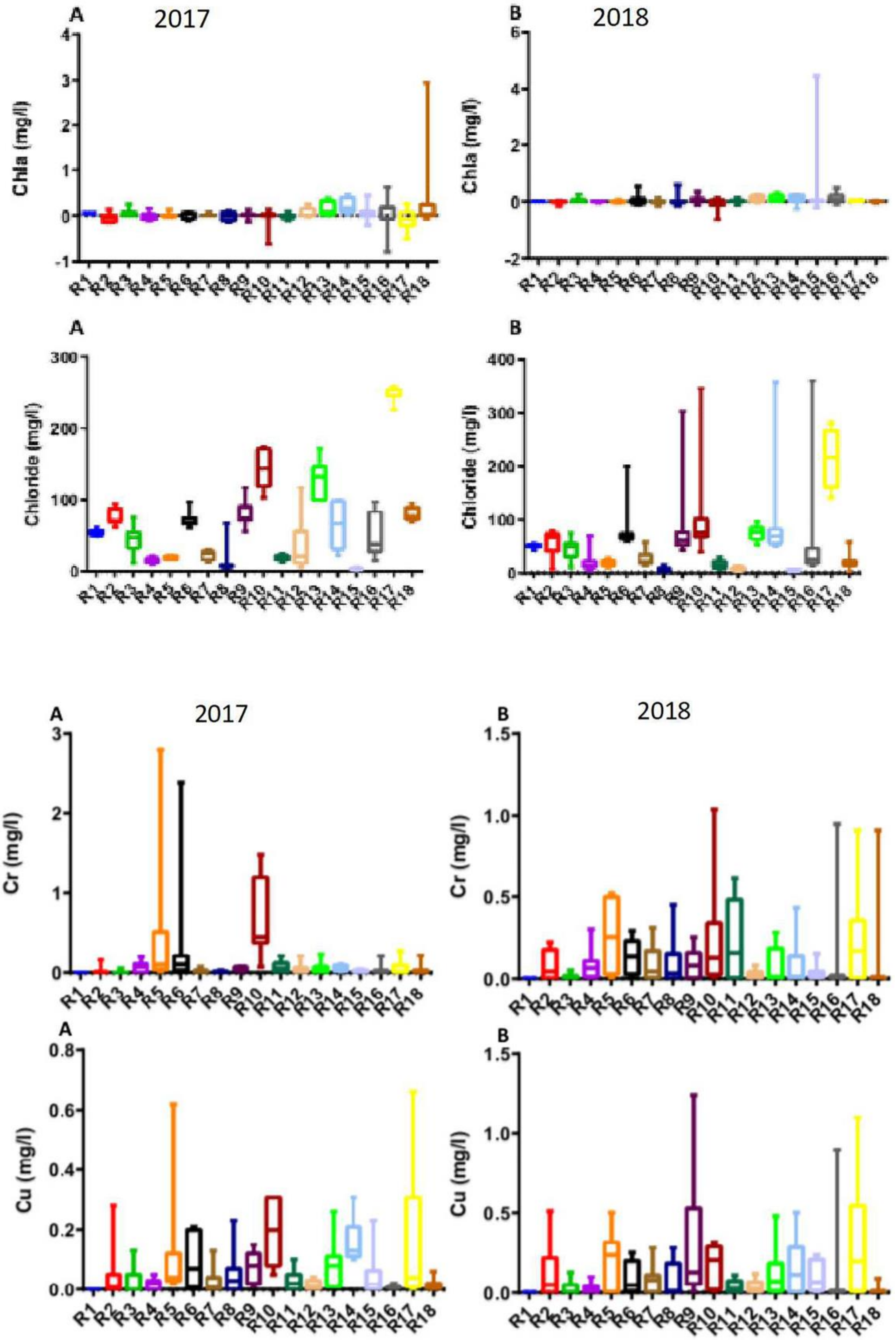



**Figure 4.3 Boxplots showing variations of physicochemical parameters ( Chl a, Cl-, Cr, Cu) in sampling sites during the study period, years (A) 2017 and (B) 2018.**

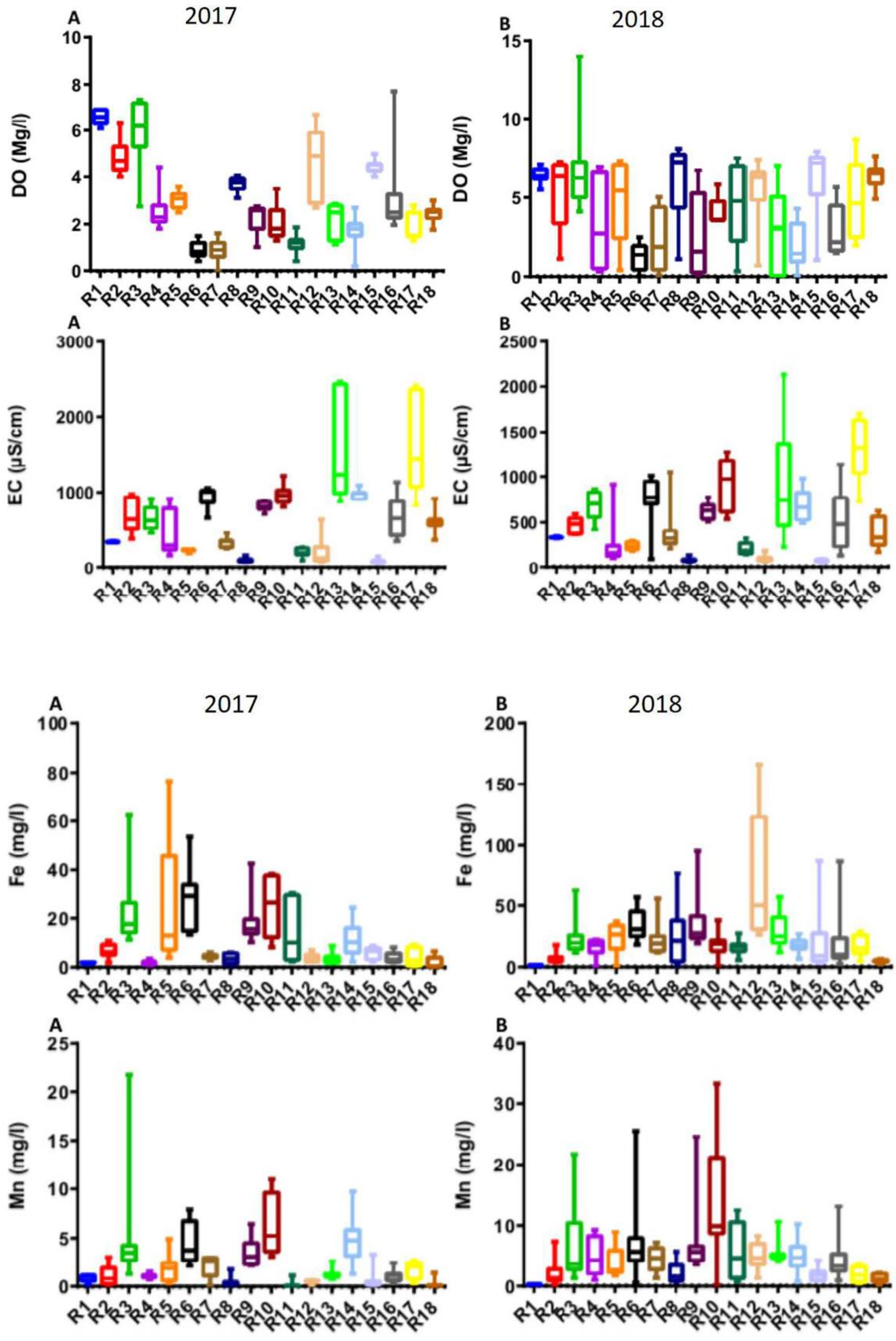



**Figure 4.4 Boxplots showing variation of physicochemical parameters (DO, EC, Fe, Mn) in sampling sites during the study period, years (A) 2017 and (B) 2018.**

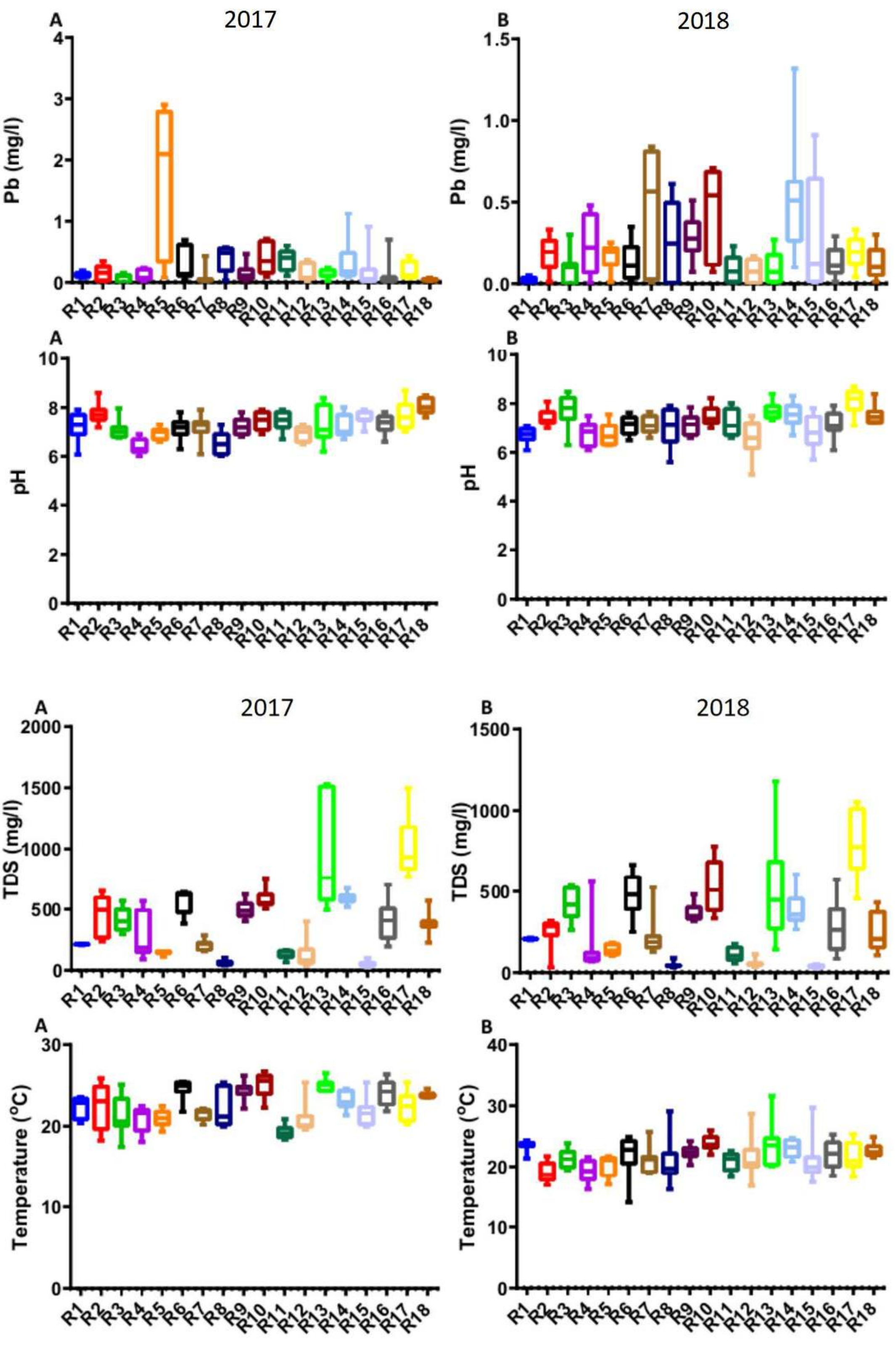



**Figure 4.5 Boxplots showing variation of physicochemical parameters (Pb, pH, TDS, Temp.) in sampling sites during the study period, years (A) 2017 and (B) 2018.**

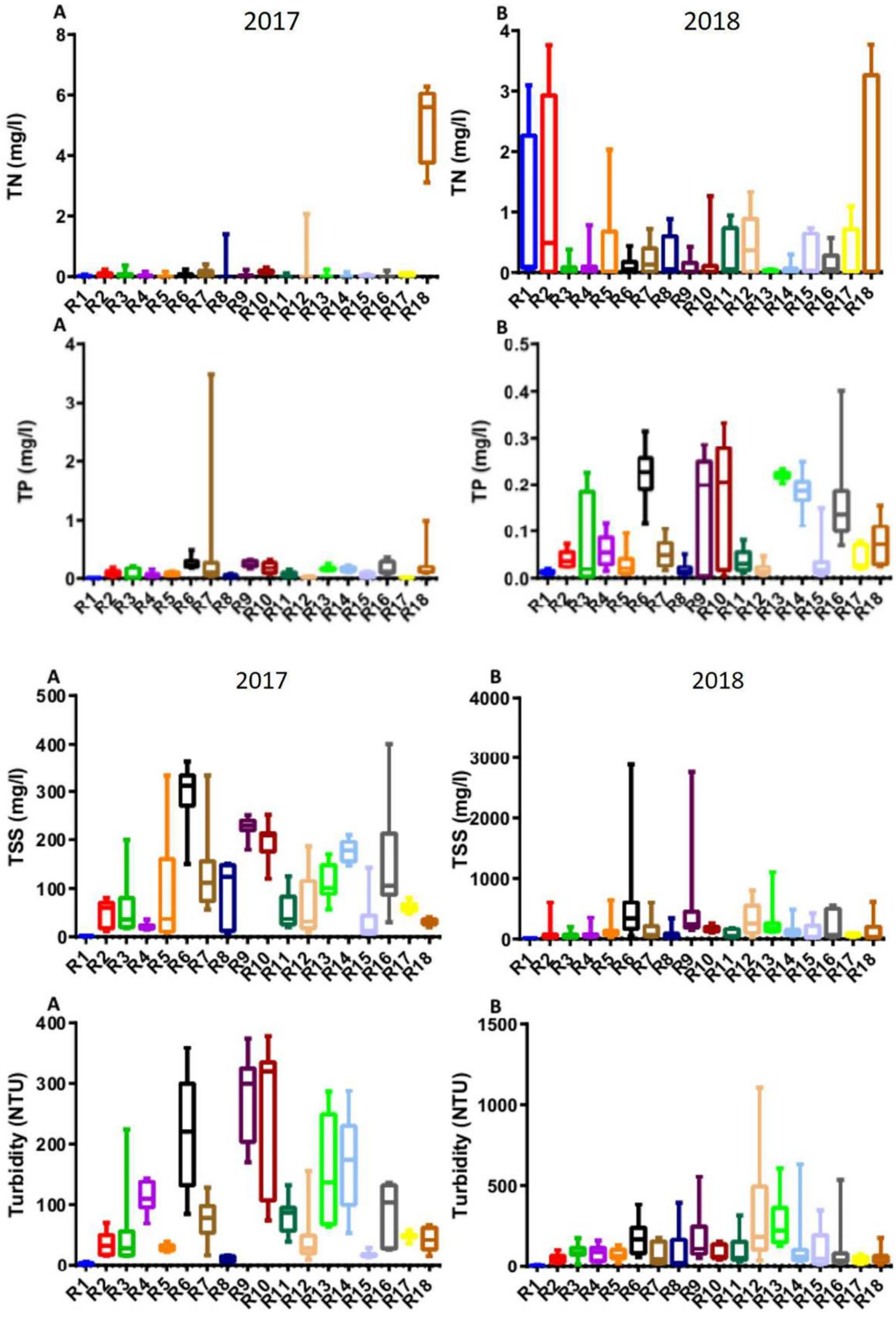



**Figure 4.6 Boxplots showing variation of physicochemical parameters (TN, TP,TSS, turbidity) in sampling sites during the study period, years (A) 2017 and (B) 2018.**

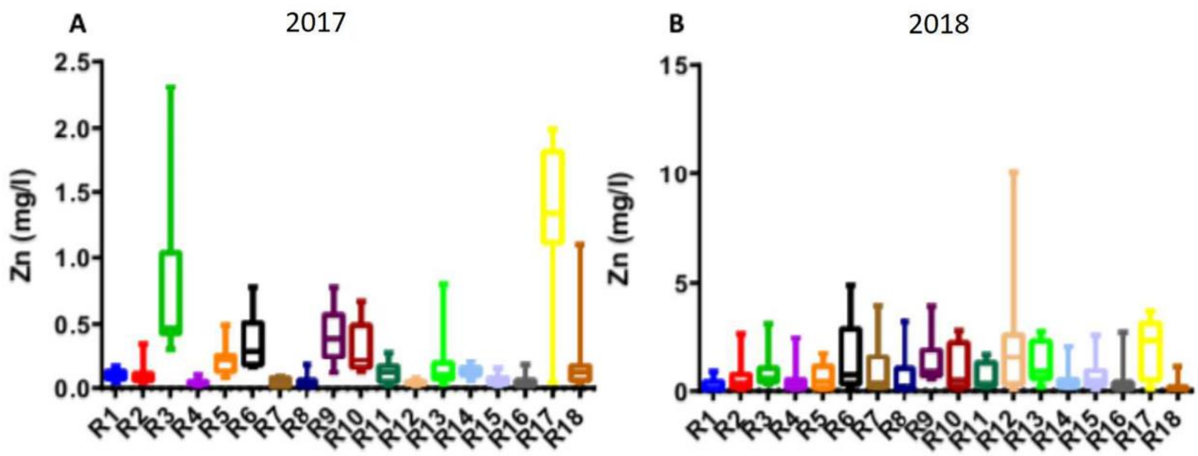



**Figure 4.7 Boxplots showing variation of Zn in sampling sites during the study period, years (A) 2017 and (B) 2018.**

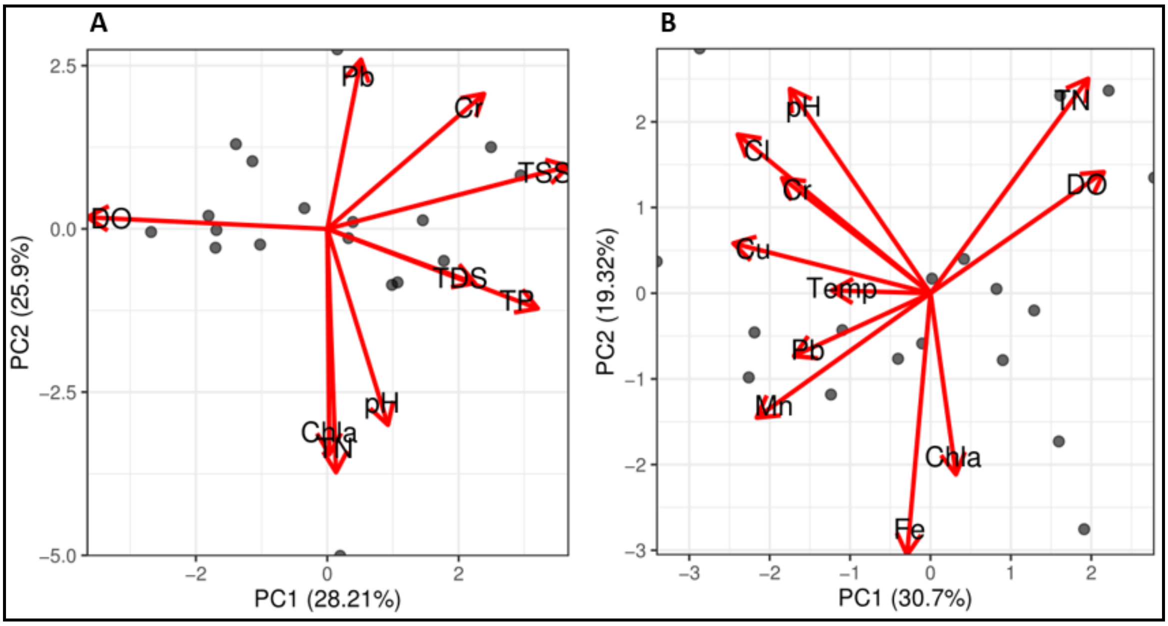



**Figure 4.8 PCA ordination plot of the 18 Research stations, indicating the relative contribution to pollution of each physicochemical variable denoted as a vector and Research station indicated as circle symbols. A & B are the years 2017 & 2018 respectively.**

**Table 4.3 The results of Kruskal-Wallis test showing the significant physicochemical variables at p< 0.05 in the years 2017 and 2018 (ns- not significant).**

| Parameter | 2017 | 2018 |
|---|---|---|
| Chl *a* | < 0.001 | < 0.001 |
| Cl | ns | < 0.001 |
| Cr | < 0.001 | < 0.001 |
| Cu | ns | < 0.001 |
| DO | < 0.001 | < 0.001 |
| Fe | ns | < 0.001 |
| Mn | ns | < 0.001 |
| Pb | < 0.001 | < 0.001 |
| pH | < 0.001 | < 0.001 |
| TDS | < 0.001 | ns |
| Temp | ns | < 0.001 |
| TN | 0.041 | < 0.001 |
| TP | < 0.001 | ns |
| TSS | < 0.001 | ns |

### 4.3.3 LULCC relationship with water quality variables

LULCC and WQ data were further subjected to Pearsons' Correlation statistical analysis. The Pearsons' Correlation coefficient, r values higher than 0.5 were considered significant. The correlation coefficient, r output for the relationship between LULCC and water quality parameters is presented in Appendix IV. Built-up (urban) land use was significantly correlated with most of the WQ parameters; EC (r=0.50), TSS (r=0.58), Fe (r=0.85), Mn (r=0.81), Pb (r=0.62) and BOD (r=0.714), but negatively correlated with DO (r=0.3). The urban area had the highest overall percentage LULCC of 233.76% from 1990 to 2018 (table 4.2). Agricultural land use had an overall 221.01% LULCC from 1990 to 2018, but showed weak correlation with WQ parameters; DO (r=0.04) and Pb (r=0.05), but negatively correlated with Mn (r=0.5). Shrubland had positive correlation with EC (r=0.63) and Mn (r=0.5). Bareland, Open water, and forest had no significant correlation with WQ and the overall percentage change from 1990 to 2018 was negative (table 4.2).

Built-up (urban) land use was subjected to multiple regression analysis (MRA) for it strongly correlated with most WQ parameters (Appendix IV). This assessed the relationship between the LULCC data as dependent variable, and water quality parameters as predictor variables. The output showed that EC, DO, Zn, and Pb, with $R^2$ values of 0.983, 0.918, 0.938, and 0.961 respectively, and were significantly associated with built-up (urban) land use only ($p < 0.009$, $p < 0.042$, $p < 0.031$, and $p < 0.02$). This is indicated in bold in Table 4.4, and were significantly associated with Built-up (urban) land use only ($p < 0.009$, $p < 0.042$, $p < 0.031$, and $p < 0.02$) (Table 4.4). The inference is that over 90% of the variations in EC, DO, Zn, and Pb within the catchment could be explained by urban land use. The P-values of the aforementioned analysis were less than $p < 0.05$, thus their coefficients were considered statistically significant.

**Table 4.4 The multiple regression model output with Built-up (Urban) land selected as environmental predictor and denoted by superscript "a". $R^2$ values are presented and the significant p-values ($p < 0.05$) are indicted in bold.**

| Dependent variable | R | $R^2$ | Adj. $R^2$ | Std. Error of the Estimate | P-value |
|---|---|---|---|---|---|
| EC | 0.991[a] | **0.983** | 0.974 | 7.336 | **0.009** |
| DO | 0.958[a] | **0.918** | 0.877 | 0.215 | **0.042** |
| pH | 0.875[a] | 0.766 | 0.648 | 0.188 | 0.125 |
| TURB | 0.297[a] | 0.088 | -0.368 | 28.355 | 0.703 |
| Cl | 0.822[a] | 0.676 | 0.514 | 0.996 | 0.178 |
| TSS | 0.758[a] | 0.575 | 0.362 | 22.311 | 0.242 |
| Fe | 0.837[a] | 0.701 | 0.552 | 5.075 | 0.163 |
| Zn | 0.969[a] | **0.938** | 0.907 | 0.047 | **0.031** |
| Mn | 0.752[a] | 0.565 | 0.347 | 0.946 | 0.248 |
| Cu | 0.785[a] | 0.617 | 0.233 | 0.016 | 0.425 |
| Cr | 0.134[a] | 0.018 | -0.473 | 0.035 | 0.866 |
| Pb | 0.980[a] | **0.961** | 0.942 | 0.023 | **0.020** |

## 4.4 Discussion

### 4.4.1 LULCC spatial structure

LULCC in the period between 1990 and 2018 depicted a progressive increase in anthropogenic activities, including urban expansion and infrastructural developments, especially along Thika super highway, Mombasa Road and Kangundo road with high concentration of human settlements (Kitheka, 2019; Kitheka et al., 2022**)**. In addition, there are other developments such as industrial parks and export processing zones such as Kapa Oil refineries, Simba cement manufacturing, Athi River tanneries, Kenya meat commission factories, chemical industries, and textile plants (Kitheka, 2019; Kitheka et al., 2022**)**. The research finding is similar to previous work by Koskey et al (2021) who studied LULCC in

Kamweti and Njoro River catchments and revealed massive settlement and industries such as Njoro canning factory, Greenhouses and Milk processing plants at the catchment.

In Kenya, the provision of housing is on the rise in both urban and rural areas, with the ministry of lands and urban development outlining the demand for new low and medium-cost houses to be approximately 200,000. Thereby, the conversion of shrubland and forests into agricultural lands and urban settlements. This is in line with an observation supported by WHO (2015), who revealed that the unprecedented increase in human population, especially in the global south, has resulted in the clearance of vegetation cover for purposes of agricultural activities to meet the ever-increasing food demand and for housing (Lambin et al., 2003).

### 4.4.2 Water quality Spatial-temporal distribution

The findings from the present study revealed that increase in nutrients, TN and TP in 2017 could be as a result of concentration in low volumes of river water in addition to atmospheric deposition during the dry period. Similar finding was reported by Vuai et al. (2005) who found out that nutrient deposition in Lake Victoria was as a result of bio-accumulation of particulate matter in the atmosphere during dry season. Cl, Cu, Fe, and Mn increased in 2018, and the rest of the physicochemical parameters cut across both years, indicating the variability that might be attributed to seasonal influence as temperature and discharge vary with rainfall changes (Appendix VII and X). This demonstrated that the high TSS in the Upper Athi River was a consequence of the long rainy seasons causing increased inundation of the catchment. In this study, the variation of rainfall patterns and associated discharge trends may have influenced the variation in concentrations of the physicochemical variables. This is in agreement with the ‘‘urban stream syndrome’’ theory by Walsh et al. (2005), who postulated that streams and rivers traversing urbanized catchments are characterized by increased heavy metals, nutrients, and anions, resulting in degraded water quality. This scenario can be aggravated by increased runoff from intense precipitation, causing nutrients and chemicals to influx into the streams. Kikuyu springs were considered a reference site in the present study since they were less impacted by human activities and were protected springs (Appendix 1). This is consistent with a previous study by Ding et al. (2017), who demonstrated that referenced sites in the Upper Mekong River Basin, China, remained lowly impacted by parameters likely to degrade the water quality (Walsh et al., 2005; Ding et al., 2017).

### 4.4.3 Impact of LULCC on the spatial-temporal trend of water quality

The present study revealed that water quality in the Upper Athi River watershed was directly influenced by LULCC changes, a finding similar to Muriithi (2016), who studied the impact of LULCC on water quality in the semi-arid sub-watersheds of Laikipia and Athi River basins. These changes are likely to be caused mainly by anthropogenic activities. Among the human activities in the watershed which include human settlement along the streams, industrial establishments, construction of impervious road surfaces and vegetation removal resulted to water quality degradation.

In the present study, Urban Land use (Built-up araea) showed strong positive relationship with heavy metals, specifically Pb and Zn, while a negative relationship with DO, a finding that is similar to previous study by Kithiia & Mutua (2006) who worked on Nairobi River sub-catchments and revealed that increased concentrations of heavy metals maybe influenced by both point and non-point source pollution. The large volumes of domestic, municipal and industrial wastewaters associated to dense populations and manufacturing industries in EPZ, Athi River, Nairobi industrial areas, Ruiru and Thika towns including Kibra and Mathare informal settlements are washed into the streams especially during the wet seasons (Appendix

VII). In addition, urban areas have resulted to an expanded impervious surface, leading to accelerated stream flows and increased runoff volumes (Zhou et al., 2012, Mbao et al., 2020; Mbao et al., 2022). These impervious storm runoffs, wash different types of heavy metals into streams and rivers, consequently increasing pollutants concentrations. The heavy metals pollutants such as Pb and Zn have the potential of lowering DO level due to their oxidation. Additionally, increased concentrations of $Pb^{+}$ and $Zn^{+}$ cations raised EC levels in the present study, a finding that is in agreement with previous studies by Kithiia (2021) who demonstrated a long-term elevation of EC along urbanized Nairobi River, Kenya and noted a declining trend in water quality downstream as the river traversed the city central business district.

Volatilisation from land and water surfaces and subsequent atmospheric transport and deposition of metals pose environmental pollution risks (Hecky et al., 2005). The UARC is within the tropics and is likely to undergo a similar process.

## 4.5. Conclusion

The combination of the iterative self-organizing data (ISODATA) unsupervised classification technique and water quality data were used to assess LULC changes in the Upper Athi River Catchment, and the findings will enable the watershed managers to employ relevant actions against inappropriate human activities or occupation of the watershed. In addition, the study has revealed that the catchment is being degraded by human activities such as agricultural expansion, urbanization and infrastructural development. For example, there was LULCC from 1990 to 2018 for urban area and agriculture with an increment of 233.8% and 221% respectively. This observation is attributed to decrease in shrubland, Bareland, open water and forest from 1990 to 2018 to provide room for shelter and industries in Upper Athi River Catchment in towns like Athi River town, kiambu, Thika and Nairobi city with a high concentration of human settlements as well as industrial parks and export processing zones such as Kapa Oil refineries, Simba cement manufacturing, Athi River tanneries, Kenya meat commission factory, Chemical industries, spinners and spinners, and textile plants, among others. Further, anthropogenic activities directly influenced the water quality, and the highly degraded study areas were located in urban areas and therefore more exposed to contamination by nutrients and heavy metal pollutants from agricultural, domestic, and industrial effluents.

Therefore, the study demonstrated that the LULCC for urban development has significantly degraded the water quality in the Upper Athi River catchment. Based on the results of the study, it could be concluded that significant land cover degradation is expected to occur in the future if mitigation activities such as improving housing infrastructure, wastewater treatment plants, and enforcement of the laws on industrial effluents are not undertaken in the Upper Athi River Catchment, posing a great threat to the biodiversity conservation and survival of local downstream communities and urban dwellers in the catchment area.

# CHAPTER 5

# 5.0 APPLICATION OF QUAL 2KW AND FORECASTING MODELS FOR ASSESSMENT OF POLLUTANTS IN UPPER ATHI RIVER CATCHMENT

This chapter deals with the results of QUAL2KW and forecasting models in monitoring the water quality/heavy metals in the Upper Athi River catchment, discussion, conclusion and recommendations

## 5.1 Introduction

Degradation of water quality in developing countries is unprecedently threatening global water resources (UNEP 2016). The sources of water pollution vary from place to place, but they normally include soil erosion, municipal sewage, agricultural chemicals, and industrial effluent (Kithiia, 2012; Ochieng et al., 2022; Uhlířová et al., 2009). The pollutants adversely affect biodiversity, leading to the degradation and loss of ecosystems. In addition, pollution creates health hazards and reduces industrial capacity by increasing the costs of removing pollutants from water or through effluent or wastewater treatment. In many developing countries, this situation has been attributed to the increasing desire to achieve industrialization status (UNEP, 2016). Degradation of the river's water quality has been increasing in the recent past, thereby adversely affecting the downstream communities relying on the river for various uses (UNEP, 2016). The upper parts of the Athi river basin have experienced rapid population growth and industrialization that have led to the encroachment of wetlands and forests (Kitheka, 2019; Kitheka et al., 2022**)**. The diverse land use activities in the basin have been shown to contribute immensely to water quality degradation and pollution (Kithiia, 2012; Kitheka, 2019; Kitheka et al., 2022).

In general, water quality modeling in rivers and streams has been applied more extensively in developed countries than in developing nations (Bui et al., 2019). In the USA, Hobson (2013) used QUAL2Kw as a decision support tool for Silver Creek Water Shade and found that modeling could be more cost-effective than regular water quality monitoring. For instance, in the Cértima River in Portugal, the Qual2Kw model showed that the river was highly contaminated with high levels of nutrients (Song et al., 2020; Zhang et al., 2012), although neither phosphorous nor nitrogen were limiting the proliferation of algal blooms (Schmidt et al., 2019). QUAL2kw is a one-dimensional model with many applications, especially in river channels with non-uniform but steady flow and a roughly constant pollution loading (Chowdhury et al., 2018; Flynn et al., 2015; Ye et al., 2013; Zhang et al., 2015; Zhu et al., 2015). In simulation, QUAL2kw factors in both the point and non-point pollution sources (Pelletier et al., 2006). The usage of the model has been far and wide, and there have been recent modifications to the model to allow for a more robust simulation of river and stream water quality (Chaudhary et al., 2018; Kalburgi et al., 2015; Zhang et al., 2014). A general mass balance equation is used to guide the model in the simulation of concentration constituents within the water column (Santy et al., 2020). The QUAL2kw model calibration process is geared towards determining model parameter values that best fit the modeled system (Yin and Seo, 2013). Both manual and automatic approaches are used to calibrate the Qual2Kw model. The manual calibration depends on the user's ability, and it’s usually done by varying specific parameters, monitoring the final output, and repeating the process until the user is satisfied with the results (Rafiee et al., 2014; Abidin et al., 2018; Cho and Lee, 2019). On the other hand, automatic calibration applies internal inbuilt algorithms that are based on specific stoichiometry constants and rates (Nagisetty et al., 2019; Zhu et al., 2015). The automatic calibration optimizes the goodness of fit from the results of the model and compares data measured through the in-built algorithm (Hadgu et al., 2014; Kamal et al., 2020; Tang et al., 2014). The in-built algorithm is the weighted average of the normalized root-mean square error (RMSE) of the variations between observed data and water quality parameter model predictions (Chen et al., 2018; Xin et al., 2019). The fitness function maximized by the genetic algorithm is given in equation 1:

$$f(x) = \lfloor \sum_{i=1}^{n} w_1 \rfloor \left[ \sum_{i=1}^{n} \frac{1}{w_i} \left[ \frac{\sum_{j=1}^{m} O_{ij}/m}{\left[\sum (P_{ij} - O_{ij})^2/m\right]^{1/2}} \right] \right] \text{………. Equation 1}$$

Where $O_{ij}$ is observed data values, $P_{ij}$ is the predicted values, $w_i$ is the weighting factor, m is the observed and predicted values pairs, and n is the number of different parameters within the RMSE reciprocal. The detailed procedure of the QUAL2kw model calibration is well outlined by Pelletier et al., (2006). QUAL2kw system parameters required for calibration were obtained from existing literature and the model user manual (Zhang et al., 2020).

Forecasting tools have been developed and designed to apply past happenings and present information regarding possible future scenarios of certain parameters (Fan et al., 2021; Eskafi et al., 2021; Sharma et al., 2018; Katimon et al., 2018; Abdeveis et al., 2020; Babamiri and Marofi, 2021). Our present study on the forecasting of future water quality trends was undertaken in the Upper Athi River basin in Kenya, whose headwater streams, such as Nairobi, Ngong, and Mathare, drain areas with varying land use activities. The prediction of future trends was undertaken in two phases: the longitudinal water quality profile, which was carried out using the QUAL2Kw model, and the second phase of predicting future water quality trends, which was performed using the SPSS forecasting tool. The objective of the study was to generate scenarios to predict future water quality trends in the river by utilizing the quantitative technique in the simulation of water quality parameters due to its minimal errors compared to qualitative forecasting.

## 5.2 Materials and methods

### 5.2.1 Study Area

In Kenya, the Athi River drainage basin is considered the fourth largest drainage system, with a total surface area of 69,930 $km^2$ (Kitheka, 2019) (Figure. 5.1). However, the Upper Athi River, where this study was done, has a surface area of about 6754 $km^2$, which is equivalent to about 9.7% of the total basin area (Kitheka et al., 2022). The river originates from the Central Kenya highlands, especially the Ngong Hills, Kikuyu Escarpment, and southern parts of the Aberdares ranges. The upper section of the Athi River basin in the Kenya Highlands is densely populated, with approximately 200–300 persons per $km^2$, with intensive crop cultivation dominating the area (Prasol Training and Consulting Ltd., 2012). Major crops cultivated here include various horticultural crops, coffee, and tea (Prasol Training and Consulting Ltd., 2012). The main tributaries of the upper Athi River include the Nairobi River, Ndarugu Athi, Mbagathi, and Ruiru rivers (Figure 5.1), which traverse densely populated areas within the Nairobi metropolitan area with varied anthropogenic activities such as commercial, industrial, informal settlements, agricultural, deforestation, solid waste disposal, wetland, and riparian encroachment (Kitheka et al., 2022).

### 5.2.2 Water Quality Sampling

The study established 18 sampling stations along the main Athi River and its tributaries in order to determine the spatial distribution of concentrations of key water quality parameters. However, only four sampling stations along the Athi River stretch were considered for the modelling, that is Mbagathi station, downstream EPZA WWTP discharge point, Fourteen falls and Athi at Wamunyu. Water quality data was collected during the whole study period, years 2017 and 2018. The in-situ measurements for physicochemical parameters, including EC, DO, Temp., and pH; collection and analysis of water samples for various parameters is discussed in detail in Chapter 3 (pages 44-51).

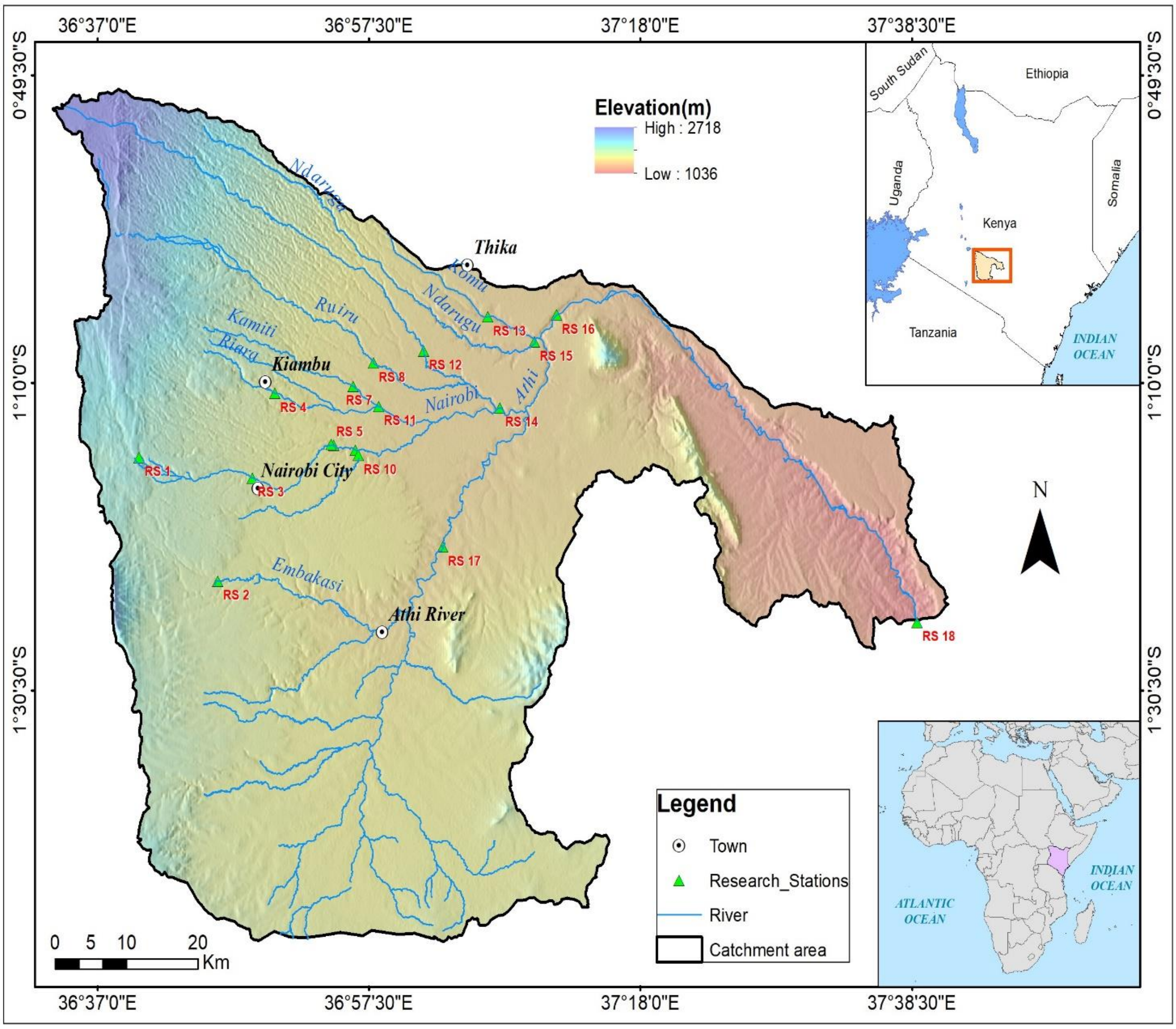



**Figure 5.1 Map showing the study area in the Upper Athi River Catchment.**

Note: The key features of the rivers Research stations (sampling sites) and drainage area have been described in more detail in Chapter 3.

### 5.2.3 QUAL2Kw Methodology

The QUAL2Kw tool was used for modeling by inputting the physicochemical variables. Four sampling stations established along the Athi River, namely, Mbagathi Station, d/s EPZA WWTP discharge point, Fourteen Falls, and Athi at Wamunyu, were used for modeling, for the model requires a continuous river channel. The modeled stretch had a total length of 152 km and was divided into four sections of varying lengths, which were mainly dictated by the position of the research stations. Discharge/inflow data were sourced from WRA. Mbagathi and Kikuyu springs stations are headwater stations. Mbagathi station was chosen to define the upper boundary conditions because of its natural status, since Kikuyu springs are a water supply for the city and are protected by Nairobi City Water and Sanitation Company (NCWSCO).

### 5.2.4 Forecasting Methodology

In the present study, the monthly data for the period 2015–2018 were utilized for modeling and forecasting. Long or increased historical data periods increase the error and have a significant effect on the general scenarios (Nair and Sarin, 1979). The Excel forecasting feature Exponential Triple Smoothing (ETS) was used to fill in the missing data for the actual stations. The graphs generated future scenarios with upper, average, and lower values. The line of best fit explained the predicted values. The observed monthly data for the period 2015–2018 was used to predict the monthly data for the period 2019–2030 (Abdeveis et al., 2020). The SPSS Statistical Package Version 21 was used for data analysis, in which the updated trends package offers automation for the most optimal model from each class depending on several performance measures (Attanayake and Perera, 2021). The water quality data for BOD, Cl, COD, DO, EC, Iron, pH, TDS, Temp, TSS, and Turb. were obtained for the years 2015 to 2018. The 2015 and 2016 data were sourced from WRA but had data gaps that were filled using the linear forecasting tool in Excel. The years 2017 and 2018 were observed and had all the monthly data available. Effective forecasting of data requires at least 3 years of constant data, and therefore, the four sets of years were chosen for effective forecasting and optimal minimization of errors.

### 5.2.5 Calibration of QUAL2Kw model

The objective of model calibration was to determine the values for the model parameters that suit the QUAL2Kw model. The QUAL2Kw data was simultaneously organized for model calibration as well as validation. The model was calibrated using monthly average data for the dry season (December, January, and February), and validation was performed using monthly average data for the wet season (March, April, and May). For this study, the model was auto-calibrated using observed wet spell water quality data. Appendix II shows the calibration parameters for the QUAL2Kw.

### 5.2.6 Relationship between river discharge and water quality parameters

The relationship between river discharge and water quality parameters, such as correlation and regression analyses, was determined with the objective of determining the accuracy of the model in forecasting the actual measured water quality data. To determine the relationship between river discharge and the water quality parameters, correlation analysis was undertaken in the R (Version 3.6.0, R Development Core Team, 2019) vegan package (Oksanen et al., 2019). To determine whether discharge variables could explain the variation in physicochemical parameters, linear regression analysis was performed in the R (Version 3.6.0, R Development Core Team, 2019) vegan package (Oksanen et al., 2019). The standard deviations, means, minimum, and maximum values were computed using Excel Stat.

## 5.3 Results

### 5.3.1 Longitudinal distribution of the water quality parameters

There was a remarkable longitudinal distribution of the water quality parameters in the upper Athi river basin. Temperature increased as the distance increased from Athi at Wamunyu (40.8km) to Athi at EPZA (140km) upstream and this station had the highest temperature of 24 ºC (Figure. 5.2F). EC results from the calibrated data had similar trend along the river stretch like the temperature (Figure. 5.2D). TSS decreased downstream along the Athi River stretch and was recorded lowest level at Wamunyu with a value of 20 mg/l (Figure 5.2I).

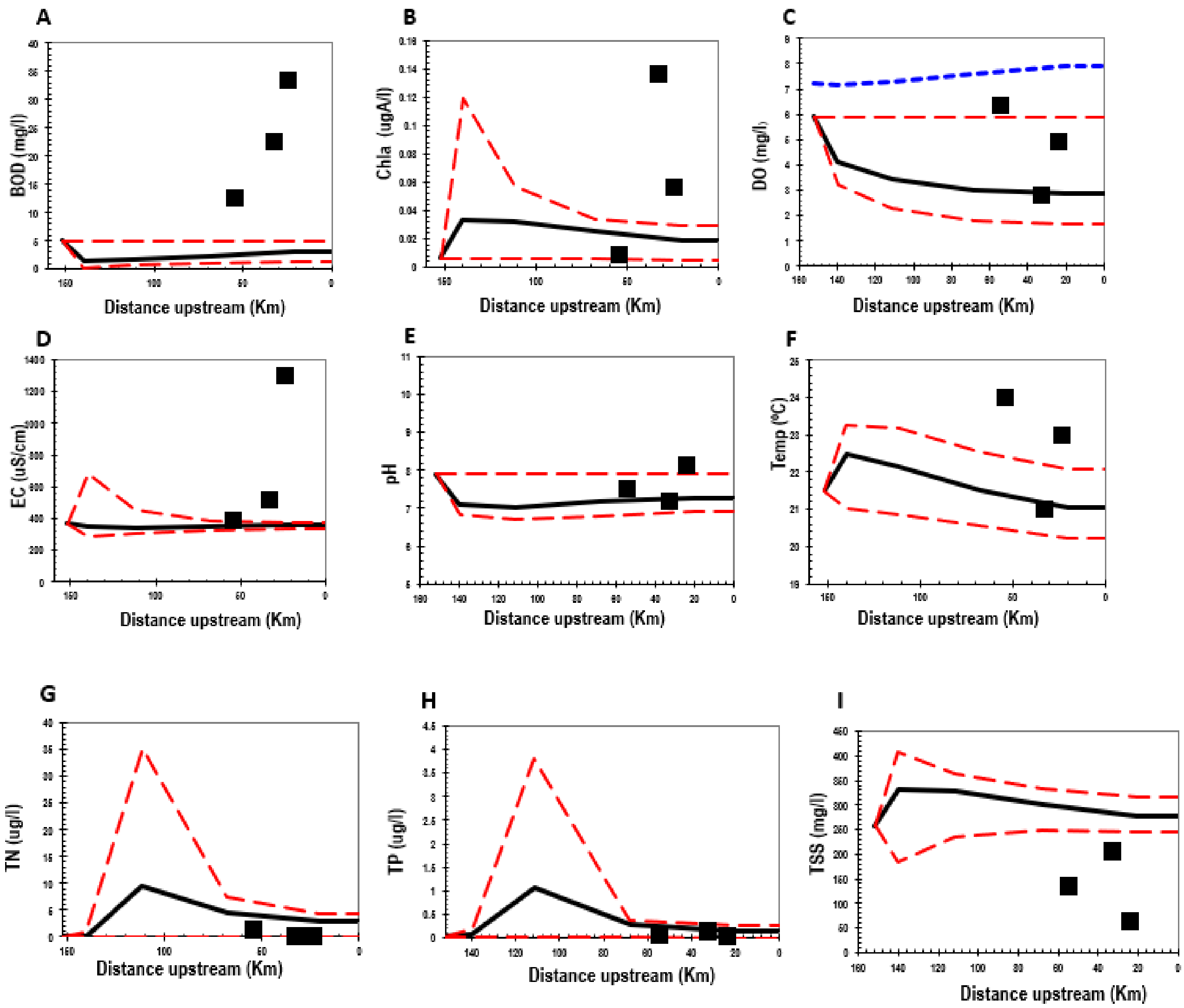



**Figure 5.2 The QUAL2kw calibration graphs of physicochemical parameters sampled from the Upper Athi River Catchment; The red dotted lines are maximum and minimum predicted physicochemical values, while the black line is average predicted WQ values. The black squares are the observed values.**

### 5.3.2 Model Validation

The model validation was carried out according to Attanayake and Perera (2021). The results showed that the validated graphs differed remarkably from the calibrated results (Figure 5.3A-I). The validated results were more conspicuous with reference to the observed results from the sampling stations. The BOD (Figure 5.3A), Chl *a* (Figure 5.3B), and the nutrients (TN and TP; Figures 5.3G and 5.3H, respectively) showed similar trends along the river stretch. The concentration of BOD increased downstream from Mbagathi (RS2) to Wamunyu (RS18), from an average of 5.0 mg/l to 19.68 mg/l, respectively.

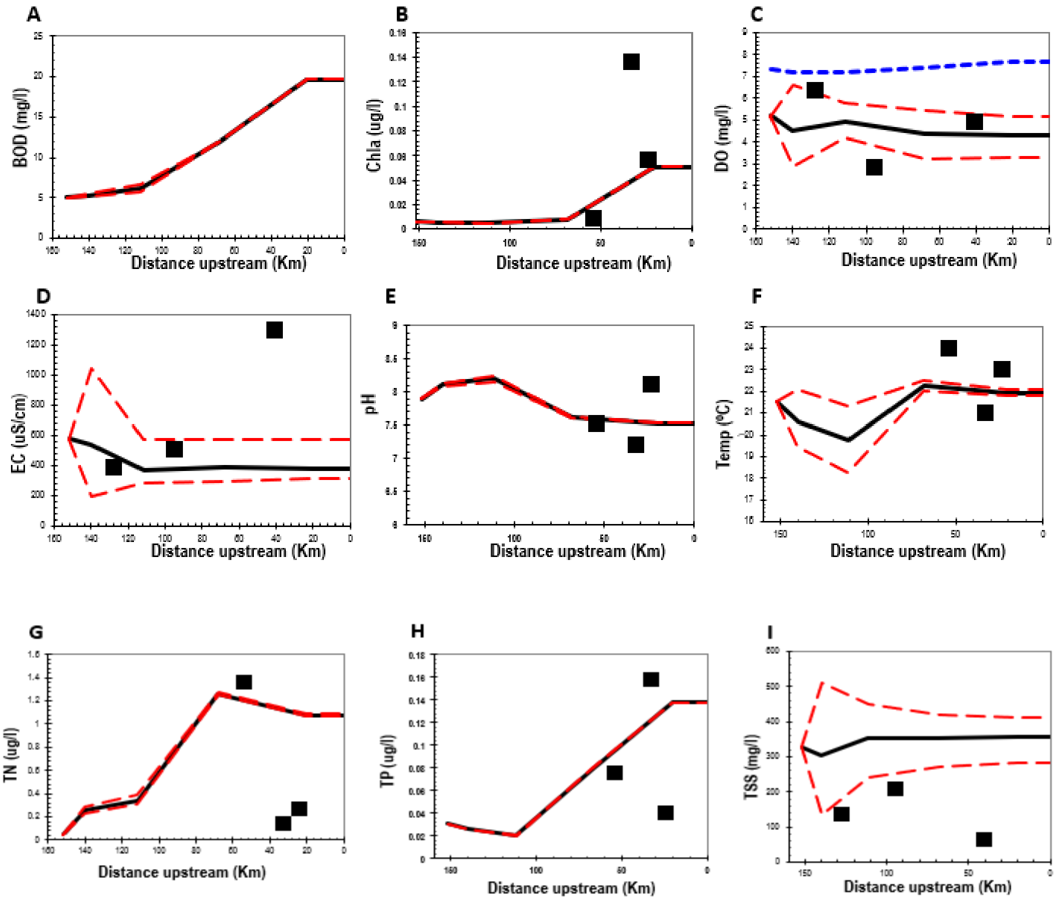



**Figure 5.3 The QUAL2kw validation graphs of physicochemical parameters sampled from Upper Athi River Catchment; The red dotted lines are maximum and minimum predicted physicochemical values, while the black line is average predicted WQ values. The black squares are the observed values.**

For Chl *a*, Mbagathi station the concentrations remained at 0.006mg/l for Max, Min and average. On the contrary, Chl *a* at Wamunyu ranged from 0.05–0.057 mg/l, with an average of 0.051 mg/l. Total nitrogen and phosphorus for Mbagathi were also similar, at 0.048 mg/l and 0.03 mg/l, respectively. The prediction of TN ranged from 1.07 to 1.09 mg/l, and TP: Max and Min were 0.138 mg/l.

The observed water quality variables were compared with predicted values for the calibration and validation runs. The results for water temperature, EC, TSS, BOD, TN, TP, Chl *a*, and pH were subjected to regression analysis. The largest disparity in results observed during the calibration period was with EC, with a standard error of 6.75 and an R-squared value of 0.99. The TP had an R-squared value of 0.93 and a standard error of 0.01. During the validation period, out of all the selected water quality parameters, none presented a standard error greater than 1.0. The computed values were in the range of 0.01–0.42, and the R-squared values were in the range of 0.66–0.99. Hence, the validated data agreed very well with the simulated data. The consequent R-squared and standard error values computed are presented in Table 5.1.

**Table 5.1 $R^2$ and standard error for calibrated and validated water quality data from Upper Athi River Basin.**

| | Calibration | | Validation | |
|---|---|---|---|---|
| | $R^2$ | Std. Error | $R^2$ | Std. Error |
| Temperature | 0.88 | 0.47 | 0.82 | 0.34 |
| Electrical Conductivity | 0.99 | 6.75 | 0.99 | 0.42 |
| Total Suspended Solids | 0.97 | 4.25 | 0.94 | 0.06 |
| $BOD_5$ | 0.88 | 5.44 | 0.66 | 0.30 |
| Total Nitrogen | 0.70 | 0.04 | 0.75 | 0.11 |
| Total Phosphorous | 0.93 | 0.01 | 0.94 | 0.01 |
| Chlorophyll *a* | 0.97 | 0.03 | 0.89 | 0.02 |
| pH | 0.98 | 0.13 | 0.99 | 0.11 |

### 5.3.3 Forecasting of the future monthly and annual trends in physicochemical parameters

The mean absolute error (MAE), root mean squared error (RMSE), and mean absolute percentage error (MAPE) were all used in linear regression to minimize the prediction errors of all the data points (Saigal and Mehrotra, 2012). The closer the value of MAE to 0, the better, while RMSE values between 0.2 and 0.5 reveal that the model is relatively robust to accurately predict the data. On the other hand, MAPE> 50% is considered good for prediction.

In the present study, comparative results for the monthly sum of BOD between the observed and predicted BOD showed seasonal fluctuations (Figure 5.4), with means of 18.78 mg/l and 31.30 mg/l, respectively (Table 5.2). The test results of the model revealed that MAE = 8.61, RMSE = 14.02, and MAPE = 50.38 (Table 5.2), indicating average model performance for the estimated variables and less confidence in the application for the predicted variables. The sum of monthly chloride concentrations between the observed and predicted values followed a linear trend for both periods, with a peak in November (Figure. 5.4). The observed and predicted chlorine averages were 47.28 and 47.00 mg/l, respectively (Table 5.2). The test results for the model revealed MAE = 22.11, RMSE = 45.34, and MAPE = 52.34 (Table 5.2), an indicator of poor model performance. For the COD, the results of the observed and predicted values showed relatively parallel fluctuations (Figure 5.4), with means values of 688.51 mg/l and 657.69 mg/l, respectively (Table 5.2). The test results of the model revealed MAE = 295.13, RMSE = 455.78, and MAPE = 218.06 (Table 5.2), indicating poor performance and low confidence in the application and reliability of the predicted values.

DO results showed great variation between the observed and predicted values (Figure. 5.4), with means of 3.61 $mgO_2/l$ and 2.68 $mgO_2/l$, respectively (Table 5.2). The test results for the model revealed MAE = 0.688, RMSE = 0.994, and MAPE = 18.8 (Table 5.2), depicting the reliability of the predicted variables. The EC results showed a relatively linear trend for observed EC but fluctuations for predicted EC (Figure. 5.4), with means of 693.1 and 401.5 µS/cm, respectively (Table 5.2). The test results of the model revealed MAE = 169.6, RMSE = 229.9, and MAPE = 33.1 (Table 5.2), which raises concern over the estimated variables. For iron (Fe), the results of the observed and predicted values showed fluctuations with similar trends (Figure. 5.4) and a mean of 6.82 mg/l and 11.02 mg/l, respectively (Table 5.2). The test results of the model revealed MAE = 5.95, RMSE = 10.75, and MAPE = 169.94 (Table 5.2), thus an indicator of the reliability of the predicted variables.

The results showed a slightly lower pH value for predicted values in relation to observed values (Figure 5.4), with a mean of 7.49 and 7.37 for observed and predicted pH, respectively (Table 5.4.). The test results for the model revealed MAE = 0.295, RMSE = 0.372, and MAPE = 4.023 (Table 5.2), which gives great confidence to the application of the predicted variables. Comparative results of monthly TDS between observed and predicted showed seasonal variations for observed TDS and a relatively linear trend for predicted TDS (Figure 5.4), with a mean of 398.89 mg/l and 394.58 mg/l for observed and predicted TDS, respectively (Table 5.2). The test results of the model revealed MAE = 94.56, RMSE = 130.02, and MAPE = 36.28 (Table 5.2), which lowered the confidence of the predicted variables.

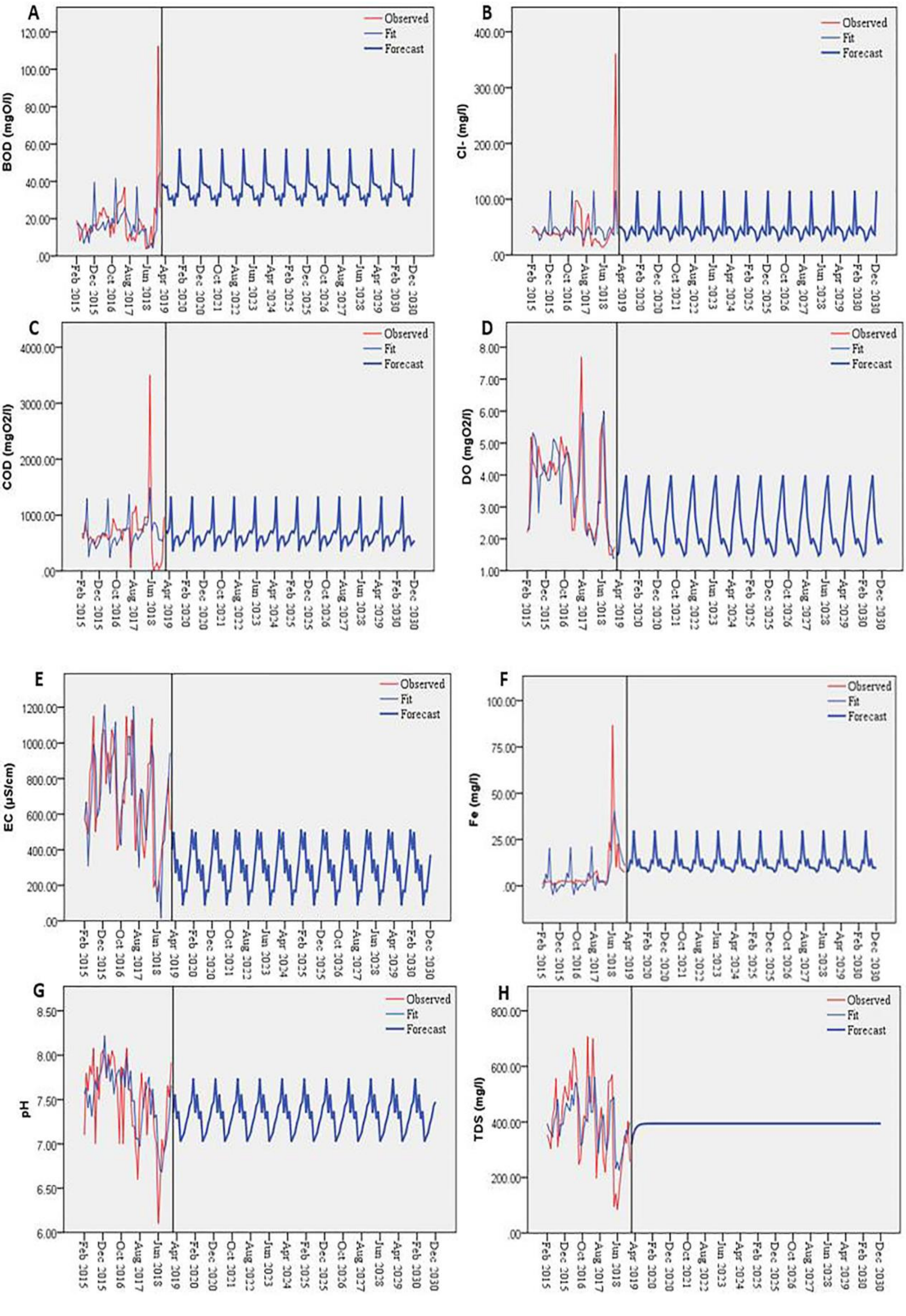
Temperature values showed a relatively linear trend for the observed and predicted, but both had slight fluctuations (Figure 5.4), with means of 23.92 and 22.99, respectively (Table 5.2). The test results of the model revealed MAE = 1.49, RMSE = 1.92, and MAPE = 6.29 (Table 5.2), indicating good model performance and giving confidence to the application of the model for the variables.

The TSS results between the observed and predicted values showed general fluctuations (Figure. 5.4), with means of 163.67 mg/l and 96.96 mg/l for the observed and predicted values, respectively (Table 5.2). The test results revealed MAE = 69.74, RMSE = 107.63, and MAPE = 78.56 (Table 5.2), which lowers confidence in applying the predicted variables.

The comparative results of the monthly sum of turbidity between the observed and predicted values showed seasonal fluctuation (Figure. 5.4), with means of 81.32 NTU and 82.28 NTU, respectively (Table 5.2). The test results of the model revealed MAE = 41.27, RMSE = 65.87, and MAPE = 68.54 (Table 5.2), which revealed relatively poor model reliability over the estimated variables.

**Table 5.2 Model descriptive statistics of the physicochemical parameters in Upper Athi River catchment.**

| | Developed Model | Min | Mean | Max | Stdev |
|---|---|---|---|---|---|
| EC (µS/cm) | 2015 – 2018 | 135.2 | 693.1 | 1150.0 | 276.2 |
| | 2019 – 2030 | 114.4 | 401.5 | 1214.8 | 244.2 |
| Chloride | 2015 – 2018 | 14.0 | 47.3 | 360.0 | 49.4 |
| | 2019 – 2030 | 26.0 | 47.0 | 115.1 | 21.8 |
| DO (mg/l) | 2015 – 2018 | 1.5 | 3.6 | 7.7 | 1.4 |
| | 2019 – 2030 | 1.4 | 2.7 | 6.0 | 1.1 |
| pH | 2015 – 2018 | 6.1 | 7.5 | 8.1 | 0.5 |
| | 2019 – 2030 | 6.7 | 7.4 | 8.2 | 0.3 |
| TSS (mg/l) | 2015 – 2018 | 20.0 | 163.7 | 552.0 | 133.2 |
| | 2019 – 2030 | 76.0 | 97.0 | 552.0 | 94.4 |
| BOD (mg/l) | 2015 – 2018 | 4.0 | 18.8 | 112.5 | 15.6 |
| | 2019 – 2030 | 4.3 | 31.3 | 57.5 | 11.4 |
| Fe (mg/l) | 2015 – 2018 | 0.4 | 6.8 | 86.7 | 13.2 |
| | 2019 – 2030 | 5.0 | 11.0 | 40.2 | 7.7 |
| COD | 2015 – 2018 | 116.8 | 688.5 | 3500.0 | 493.7 |
| | 2019 –2030 | 238.0 | 657.7 | 1489.4 | 239.8 |
| TDS | 2015 – 2018 | 83.2 | 398.9 | 706.9 | 152.3 |
| | 2019 – 2030 | 225.5 | 394.6 | 564.4 | 41.6 |
| Temp | 2015 – 2018 | 18.4 | 23.9 | 29.0 | 2.4 |
| | 2019 – 2030 | 18.2 | 23.0 | 27.3 | 1.4 |
| TURB (NTU) | 2015 – 2018 | 12.5 | 81.3 | 534.0 | 77.7 |
| | 2019 – 2030 | 3.7 | 82.3 | 223.6 | 46.6 |


A
BOD (mgO/l)
B
Cl- (mg/l)
C
COD (mgO2/l)
D
DO (mgO2/l)
E
EC (µS/cm)
F
Fe (mg/l)
G
pH
H
TDS (mg/l)
Observed
Fit
Forecast
Feb 2015
Dec 2015
Oct 2016
Aug 2017
Jun 2018
Apr 2019
Feb 2020
Dec 2020
Oct 2021
Aug 2022
Jun 2023
Apr 2024
Feb 2025
Dec 2025
Oct 2026
Aug 2027
Jun 2028
Apr 2029
Feb 2030
Dec 2030

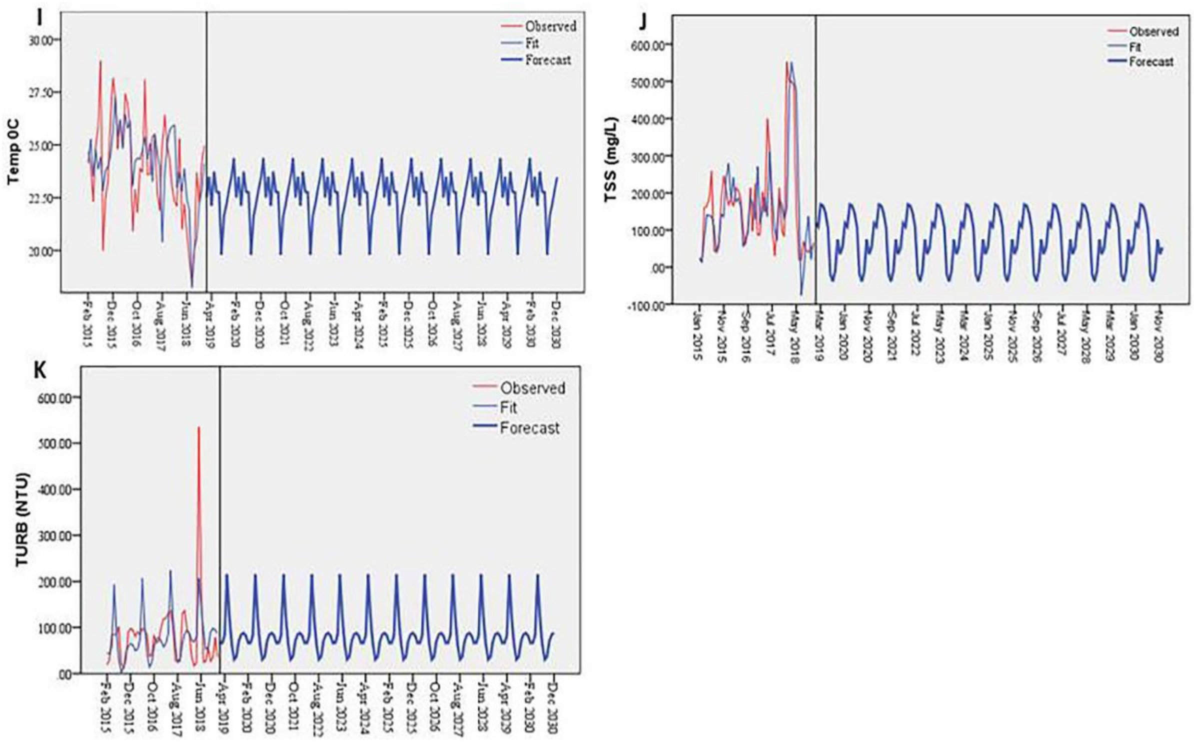
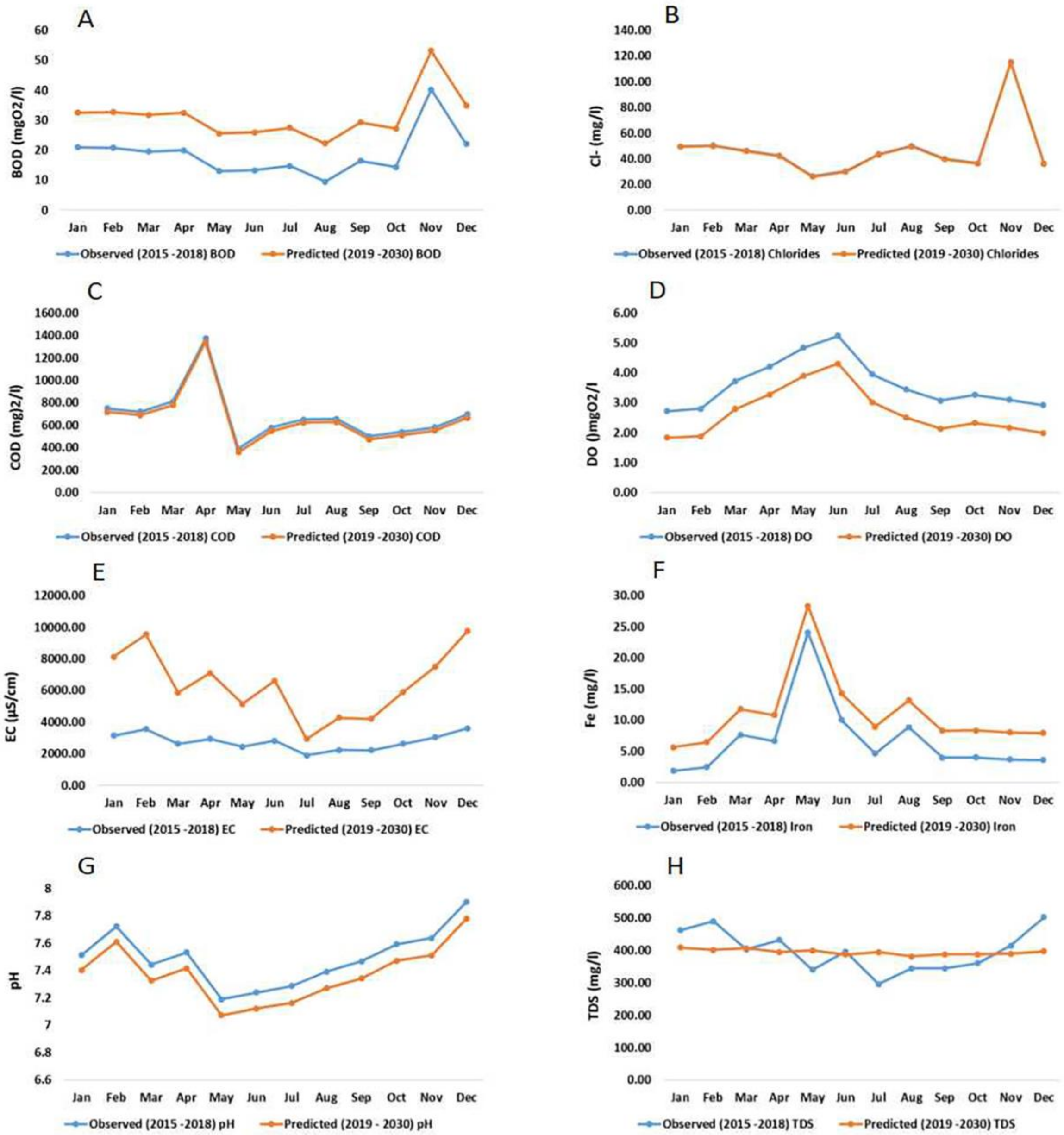



**Figure 5.4 The observed and simulated physicochemical parameters values in the Upper Athi River Catchment.**

### 5.3.4 Comparison of the observed/ measured and simulated physicochemical parameters

Even though our model was limited to river discharges, previous models in the upper Athi River revealed that rainfall as well as other socioeconomic factors such as population growth, urban development, forestry, and agricultural activities have been used to forecast the physicochemical conditions of this region and have achieved good performance. In the present study, based on the generated results observed and predicted curves exhibited BOD values of 18.8 mg/l and 31.3 mg/l respectively (Figure 5.5A & Table 5.2). For chlorides, the change between the observed and predicted curves was minimal (mean 47.0 mg/l), except November with a peak value of 115 mg/l (Figure 5.5B) & Table 5.2). COD concentrations presented almost similar values for both observed and predicted periods (Figure. 5.5C). Based on the generated results, DO concentration declined to the future with a mean of 5.2 mg/l and 4.3 mg/l, for observed and predicted respectively (Figure 5.5D), but with a maximum and Minimum values of 7.8 mg/l and 6 mg/l respectively (Table 5.2). As per figure 5.5E, Electrical conductivity showed an increasing trend to the future. Iron was at its peak in May with values of 24 mg/l and 28 mg/l for the observed and predicted curves respectively (Figure 5.5F). There were fluctuations for pH, TDS, Temp, and TDS between the observed and predicted periods that had similar patterns and the future was not predictable. The observed and predicted curves for Turbidity superimposed with a peak of 220 NTU (Figure 5.5K).



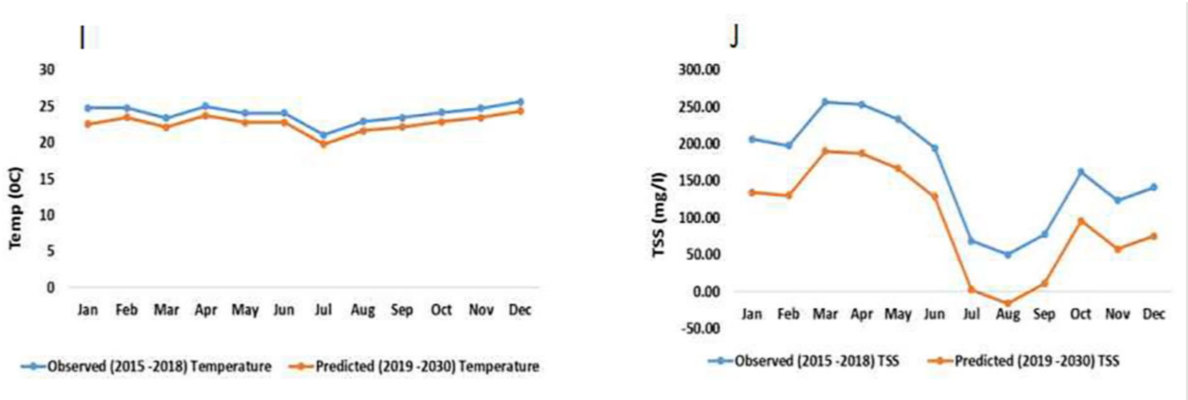



**Figure 5.5 The observed and predicted values of the physicochemical parameters in the Upper Athi River Catchment.**

### 5.3.5 Relationship between discharge and water quality variables

There was a strong direct relationship between discharge and many of the physicochemical parameters (Table 5.3). The correlation between river discharge values and water quality parameters revealed that there was a strong significant ($p < 0.05$) relationship between river discharge and turbidity at Nairobi Museum, Thiririka, Ruiru, and Kamiti (r= 0.63, 0.96, 0.61 and 0.98 respectively). This is mainly due to the important role played by discharge, which is partially a key mechanism via which eroded soil ends up in streams. Similarly, a strong significant ($p < 0.05$) relationship between river discharge and Chlorides was detected at Nairobi Museum, Kiu, and Kamiti (r= -0.73, 0.71, and 0.64, respectively). For TSS, strong significant ($p < 0.05$) relationship was revealed at 14 Falls (Munyu), Wamunyu, Thiririka, Ndarugu, Kiu and Kamiti (r= 0.56, 0.94, 0.89, 0.78, 0.53 and 0.91 respectively). Finally, for Fe and Zn all the sites showed significant ($p < 0.05$) relationship with the exception of Wamunyu sampling station. Periods of increased discharge were characterized with high TSS while low stream discharges experienced low TSS (Kitheka et al., 2022).

**Table 5.3 Correlation values between discharge and water quality parameters at different sites in Upper Athi River catchment. Bold shows coefficient values over 50%.**

| | TURB | Cl | TSS | Fe | Zn |
|---|---|---|---|---|---|
| Munyu 14 Falls | 0.35 | 0.36 | **0.56** | **0.88** | **0.90** |
| Wamunyu | -0.43 | -0.08 | **0.94** | 0.45 | -0.37 |
| Mbagathi | -0.05 | -0.08 | -0.12 | **0.87** | **0.62** |
| Nairobi Museum | **0.63** | **-0.73** | -0.28 | **0.81** | **0.86** |
| Thiririka | **0.96** | -0.16 | **0.89** | **0.88** | **0.78** |
| Ndarugu | 0.26 | -0.34 | **0.78** | **0.84** | **0.81** |
| Ruiru | **0.61** | -0.47 | 0.26 | **0.78** | **0.74** |
| Kiu | 0.30 | **0.71** | **0.53** | **0.83** | **0.74** |
| Kamiti | **0.98** | **0.64** | **0.91** | **0.76** | **0.82** |
| Ruiruaka | -0.24 | 0.17 | 0.13 | **0.77** | **0.73** |

## 5.4 Discussion

### 5.4.1 Comparison of the observed/measured and simulated physicochemical parameters

The water quality parameters for the calibration and the validation showed that the largest disparity in results observed during the calibration period was with EC, with a standard error of 6.75 and an $R^2$ value of 0.99. During the validation period, out of all the selected water quality parameters, none presented a standard error greater than 1.0. The computed values were in the range of 0.01–0.42 and $R^2$ values in the range of 0.66–0.99. Therefore, in our present study, the validated data fairly well agreed with the simulated data (Table 5.1). As previously observed by Hadgu et al. (2014), the QUAL2Kw model calibration results were moderately in agreement with the actual measured data. Additionally, the RMSE between the simulated and observed values in the study by Waturu et al. (2022) showed minimal disparity in DO, BOD, and pH, which is in line with our present study, thus inferring that the QUAL2Kw model can be applied in water quality monitoring of the Upper Athi River with minimal data.

### 5.4.2 Forecasting of future trends in water quality parameters

Forecasting future trends in water quality parameters is important in decision-making to improve conditions if the forecasts show a deteriorating state of certain parameters (Katimon et al., 2018; Kumar, 2017; Taneja et al., 2016). For this study, the water quality parameters considered for forecasting were BOD, Chloride, COD, DO, EC, Iron, pH, TDS, Temperature, TSS, and Turbidity because they had available historical data. The findings from the present study revealed that the unprecedented increase in TN levels, BOD, COD, Cl, Fe, and TSS are in agreement with the concept of ‘‘urban stream syndrome’’, postulated by Walsh et al. (2005) and emphasized that streams running through urban areas are characterized by increased nutrient levels coupled with degraded physicochemical quality. However, from the findings, the river discharge alone does not strongly explain the concentrations of the physicochemical parameters, hence the need to incorporate other variables like rainfall and socioeconomic factors, as done by Kitheka et al. (2020) in their previous studies in the same basin. Further, in our present study, COD concentrations increased almost twofold, especially during the wet seasons, which is in agreement with previous studies by Mbao et al. (2020), who studied the Qiantang River Basin, and Ding et al. (2017), who worked on the Xishuangbanna watershed of the upper Mekong River Basin, China, who associated the increased COD with the oxidized cations present in industrial and domestic effluents washed by runoffs from the catchment into the streams. In relation to BOD, the results are in line with a previous study by Kithiia et al. (2006), who studied the Nairobi River sub-basins and revealed that the unprecedented population increase within the city piled pressure on the existing drainage and sewage system that occasioned frequent sewer bursts, causing increased BOD levels in stream waters, especially during the rainy seasons. As previously observed by Kithiia (2007), the increased BOD concentrations are associated with an increased level of partially treated or untreated wastewater from both point and non-point sources in the catchment. In the present study, the high mean concentration of TSS in observed and predicted scenarios may infer that there are high erosion activities within the river channel (Shah et al., 2014). Similarly, closely related to TSS is turbidity, which in the present study was high in the wet season attributed to the heavy rains that eroded the top soil into the river channel (Rügner et al., 2013). Other chemical compounds, specifically $Fe^{2+}$ and Cl-, in this study also increased slightly with discharge, thus supporting the ‘‘urban stream syndrome" (Walsh et al., 2005) which envisages that the causes of water chemistry variation patterns are primarily attributed to events that determine the supply of pollutants (Rügner et al., 2013). Finally, it can be inferred that the model results for the future represent exactly similar trends compared to the observed data.

## 5.5 Conclusion

Water quality modeling is a tool that is becoming increasingly useful in obtaining crucial information needed for optimal water quality management. This present study demonstrated that the free software QUAL2Kw was used to simulate scenarios of pollutants along the Athi River, Kenya, which drains a heavily industrialized and densely populated area. Scenario-based planning has grown in popularity as a management tool for articulating future water quality models. The forecasting model was used to predict future water quality scenarios for the upper Athi River basin. The model was used to predict the future trends of BOD, chloride, COD, DO, EC, iron, pH, TDS, temperature, TSS, and turbidity in the Upper Athi river catchment. The pH had slightly higher values for future trends compared to observed values, and the observed and simulated TSS data had similar future trends. The predictions for BOD and iron concentration increased in the future, but there was a minimal difference between the observed and predicted chloride levels, which posed no threat to the environment. According to this study, it can be concluded that the EC, BOD, and Fe showed a temporal increasing trend for future prediction results. Therefore, this poses a risk of the pollutants increasing to unsafe levels if no appropriate management action is taken.

# CHAPTER 6

# 6.0 GENERAL DISCUSSIONS, CONCLUSIONS AND RECOMMENDATIONS

This chapter deals with the general discussions, conclusions and recommendations of all the objectives covered in the present study.

## 6.1 Discussion

This research study assessed the Upper Athi River Catchment (UARC) water quality status, analysed the variation in physicochemical parameters, evaluated the spatial-temporal water quality variation in relation to LULCC using Geographic Information System (GIS) and Remote Sensing technology, and generated scenarios of future trends for water quality in the catchment using a forecasting tool and the QUAL2Kw model for longitudinal prediction.

The findings of the study attributed rapid industrialization coupled with an increased human population in the UARC that has led to increased heavy metal contamination. In the upper parts of the catchment, like Ngong River, heavy metal concentrations were high (Mn: 10.08 mg/l, Cr: 0.48 mg/l, Pb: 0.43 mg/l, and Cu: 0.18 mg/l). The increased heavy metal concentrations in the catchment could be due to effluents from the Nairobi industrial area, the Dandora dumping site, and the Nairobi Central Business District (Kithiia, 2007 & 2010). There was a positive correlation between urban environment (built-up area) and deteriorated water quality, with Cr ($r = 0.56$) and Pb ($r = 0.80$) as the most significant parameters. Li and Bai (2021) observed that urban and agricultural lands produced much higher pollution on surface waters than other land surfaces. Compared to guidelines by USEPA Risk Based (RB) and KEBS/WHO, 2005 guidelines, the concentration recorded exceeded the recommended levels (Fe 0.3 mg/l, Mn 0.4 mg/l). When concentration levels of heavy metals exceed acceptable limits, they become toxic to organisms and negatively impact the ecosystem.

This study demonstrated the unprecedented increase in pollutant levels in line with the concept of the “urban stream syndrome" (Walsh et al., 2005). Kithiia and Mutua (2006) found that in the Nairobi River sub-catchment population continually increased, piling pressure on the existing drainage and sewerage systems, which occasioned frequent sewer bursts causing increased BOD levels in stream waters, especially during the rainy seasons. The BOD and COD values obtained in this study were well beyond the permissible limits set by USEPA and KEBS/WHO (2005) guidelines. Other parameters and nutrients of concern, such as nitrates and phosphorus, are often associated with eutrophication problems. Higher concentrations can cause algae blooms, which make water unsuitable for aquatic life. High phosphate concentration levels can be a result of human activities or detergents containing phosphates and waste discharge through leakage from septic systems that end up in rivers as a result of surface runoff or direct discharge.

For LULCC in the study area, it was observed that bareland, shrubland and forest decreased considerably from 1990 to 2018 with -30.25%, -13.05% and 11.66% respectively, mainly due to conversion into agricultural and urban land uses, whose increase was 221% and 233.76% respectively in the same period. Therefore, this could be attributed to the growing demand for agricultural land to increase food production and for urban areas to provide room for shelter and industries in Nairobi city and its environs (Athi River, Kiambu and Thika towns). Nairobi city and environs have the highest concentration of human settlements, with a population density of 6,247/km$^2$ (Kenya National Bureau of Statistics website) as per the 2019 census, including some of the largest informal settlements like in Africa, some with no sewerage systems.

Anthropogenic activities directly influence water quality; the highly degraded study areas were located in urban areas and therefore more exposed to contamination by nutrients and heavy metals from agricultural, domestic, and industrial effluents. This study has demonstrated that significant land cover degradation is expected to occur if mitigation measures are not undertaken in the Upper Athi River Catchment. This will pose a great threat to the conservation of biodiversity and the survival of local communities and urban dwellers.

For modeling, prediction of water quality trends was undertaken in two phases: the development of a longitudinal water quality profile and the prediction of future water quality trends. The correlation analysis for the QUAL2Kw model between the observed and the longitudinally predicted water quality parameters yielded strong $R^2$ values in the range of 0.66–0.90, with a standard error ranging between 0.01 and 0.42. This indicates that the model is reliable for predicting water quality parameters in the river. A similar observation by Waturu et al. (2022) showed that the QUAL2Kw model calibration results were moderately in agreement with the actual measured data. It is concluded that the model can be used to predict water quality variables along a river even with minimal data.

Forecasting future trends in water quality parameters is important in decision-making to improve conditions, especially if forecasts show a deteriorating state of certain parameters (Katimon et al., 2018; Kumar, 2017; Taneja et al., 2016). The current study considered BOD, chloride, COD, DO, EC, iron, pH, TDS, temperature, TSS, and turbidity water quality parameters for future prediction based on available historical data. It was shown that in the future, DO will decrease, indicating a decline to year 2030 with values of 7.8 mg/l and 6 mg/l for the observed and predicted curves, respectively, while BOD, COD, Fe, and iron are projected to increase. COD concentrations increased almost two-fold, which is in agreement with previous studies by Mbao et al. (2020) and Ding et al. (2017). The increased COD was attributed to the oxidized cations present in industrial and domestic effluents washed by runoff from the catchment into the rivers and streams. The BOD concentrations are also projected to increase due to untreated or partially treated wastewater from point and non-point sources (Hadgu et al., 2014; APHA, 12; Rosenquist et al., 2013). It can be inferred that the model results for the future were reliable when projected trends were compared with the observed data.

## 6.2 Conclusion

1. The findings of the study revealed that various physicochemical parameters have rendered the water unfit for human consumption and aquatic life as well as industrial use in UARC.
2. LULCC for Urban development has significantly degraded the water quality, posing a great threat for survival of riparian community as well as aquatic life, hence, mitigation measures are necessary.
3. Generation of scenarios models:

i. QUAL2Kw for longitudinal prediction was found to be a good tool and cheap method for water quality assessment compared to the common water quality monitoring that involve sampling and laboratory analysis.

**ii.** The models demonstrated that BOD, Fe and TSS concentration increased along the river, while BOD, Fe and EC showed temporal increasing trends to the future. In addition, DO decreased to the future indicating a sign of depletion perhaps due to increasing pollution in the river.

### 6.3 Recommendations from the study

1. Nairobi City and environs (Athi River, Kiambu, Thika and other urban settlements) should adopt Kenya Water Act, 2016 which requires all water companies in the country to establish and maintain sewerage and drainage works. This study recommends that the companies be proactive to plan and build enough sewer systems and devise ways for proper wastewater disposal.

2. The study was able to develop scenarios utilizing QUAL2Kw model to collect Water Quality data without the need for the costly Laboratory water quality sampling and testing and the forecasting technique to predict the future WQ status. Therefore, policymakers may utilize these techniques to strengthen environmental policy on water pollution.

## 6.4 Areas for further research

To understand the role of geology as a source of surface water pollution, further research should be carried out to investigate on levels of contaminants that emanate from groundwater. WRA is the government agent responsible in monitoring water quality and quantity of water resources. Besides monitoring borehole water levels, the quality of groundwater is paramount for it’s a source of recharge of river water.

The study found out that the main land uses in UARC were built-up (urban) area and agriculture. The major human activities in urban area include manufacturing industries spatially distributed in Nairobi city and its environs (Thika, Kiambu and Athi River town). The industries have air emissions which pollute the atmosphere. The agricultural field are bound to have residue phosphorous and Nitrogen based fertilizers that may pollute the atmosphere during dry and hot weather. The atmospheric pollution (toxic metals and nutrients may end up being deposited into the surface waters. Therefore, research on atmospheric pollutant deposition into surface water bodies is recommended.

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# 8.0 PUBLICATIONS

1. Waturu, M., Sitoki, L., Lalah, J., Mbao, E., and Kahuthu, W. 2022. Application of QUAL2kw and Forecasting models for assessment of pollutants in upper Athi River catchment in Kenya. African Journal of Pure and Applied Sciences 3(2):221-236. https://doi.org/10.33886/ajpas.v3i2.296

**2.** Waturu, M., Sitoki, L., Lalah, J., Chasia, S., and Mbao, E. 2023. Effect of land-use-land-cover-changes on water quality in the Upper Athi river catchment in Kenya. African Journal of Aquatic Sciences 1-13. DOI https://doi.org/10.2989/16085914.2023.2207098

# 9.0 APPENDICES

## Appendix I: Research Stations Coding

| Code | Site Name |
|---|---|
| RS1 | Kikuyu Springs |
| RS2 | Mbagathi |
| RS3 | Nairobi River at museum |
| RS4 | Riara River |
| RS5 | Ruiruaka River |
| RS6 | Mathare River |
| RS7 | Kiu River |
| RS8 | Ruiru River |
| RS9 | Nairobi River at Njiru |
| RS10 | Ngong River at Njiru |
| RS11 | Kamiti River |
| RS12 | Thiririka River |
| RS13 | Komo River |
| RS14 | Nairobi River downstream Dandora WWTP |
| RS15 | Ndarugu River |
| RS16 | Athi River at Fourteen Falls |
| RS17 | Athi River downstream of EPZA WWTP |
| RS18 | Athi River at Wamunyu |

**Appendix II: Qual2Kw Calibrated Parameters**

| **Parameter** | **Value** | **Units** | **Symbol** | **Min value** | **Max value** |
|---|---|---|---|---|---|
| Stoichiometry: | | | | | |
| Total Nitrogen | 8.20000 | gN | gN | 5 | 9 |
| Total Phosphorus | 1.47355 | gP | gP | 0.5 | 2 |
| Dry weight | 100.000 | gD | gD | 100 | 100 |
| Chlorophyll α | 1.63939 | gα | gα | 0.5 | 2 |
| Inorganic suspended solids: | | | | | |
| Settling velocity | 1.96434 | m/d | vi | 0 | 2 |
| Oxygen: | | | | | |
| Dissolved Oxygen | User model | | | | |
| Slow CBOD: | | | | | |
| Hydrolysis rate | 0.14885 | /d | khc | 0.05 | 0.25 |
| Temp correction | 1.05302 | | qhc | 1 | 1.07 |
| Oxidation rate | 3.99805 | /d | kdcs | 0 | 5 |
| Temp correction | 1.01817 | | qdcs | 1 | 1.07 |
| Fast CBOD: | | | | | |
| Oxidation rate | 0.09505 | /d | kdc | 0 | 5 |
| Temp correction | 1.01456 | | qdc | 1 | 1.07 |
| Organic N: | | | | | |
| Hydrolysis | 0.06795 | /d | khn | 0.05 | 0.3 |

| Parameter | Value | Units | Symbol | Min value | Max value |
|---|---|---|---|---|---|
| Temp correction | 1.06149 | | qhn | 1 | 1.07 |
| Settling velocity | 1.80153 | m/d | von | 0.05 | 2 |
| Ammonium: | | | | | |
| Nitrification | 2.95959 | /d | kna | 0.05 | 3 |
| Temp correction | 1.01184 | | qna | 1 | 1.07 |
| Nitrate: | | | | | |
| Denitrification | 0.31902 | /d | kdn | 0 | 2 |
| Temp correction | 1.01938 | | qdn | 1 | 1.07 |
| Sediment denitrification transfer coeff. | 0.98018 | m/d | vdi | 0 | 1 |
| Temp correction | 1.00234 | | qdi | 1 | 1.07 |
| Organic P: | | | | | |
| Hydrolysis | 0.09363 | /d | khp | 0.05 | 0.3 |
| Temp correction | 1.04525 | | qhp | 1 | 1.07 |
| Settling velocity | 1.44226 | m/d | vop | 0.05 | 2 |
| Inorganic P: | | | | | |
| Settling velocity | 1.56050 | m/d | vip | 0 | 2 |
| Sed P oxygen attenuation half sat constant | 1.76842 | $mgO_2/L$ | kspi | 0 | 2 |

**Appendix III: Mean values for physicochemical parameters (two decimal points)**

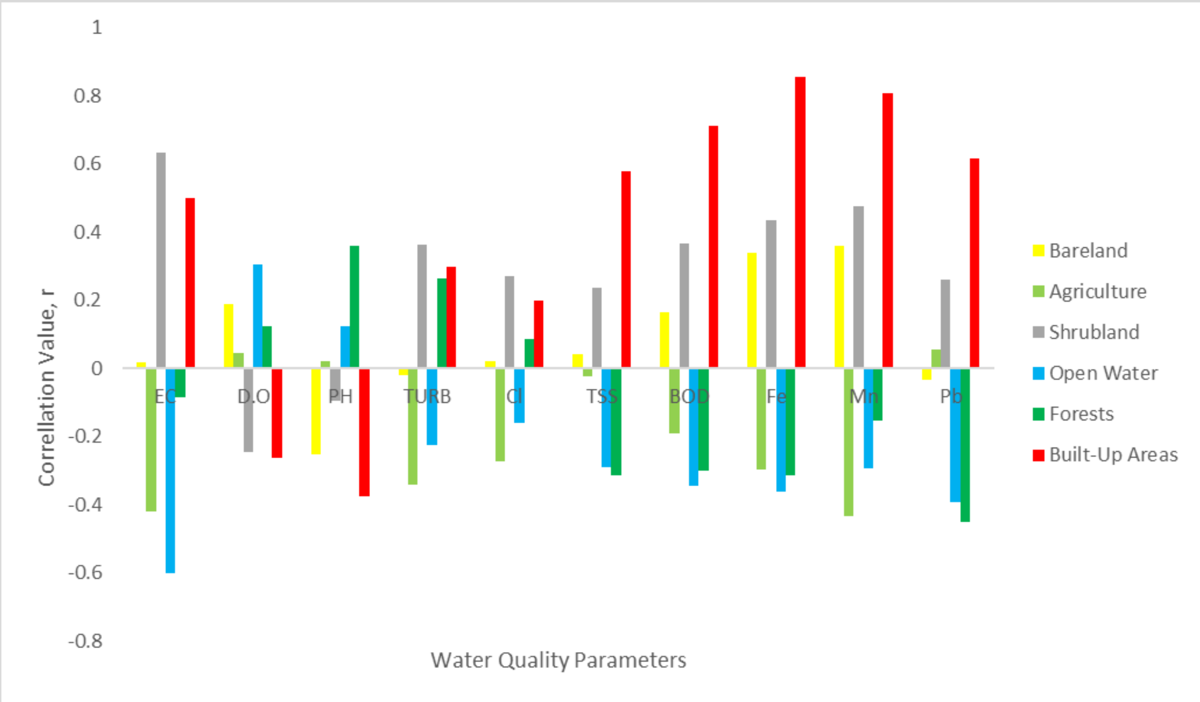
| | 14 Falls | Wamunyu | EPZA | Mbagathi | Nrb Museum | Ruai | Nrbi Njiru | Thiririka | Ndarugu | Komo | Ruiru | Kiu | NgongNjiru | Kamiti | Mathare | Ruiruaka R | Riara | Kikuyu Springs |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Chla_2017 | 0.05 | 0.34 | -0.10 | -0.04 | 0.05 | 0.24 | 0.01 | 0.08 | 0.06 | 0.15 | 0.00 | 0.01 | -0.02 | 0.00 | 0.01 | 0.01 | 0.01 | 0.06 |
| Chla_2018 | 0.14 | 0.01 | 0.06 | -0.01 | 0.04 | 0.13 | 0.07 | 0.13 | 0.40 | 0.13 | 0.03 | 0.00 | -0.05 | 0.02 | 0.09 | 0.01 | 0.02 | 0.00 |
| Cl_2017 | 50.36 | 79.91 | 250.77 | 75.64 | 44.55 | 63.64 | 81.85 | 34.79 | 3.00 | 128.18 | 13.13 | 21.95 | 144.09 | 18.82 | 72.64 | 18.64 | 15.36 | 54.18 |
| Cl_2018 | 57.00 | 20.67 | 216.19 | 58.25 | 44.58 | 92.21 | 81.63 | 7.67 | 4.58 | 75.42 | 6.29 | 27.38 | 100.67 | 15.46 | 78.33 | 18.54 | 19.00 | 50.58 |
| Cr_2017 | 0.04 | 0.03 | 0.07 | 0.03 | 0.01 | 0.05 | 0.05 | 0.04 | 0.01 | 0.05 | 0.01 | 0.02 | 0.72 | 0.07 | 0.31 | 0.44 | 0.08 | 0.00 |
| Cr_2018 | 0.09 | 0.08 | 0.24 | 0.08 | 0.01 | 0.09 | 0.09 | 0.02 | 0.04 | 0.07 | 0.09 | 0.08 | 0.23 | 0.23 | 0.13 | 0.26 | 0.09 | 0.00 |
| Cu_2017 | 0.01 | 0.02 | 0.14 | 0.05 | 0.03 | 0.16 | 0.08 | 0.02 | 0.05 | 0.09 | 0.05 | 0.02 | 0.19 | 0.03 | 0.09 | 0.14 | 0.02 | 0.00 |
| Cu_2018 | 0.08 | 0.01 | 0.30 | 0.12 | 0.03 | 0.15 | 0.31 | 0.04 | 0.11 | 0.12 | 0.07 | 0.08 | 0.17 | 0.04 | 0.09 | 0.20 | 0.03 | 0.00 |
| DO_2017 | 3.23 | 2.43 | 1.84 | 4.85 | 6.06 | 1.73 | 2.22 | 4.85 | 4.49 | 2.18 | 3.71 | 0.88 | 2.01 | 1.21 | 0.90 | 3.07 | 2.50 | 6.57 |
| DO_ | 2.8 | 6.35 | 4.9 | 5.46 | 6.7 | 1.8 | 2.5 | 5.5 | 6.3 | 2.8 | 6. | 2.3 | 4.04 | 4.5 | 1.2 | 4.7 | 3. | 6.4 |

| | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2018 | 2 | | 3 | | 6 | 5 | 0 | 8 | 5 | 8 | 12 | 9 | | 3 | 4 | 1 | 42 | 3 |
| EC_2017 | 670.18 | 620.00 | 1579.36 | 686.27 | 645.70 | 974.00 | 821.18 | 205.05 | 83.45 | 1593.27 | 105.8 | 341.15 | 956.64 | 206.8 | 944 | 236.29 | 457 | 344.4 |
| EC_2018 | 514.53 | 389.61 | 1302.04 | 475.22 | 684.83 | 691.50 | 622.67 | 104.14 | 79.55 | 948.03 | 84.04 | 380.72 | 925.04 | 207.1 | 747.1 | 235.05 | 282.7 | 331.1 |
| Fe_2017 | 4.05 | 1.79 | 4.12 | 6.63 | 24.76 | 10.93 | 17.91 | 3.79 | 5.88 | 3.50 | 3.35 | 4.52 | 25.55 | 14.81 | 28.90 | 26.30 | 1.67 | 1.95 |
| Fe_2018 | 19.19 | 4.67 | 16.97 | 7.15 | 24.50 | 17.91 | 35.12 | 72.45 | 21.60 | 29.53 | 24.63 | 23.79 | 17.84 | 15.65 | 34.27 | 24.13 | 15.67 | 1.27 |
| Mn_2017 | 1.05 | 0.22 | 1.72 | 1.12 | 5.63 | 4.82 | 3.31 | 0.46 | 0.59 | 1.24 | 0.52 | 2.14 | 6.34 | 0.14 | 4.42 | 2.09 | 1.08 | 0.87 |
| Mn_2018 | 4.53 | 1.18 | 1.94 | 1.95 | 6.39 | 5.16 | 7.95 | 5.06 | 1.91 | 5.39 | 2.22 | 4.47 | 13.82 | 5.73 | 7.53 | 3.97 | 5.03 | 0.21 |
| Pb_2017 | 0.12 | 0.04 | 0.19 | 0.16 | 0.06 | 0.33 | 0.15 | 0.15 | 0.17 | 0.13 | 0.40 | 0.08 | 0.41 | 0.36 | 0.32 | 1.74 | 0.10 | 0.13 |
| Pb_2018 | 0.13 | 0.13 | 0.19 | 0.18 | 0.08 | 0.50 | 0.28 | 0.08 | 0.33 | 0.10 | 0.26 | 0.45 | 0.44 | 0.09 | 0.14 | 0.17 | 0.24 | 0.03 |
| pH_2017 | 7.33 | 8.06 | 7.65 | 7.72 | 7.10 | 7.24 | 7.20 | 6.95 | 7.54 | 7.25 | 6.55 | 7.25 | 7.48 | 7.40 | 7.14 | 6.94 | 6.41 | 7.22 |
| pH_2018 | 7.16 | 7.53 | 8.12 | 7.41 | 7.69 | 7.55 | 7.14 | 6.55 | 6.85 | 7.69 | 7.01 | 7.12 | 7.47 | 7.20 | 7.12 | 6.75 | 6.78 | 6.72 |
| TDS_2017 | 401.34 | 384.15 | 1038.18 | 449.27 | 405.01 | 593.10 | 498.92 | 126.33 | 51.96 | 976.57 | 64.88 | 211.51 | 584.45 | 126.7 | 560.5 | 145.82 | 282.0 | 213.5 |
| TDS | 28 | 247. | 792 | 273. | 421 | 39 | 36 | 57. | 40. | 517 | 46 | 20 | 540. | 11 | 480 | 138 | 15 | 20 |

| | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| _2018 | 4.11 | 63 | .33 | 71 | .71 | 2.14 | 5.13 | 15 | 16 | .28 | .20 | 8.32 | 75 | 1.8 | .8 | .98 | 7.3 | 5.9 |
| Temp_2017 | 24.10 | 23.86 | 22.26 | 22.67 | 21.53 | 23.20 | 24.40 | 20.88 | 21.76 | 25.01 | 22.30 | 21.53 | 25.00 | 19.41 | 24.46 | 21.03 | 20.86 | 22.32 |
| Temp_2018 | 22.01 | 22.63 | 21.55 | 19.07 | 21.32 | 23.07 | 22.41 | 21.65 | 20.75 | 23.43 | 21.06 | 20.95 | 24.00 | 20.83 | 21.95 | 20.14 | 19.19 | 23.53 |
| TN_2017 | 0.04 | 5.08 | 0.06 | 0.05 | 0.06 | 0.02 | 0.04 | 0.29 | 0.02 | 0.03 | 0.13 | 0.13 | 0.17 | 0.01 | 0.05 | 0.02 | 0.04 | 0.02 |
| TN_2018 | 0.15 | 1.37 | 0.27 | 1.33 | 0.06 | 0.05 | 0.09 | 0.45 | 0.24 | 0.02 | 0.29 | 0.20 | 0.16 | 0.32 | 0.10 | 0.37 | 0.14 | 0.90 |
| TP_2017 | 0.17 | 0.22 | 0.01 | 0.10 | 0.08 | 0.16 | 0.25 | 0.01 | 0.05 | 0.17 | 0.04 | 0.51 | 0.18 | 0.07 | 0.28 | 0.08 | 0.07 | 0.00 |
| TP_2018 | 0.16 | 0.08 | 0.04 | 0.04 | 0.09 | 0.19 | 0.15 | 0.02 | 0.03 | 0.22 | 0.02 | 0.05 | 0.17 | 0.04 | 0.22 | 0.03 | 0.06 | 0.01 |
| TSS_2017 | 162.18 | 30.73 | 61.19 | 48.91 | 61.64 | 176.82 | 227.82 | 65.15 | 35.62 | 113.18 | 91.91 | 129.45 | 197.82 | 52.45 | 296.0 | 88.21 | 20.96 | 1.85 |
| TSS_2018 | 206.67 | 136.42 | 64.03 | 122.38 | 62.00 | 134.22 | 485.33 | 334.23 | 119.53 | 323.17 | 69.88 | 167.92 | 164.56 | 83.47 | 562.4 | 134.48 | 76.50 | 3.00 |
| Turb_2017 | 92.73 | 43.41 | 47.95 | 36.81 | 50.64 | 169.18 | 271.00 | 42.03 | 17.82 | 155.11 | 11.04 | 75.44 | 256.82 | 81.96 | 215.6 | 29.25 | 111.3 | 2.64 |
| Turb_2018 | 96.82 | 55.67 | 40.71 | 48.71 | 92.52 | 113.74 | 169.42 | 305.61 | 98.62 | 272.31 | 85.14 | 77.98 | 83.94 | 104.0 | 176.8 | 71.40 | 81.59 | 2.67 |

| | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Zn_2017 | 0.05 | 0.20 | 1.23 | 0.11 | 0.74 | 0.13 | 0.41 | 0.04 | 0.06 | 0.22 | 0.05 | 0.05 | 0.33 | 0.12 | 0.36 | 0.22 | 0.04 | 0.10 |
| Zn_2018 | 0.44 | 0.26 | 1.99 | 0.73 | 0.94 | 0.56 | 1.47 | 2.00 | 0.77 | 1.28 | 0.69 | 1.01 | 1.08 | 0.67 | 1.71 | 0.62 | 0.62 | 0.25 |

**Appendix IV: Relationship between LULCC and significant water quality variables for the research stations.**



**Appendix V: KEBS/WHO drinking water quality standards**

| PARAMETER | UNIT | W.H.O GUIDELINES |
|---|---|---|
| pH | -log[H+] | pH Scale 6.5 – 8.5 |
| Colour | mg/pt/l | < 15 |
| Turbidity | N. T. U. | <5 |
| Dissolved Oxygen ($O_2$) | mg/l | > 4 |
| Total Hardness | mg$CaCO_3$/l | < 500 |
| Total Alkalinity | mg$CaCO_3$/l | < 500 |
| Fluoride (F) | mg/l | < 1.5 |
| Total Dissolved Solids | mg/l | < 1500 |
| Chloride | mg/l | < 250 |
| Sodium | mg/l | < 200 |
| Zinc | mg/l | < 5 |
| Sulphates | mg/l | < 400 |
| Iron (Fe) | mg/l | < 0.3 |
| Manganese (Mn) | mg/l | < 0.1 |
| Nitrate | mg/l | < 10 |
| Lead (Pb) | mg/l | < 0.05 |
| Mercury (Hg) | mg/l | < 0.01 |
| Cyanide (CN) | mg/l | < 0.01 |
| Total Coliforms | No/100 ml | < 10 |
| Feacal Coliforms | No/100 ml | Nil |
| Nitrite | mg/l | <0.1 |

**Appendix VI: KEBS/WHO Effluent Discharge Standards**

| PARAMETER | TO SURFACE WATER | TO PUBLIC SEWER | TO PUBLIC MARINE |
|---|---|---|---|
| Ph | 6.0 -9.0 | 6.0 – 9.0 | 6.0 – 9.0 |
| BOD ( $mgO_2/l$) | 30 | 350 | 150 |
| COD ( $mgO_2/l$) | 50 | 1000 | 250 |
| Suspended solids (mg/l) | 30 | 400 | - |
| Detergents (mg/l) | - | <30 | - |
| Cyanide(mg/l) | <0.2 | <0.5 | <0.2 |
| Mercury(mg/l) | <0.01 | <0.01 | <0.01 |
| Chromium(mg/l) | <0.01 | <0.01 | <0.01 |
| Lead(mg/l) | <0.1 | <1.0 | <1.0 |
| PCB's (mg/l) | <0.003 | - | - |
| Pesticides | Absent | Absent | Absent |
| Oil and grease | Absent | Absent | Absent |
| Colour | Not objectionable | | |

**Appendix VII: River Discharge Data**

| | River Discharge Data | | | | | |
|---|---|---|---|---|---|---|
| | **2018** | **2017** | **2014** | **2010** | **2004** | **1990** |
| MBAGATHI R. | 9.8661 | 4.9759 | 2.0151 | 3.3550 | 0.0676 | 0.2704 |
| NDARUGU R. | 8.2718 | 6.7200 | 4.4297 | 2.5157 | 0.6997 | 5.3217 |
| RUIRU R. | 6.4101 | 1.5397 | 4.6297 | 3.9230 | 1.9829 | 3.8829 |
| ATHI R. D/S EPZA | 4.8661 | | 0.2496 | | | 7.9866 |
| RUARAKA R. | | 1.0370 | 1.5428 | 1.6926 | 0.7180 | 0.6332 |
| KIU R. | 0.4198 | 0.1416 | 0.1643 | 0.2816 | 0.1986 | 0.8625 |
| KAMITI R. | 2.2801 | 1.0747 | 0.2929 | 1.1561 | 0.1946 | 2.5965 |
| THIRIRIKA R. | 8.0280 | 2.3064 | 0.9872 | 4.3166 | 0.6997 | 5.3217 |
| ATHI R.@ 14FALLS | 51.4510 | 4.8186 | 8.9323 | 18.9787 | 22.9141 | 36.5241 |
| ATHI R.@ WAMUNYU | 94.7743 | 38.6715 | 40.4148 | 8.2336 | | |
| NAIROBI R. @ MUSEUM | 0.5620 | 0.4170 | 0.4170 | 0.3940 | | |

(Source of Data: Water Resources Authority, Kenya 2019)

## Appendix VIII: R Codes

**Box Plots**

```
data <- read.table("clipboard",header=T,row.names = 1)
head(data)
boxplot(data[,3]~data[,1],main="pH")
```

**Principle Component Analysis (PCA)**

```
library(vegan)
library(ggord)
data.pca <- prcomp(data[, c(1:17,2,18)], center = TRUE,scale. = TRUE)
ggord(data.pca,
    vec_ext=4, veclsz=1, veccol="red", txt=4.5, ext=0.9,
    ptslab=T, addsize=3.5, addpch="+", addcol="purple",
    poly=F, hull=F, ellipse=F,
    obslab=F, size=2,
    alpha=0.6, alpha_el=0.1,
    parse = T, coord_fix=F)
```

**Kruskaall Wallis test**

```
data<-read.table("clipboard",header = T,row.names = 1)
head(data)
kruskal.test(data)
```

## Appendix IX: Percentage (%) of LULCC

| Land Use Class (%) | 1990 | 2004 | 2010 | 2014 | 2018 |
|---|---|---|---|---|---|
| **Bareland** | 19.44 | 13 | 10.94 | 10.89 | 13.56 |
| **Agriculture** | 5.66 | 19.27 | 9.3 | 23.27 | 18.17 |
| **Shrubland** | 56.53 | 44.81 | 57.16 | 50.61 | 49.16 |
| **Open Water** | 2.07 | 5.47 | 1.59 | 1.5 | 1.63 |
| **Forests** | 16.27 | 15.91 | 19.4 | 11.95 | 14.38 |
| **Built-Up Areas** | 0.93 | 1.54 | 1.61 | 1.79 | 3.11 |
| **TOTAL** | 100 | 100 | 100 | 100 | 100 |

**Appendix X: Mean annual rainfall data in mm**

| Rainfall station (mm) | 2018 | 2017 | 2014 | 2010 | 2004 | 1990 |
|---|---|---|---|---|---|---|
| Kamwangi | 5.297 | 2.200 | 2.446 | 3.618 | 2.846 | 3.641 |
| Kieni forest | 6.645 | 3.029 | 3.575 | 4.697 | 3.703 | 4.505 |
| Uplands (Lari Forest) | 6.227 | 2.821 | 3.468 | 4.048 | 3.542 | 3.819 |
| Ruiru dam | 5.762 | 2.529 | 2.983 | 3.813 | 3.209 | 3.628 |
| Ministry of Works | 3.760 | 1.539 | 1.977 | 2.529 | 2.392 | 2.682 |
| Dagoretti | 4.458 | 1.777 | 2.327 | 3.008 | 2.670 | 2.873 |
| Ngong DO's office | 4.142 | 1.618 | 2.212 | 3.020 | 2.713 | 2.767 |
| Thika | 3.992 | 1.909 | 2.0496 | 2.449 | 2.171 | 2.836 |

## Appendix XI: Research License

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**Appendix XII: Plagiarism Report**

Margret Thesis Plagiarism Check

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