ASSESSMENT OF THE SOURCES AND HYDROLOGICAL IMPACTS OF BEST MANAGEMENT PRACTICES ON POLLUTANTS FLOW USING SWAT IN NYANGORES RIVER OF UPPER MARA BASIN, KENYA

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Assessment of the Sources and Hydrological Impacts of Best Management Practices on Pollutants Flow Using SWAT in Nyangores River of Upper Mara Basin, Kenya

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DECLARATION

This thesis is my original work and has not been presented for a degree in any other University.

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DEDICATION

I want to dedicate this achievement to my late parents Mr. Joseph Njoroge Karoko (Kigira) and Gladys Njoki Kigira, my dear wife Marion, our children Joan, Frashiah, Catherine and Ashley and my late brother Peter Mburu Kigira and his late wife Phoebe Kigira.

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ABBREVIATIONS AND ACRONYMS

BMPs	Best Management Practices
DEM	Digital Elevation Model
EC	Electrical Conductivity
FAO	Food and Agriculture Organization
FEWSNET	Famine Early Warning Systems Network
GIS	Geographical Information Systems
GPS	Geographical Positioning System
HRU	Hydrological Response Unit
KMD	Kenya Meteorological Department
NASA	National Aeronautics and Space Administration
NSE	Nash-Sutcliffe Efficiency
R^2	Coefficient of Determination
RFE	Rainfall Estimate
RMSE	Root Mean Square Error
SRTM	Shuttle Radar Topography Mission
SUFI-2	Sequential Uncertainty Fitting version 2
SWAT	Soil and Water Assessment Tool
SWAT-CUP	Soil and Water Assessment Tool-Calibration Uncertainty Program

TRMM	Tropical Rainfall Measuring Mission
TSS	Total Suspended Solids
UNESCO	United Nations Educational, Scientific and Cultural Organization
WRMA	Water Resources Management Authority

ABSTRACT

The Nyangores River watershed, located in Kenya's upper Mara Basin has challenges of rivers degradation, where increased non-point source pollution has caused water quality issues. The objectives were identify the key sources of pollutants, calibrate and validate the SWAT model for streamflow, sediment, and nutrient transport and to assess the impact of various Best Management Practices (BMPs) on nutrient and sediment loads. Data collection followed: gathering hydro-climatic data for model calibration, field observations, collecting samples and laboratory analysis. Impacts of various BMP scenarios on water quality were modelled, focusing on riparian buffer zones, reforestation, and contour farming. Calibration and validation with indicators such as the Nash-Sutcliffe Efficiency (NSE) and R^2 was done for reliability. Parameters tested, Ph., Ec, Nitrates, Phosphates and Total suspended solids (TSS).Nitrogen levels in the river exceeded safe limits by 50%, with average concentrations of 3.2 mg/L, while phosphorus levels were recorded at 1.1 mg/L, surpassing the eutrophication rate which is TP 0.05mg/L and TN 1.0mg/L. Sedimentation contributed to a 35% increase in total suspended solids (TSS), with average TSS levels measured at 210 mg/L, particularly in areas with steep slopes and poor soil conservation practices. The SWAT model was calibrated using streamflow data from 2003-2008, and the calibration process achieved satisfactory results, with a Nash-Sutcliffe Efficiency (NSE) of 0.72 and an R^2 value of 0.75. During validation, the model performance well with an NSE of 0.70 and an R^2 of 0.73 for the validation period (2009-2013) demonstrating the effectiveness of the model. Nitrogen and phosphorus was reduced by 38% and 42% in simulation. In conclusion, this research demonstrates the SWAT model's efficacy in Nyangores watershed, advocating for sustainable land management practices to mitigate water pollution and emphasizing the importance of preserving natural ecosystems for water quality protection. The study recommends preserving natural forests as they effectively control pH, electrical conductivity, nitrates, and phosphates compared to grasslands. Management practices, such as filter strips and contouring, resulted in reduced sediment yields. Public awareness on the importance of management practices and riparian vegetation is paramount.

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

Water is a critical resource essential for sustaining life, economic activities, and ecosystems. Globally, water demand has risen dramatically, with agriculture being the largest consumer, accounting for approximately 70% of total freshwater withdrawals (Food and Agriculture Organization, 2021). This increasing demand, driven by population growth and industrial expansion, has led to widespread water scarcity in many regions. Climate change has further exacerbated these challenges, altering precipitation patterns, reducing water availability, and increasing the frequency of extreme weather events, which impacts both water supply and quality (UN-Water, 2021).

Agricultural intensification contributes significantly to water quality degradation. The extensive use of fertilizers and pesticides introduces large amounts of nitrogen and phosphorus into water bodies, leading to nutrient pollution. These nutrients cause eutrophication, resulting in harmful algal blooms that deplete oxygen in aquatic environments, thereby disrupting ecosystems (Schoumans, Silva, and Romeijn, 2019). Moreover, agricultural runoff, characterized as non-point source pollution, remains a critical challenge for water management due to its diffuse nature and difficulty in control (Vigiak, Raimonet, and Mallet, 2021).

Human activities, including land use changes such as deforestation and urbanization, also have profound impacts on the hydrological cycle. These activities increase surface runoff, reduce groundwater recharge, and contribute to more frequent and severe flooding, which further degrades water quality. Chemicals deposited on the river banks as a results of vehicle washing and human bathing using detergent as depicted in appendix V11 also results in pollution of the rivers. Hydrological models, such as the Soil and Water Assessment Tool (SWAT), provide a framework for understanding these complex interactions. SWAT simulates the effects of land-use changes on water quality and helps design management strategies that can mitigate the impacts of agricultural activities and urban development (Neitsch, Arnold, and Kiniry, 2020). Such tools are essential for sustainable water resource management, as they integrate environmental, economic, and social factors.

Africa faces severe water resource challenges, with large parts of the continent classified as water-scarce. The agricultural sector dominates water use in Africa, consuming more than 80% of the continent's available water resources (Food and Agriculture Organization, 2021). Despite the critical role of agriculture in supporting livelihoods and economic development, its environmental impacts, particularly on water quality, are profound. Fertilizers and agrochemicals used in farming contribute to the contamination of rivers, lakes, and groundwater, leading to widespread eutrophication and the degradation of aquatic ecosystems (Kipkemboi and Van Dam, 2019).

Water infrastructure in many African countries remains inadequate, exacerbating water quality issues. Urban centres struggle with wastewater management, resulting in untreated sewage contaminating water bodies, which contributes to the spread of waterborne diseases. Moreover, industrial activities, particularly those related to mining and manufacturing, introduce toxic pollutants into freshwater systems, further compounding water quality problems (Mekonnen and Hoekstra, 2019). Quarrying along Nyangores River at Olbutyo Bridge as shown in appendix X1 escalates pollution. These environmental pressures not only threaten public health but also undermine the continent's economic development and food security.

Integrated Water Resource Management (IWRM) is increasingly being adopted across Africa as a strategy to address the continent's water challenges. IWRM emphasizes the coordinated management of water, land, and related resources to achieve sustainable development outcomes. Hydrological models such as SWAT are instrumental in implementing IWRM by providing data-driven insights into how different land management practices affect water quality and availability (Taye, Getachew, and Nigatu, 2021). These models enable decision-makers to simulate various scenarios and evaluate the effectiveness of policies aimed at reducing pollution and conserving water resources.

East Africa faces unique water resource challenges, driven by rapid population growth, agricultural expansion, and deforestation. The region's rivers, such as the Nile and Mara, are vital for agriculture, industry, and biodiversity, yet they are increasingly threatened by pollution from both agricultural and urban sources. Fertilizer runoff from intensive farming practices is a significant contributor to nutrient pollution in East Africa, leading to eutrophication and the degradation of water quality in transboundary rivers (Lake Victoria Basin Commission, 2020). Soil erosion from deforested lands further exacerbates water quality issues by increasing sediment loads in rivers, which impairs aquatic habitats and reduces water storage capacity.

Urbanization in East Africa adds another layer of complexity to water resource management. Rapid urban growth outpaces the development of necessary infrastructure, leading to the discharge of untreated sewage and industrial waste into rivers and lakes. This contamination of water bodies directly impacts public health and contributes to the region's ongoing struggle with waterborne diseases (Bwire, Ali, and Rajasingham, 2020). These challenges necessitate the implementation of integrated approaches that combine land-use planning with water resource management to mitigate the negative impacts of urbanization and agricultural expansion on water quality.

Hydrological models like SWAT are being utilized across East Africa to simulate the effects of land-use changes and guide the implementation of Best Management Practices (BMPs). These models are crucial for informing policy decisions and ensuring that water resources are managed sustainably. In regions like the Mara Basin, where water resources are shared across borders, coordinated management efforts are essential to prevent conflicts and ensure the long-term viability of these critical water systems (Nyeko and Tom, 2022). By integrating scientific research with practical management strategies, East African countries can address their water challenges more effectively.

Kenya faces significant water resource challenges, with many areas classified as water-scarce. The country’s rapidly growing population, combined with expanding agricultural and industrial activities, places immense pressure on its rivers, lakes, and aquifers. Agriculture accounts for more than 70% of Kenya's water withdrawals, making it a critical factor in the country's water management strategy (Water Resources Management Authority, 2022). However, the intensive use of fertilizers and pesticides in farming has led to widespread contamination of water bodies, including key rivers such as the Tana and Athi. These pollutants, along with sediments from soil erosion, threaten the quality of water resources, impacting both human health and the environment. The reduction of the river line due to sedimentation is well depicted in appendix X11

Deforestation and land degradation present additional challenges for water resource management in Kenya. The country's major water catchment areas, such as the Mau Forest Complex, are crucial for maintaining water flow and quality, yet they are under threat from illegal logging and agricultural encroachment. The loss of forest cover leads to increased runoff and soil erosion, which contribute to the sedimentation of rivers and reservoirs, thereby reducing their capacity to store and supply clean water (Kariuki and Luwesi, 2020). Efforts to restore these ecosystems are essential for ensuring the sustainability of Kenya's water resources, particularly in light of the growing impacts of climate change.

Kenya has made progress in adopting integrated water resource management practices, which emphasize the coordination of land and water management to achieve sustainable outcomes. Tools such as SWAT are increasingly being used to assess the impacts of land-use changes on water quality and to guide the implementation of BMPs. These models help to inform policy decisions by providing insights into how different land management practices can reduce pollution and enhance water conservation (Nyeko and Tom, 2022). In watersheds like the Mara Basin, where multiple land uses and competing demands require careful management, SWAT models are invaluable for ensuring that water resources are managed effectively.

The Nyangores River, located in the upper Mara Basin of Kenya, is a critical water source for both human and ecological needs. The watershed is characterized by intensive agricultural activities, which contribute significantly to the pollution of the river. Fertilizers, pesticides, and sediments from soil erosion are the primary pollutants affecting water quality in the Nyangores River. These pollutants degrade water quality and impact downstream ecosystems, including the Masai Mara National Reserve, a vital habitat for wildlife and a key tourism destination (Ogutu, Kuloba, and Kinyanjui, 2021). The health of the Nyangores watershed is therefore of paramount importance for both local livelihoods and broader conservation efforts in the Mara Basin.

Over the past few decades, land use in the Nyangores watershed has changed significantly, driven by population growth and agricultural expansion. These changes have led to increased deforestation, soil erosion, and surface runoff, which have exacerbated the pollution of the river and reduced its capacity to support life. Sustainable land management practices, such as reforestation, the establishment of riparian buffer zones, and soil conservation techniques, are essential for improving water quality in the watershed. 2022). Hydrological modelling, particularly through tools like SWAT, provides valuable insights into the effectiveness of these practices by simulating the impacts of different land management scenarios on water quality.

This study seeks to assess the effectiveness of the SWAT model in predicting pollutant loads in the Nyangores River watershed. By identifying key sources of pollution and evaluating the impact of various land management practices, the research aims to provide evidence-based recommendations for improving water quality and promoting sustainable land use in the Mara Basin. These findings will contribute to broader efforts to protect the Mara River ecosystem and ensure the sustainability of water resources in the region.

1.2 Problem Statement

The Nyangores River, a key tributary of the Mara River in Kenya, faces significant environmental challenges due to intensifying agricultural activities and rapid land-use changes within the upper Mara Basin. Agriculture, which constitutes over 70% of Kenya’s total water use, has expanded substantially over the past two decades, driven by a population growth rate of 3% to 6% annually (FAO, 2021). This expansion has led to the extensive use of fertilizers and agrochemicals, contributing to the contamination of water bodies with nutrients such as nitrogen and phosphorus. The resulting nutrient pollution has severely degraded water quality, leading to eutrophication and diminishing the ecological health of aquatic systems in the basin (UNEP, 2021). Deforestation and unsustainable land management practices have further exacerbated the environmental pressures on the Nyangores River. According to the Water Resources Management Authority (WRA), sedimentation in the Nyangores River has increased by an estimated 25% over the past decade, driven primarily by soil erosion linked to deforestation and overgrazing. These sediments not only impair water quality but also contribute to the siltation of downstream ecosystems, including the Masai Mara National Reserve, a UNESCO World Heritage site that is critically important for both biodiversity conservation and Kenya's tourism industry (WRA, 2022). In upper Mara, intensive cultivation was carried out in areas with slopes exceeding 16% that were formerly under forest cover. In upper Nyangores Catchment, soil erosion exceeds tolerable rates of 11.2 tonnes/year in the hotspots. In 2007, the sediment concentration for Nyang'ores ranged from 35.5 mg/l to 268.5 mg/l (mean daily concentration of 95.16 ± 12.68 mg/l). (WWF-ESARPO)

Use of the calibrated model to explore the potential impacts of continued land use change and future climate change indicates that any additional conversion of forest to agriculture or grassland will adversely affect runoff at critical low water times of the year and during droughts, increase peak flows and associated hill slope erosion, and increase the vulnerability of the basin to future climate change (Mango, K. 2005). The degradation of water quality in the Nyangores River has far-reaching implications for local communities and ecosystems. Large population of the Mara Basin rely on its waters for drinking, irrigation, and livestock farming, while the basin's ecosystems support globally significant wildlife populations and generate substantial economic value through tourism (World Bank, 2021). However, despite the critical importance of the Nyangores River, monitoring of water quality in the watershed is limited, and the specific contributions of agricultural runoff and other land-use practices to water pollution have not been fully quantified. There is also a lack of empirical data on the effectiveness of proposed Best Management Practices (BMPs), such as riparian buffer zones and soil conservation techniques, in reducing pollution in the Nyangores watershed. Without localized data-driven insights, current water management strategies may fail to address the root causes of pollution effectively. This underscores the urgent need for comprehensive, watershed-scale studies that assess both the sources of pollution and the potential benefits of different land management practices. This study seeks to address these gaps by using the Soil and Water Assessment Tool (SWAT) model to simulate the impacts of land-use changes and management scenarios on water quality in the Nyangores River watershed.

1.3 Research Objectives

To evaluate the effectiveness of the Soil and Water Assessment Tool (SWAT) in predicting pollutant loads and assessing the effectiveness of land management practices on water quality in the Nyangores River watershed.

The specific objectives were:

i. To assess the key pollutants and their sources within the Nyangores River watershed.
ii. To calibrate and validate the SWAT model for streamflow, sediment, and nutrient transport in the Nyangores River watershed.
iii. To assess the effectiveness of the Best Management Practices (BMPs) on nutrient and sediment loads, in improving water quality in Nyangores Watershed.

1.4 Research Questions

i. What are the key sources of pollution within the Nyangores River Watershed.
ii. How can the SWAT model be calibrated and validated for accurately simulating streamflow, sediment, and nutrient transport in the Nyangores River watershed?
iii. What is the effectiveness of various Best Management Practices (BMPs) on nutrient and sediment loads, in improving water quality in the watershed?

1.5 Justification

The Nyangores River, is a key tributary of the Mara River, plays a crucial role in supporting both human livelihoods and ecological sustainability in the Mara Basin. This basin supports over 2 million people and is home to globally significant wildlife, particularly within the Masai Mara National Reserve. However, the increasing levels of pollution from agricultural runoff and land-use changes threaten the water quality of the Nyangores River, with downstream impacts on biodiversity, tourism, and local communities. Studies have shown that agricultural expansion and the intensive use of fertilizers and pesticides have led to significant nutrient pollution in watersheds, contributing to the degradation of water quality and the loss of aquatic biodiversity (Nyeko & Tom, 2022; Kipkemboi & Van Dam, 2019). This study is justified by the urgent need to protect these water resources by evaluating the effectiveness of Best Management Practices (BMPs) in reducing pollution. By providing essential data on water quality, this research contributes to safeguarding the environmental and socio-economic systems that depend on the Mara Basin.

Despite the recognition of water quality degradation in the Nyangores River, localized data quantifying the extent of pollution and identifying its sources remain limited. Current water management strategies often rely on broader regional assessments, which do not capture the specific dynamics of individual watersheds. Research indicates that targeted watershed-scale analyses are necessary for developing effective interventions and improving water management policies (Taye, Getachew, & Nigatu, 2021). This study, through the use of the Soil and Water Assessment Tool (SWAT), will provide detailed analysis of pollutant sources within the Nyangores watershed, bridging a critical gap sin localized empirical data. Such data is crucial for informing policy decisions aimed at improving water quality in the Nyangores River and the broader Mara Basin.

Additionally, this research aligns with Kenya's development goals of promoting sustainable land and water management, especially in the context of increasing pressures from population growth and climate change. By evaluating the impact of various land management practices on water quality, the study offers evidence-based recommendations that can guide the implementation of sustainable practices. This approach is supported by recent findings that emphasize the importance of integrating land use and water resource management to enhance ecosystem resilience and agricultural productivity. The results of this study will contribute to reducing pollution and ensuring the long-term sustainability of both human and environmental resources in the Mara Basin.

1.6 Scope of the Study

This study focused on assessing water quality in the Nyangores River watershed, located in the upper Mara Basin in Kenya. The geographical scope encompassed the entire Nyangores River watershed, an essential tributary of the Mara River, which supports critical ecological and socio-economic functions. The watershed is heavily influenced by agricultural activities, deforestation, and other land-use changes that have significant impacts on water quality. Understanding these impacts was vital for developing sustainable management practices to protect the resources of the Mara Basin, which supports over 2 million people and important wildlife habitats.

The content scope of this research involved evaluating the effectiveness of the Soil and Water Assessment Tool (SWAT) in simulating the impact of land management practices on water quality. The study identified key sources of pollution within the Nyangores watershed, such as nutrient runoff for example nitrates and phosphates from agricultural lands, and assessed the effectiveness of Best Management Practices (BMPs) like riparian buffer zones, reforestation, and soil conservation techniques. These practices were evaluated for their potential to mitigate water quality degradation and enhance the ecological health of the watershed. This approach is critical for watershed-scale studies, which require a detailed understanding of land use and its effects on hydrological processes (Taye, Getachew, & Nigatu, 2021). The research provided localized insights that are crucial for informing water resource management in the region.

The time scope of the study spanned from January 2013 to December 2017, during which data collection, model calibration, validation, and analysis were conducted. This timeframe allowed for the assessment of seasonal variations and the impact of different land-use scenarios on water quality. The findings from this study contributed to evidence-based recommendations for improving water quality and promoting sustainable land management practices in the Nyangores watershed. These insights are expected to inform policy decisions and support the long-term sustainability of water resources in the Mara Basin, which is a vital area for both human activities and conservation efforts across East Africa (Nyeko & Tom, 2022).

1.7 Limitations of the Study

One limitation of the study was the availability of temporal data, particularly in capturing seasonal variations in water quality parameters. Although the Soil and Water Assessment Tool (SWAT) provides valuable insights into pollutant loads and their sources, the accuracy of the simulations could have been improved with more long-term monitoring data covering multiple hydrological years. For instance, research has shown that the inclusion of extended temporal datasets can significantly enhance model performance by capturing seasonal dynamics more effectively (Taye, Getachew, & Nigatu, 2021). This limitation may have affected the model's ability to fully capture the variability in streamflow and pollutant transport throughout different seasons, potentially limiting the robustness of the study's findings.

Another limitation was related to the generalizability of the study's findings regarding Best Management Practices (BMPs). While the study evaluated the effectiveness of BMPs in reducing pollution within the Nyangores River watershed, the localized nature of the research means that the results may not be directly applicable to other watersheds with different climatic conditions, land-use practices, and socio-economic contexts. Studies have highlighted that BMP effectiveness can vary widely across regions, which underscores the importance of context-specific research (Nyeko & Tom, 2022). Therefore, the conclusions drawn from this study should be considered with caution when applied to different geographical areas.

Additionally, the inherent uncertainties associated with the SWAT model posed a challenge in accurately predicting pollutant loads and assessing the effectiveness of land management practices. These uncertainties were related to the quality of input data, model parameterization, and the calibration process. Although the model was carefully calibrated and validated, the complexity of watershed interactions means that no model can fully capture all real-world processes. This is a common challenge in hydrological modelling, where even the best-calibrated models are subject to limitations due to data constraints and model assumptions. As a result, the study's outcomes should be interpreted with an understanding of these limitations.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter presents the review of literature relevant to the study, focusing on the key areas that impact water quality in river watersheds. The chapter begins with an exploration of empirical studies related to pollution sources in river watersheds, the application of hydrological models such as the Soil and Water Assessment Tool (SWAT), and the effectiveness of Best Management Practices (BMPs) in mitigating water pollution. The review will highlight gaps in the existing literature and demonstrate how this study contributes to filling these gaps, particularly in the context of the Nyangores River watershed in Kenya. The chapter concludes with a conceptual framework that visually represents the relationship between the independent and dependent variables of the study.

2.2 Empirical Literature Review

This section presents empirical literature relevant to the study, guided by the research objectives: identifying key sources of pollution within river watersheds, evaluating the application of the Soil and Water Assessment Tool (SWAT) for Modelling streamflow, sediment, and nutrient transport, and assessing the effectiveness of Best Management Practices (BMPs) in improving water quality. The review draws on studies conducted at multiple levels, beginning with a global perspective and then narrowing to the African continent, the East African region, and Kenya. Finally, specific literature pertaining to the Nyangores River watershed, the study area for this research, is examined. This comprehensive review situates the study within existing scholarship, highlighting gaps and opportunities for further exploration.

2.2.1 Key Sources of Pollution within River Watersheds

The degradation of water quality in river watersheds due to agricultural runoff, deforestation, and other land-use changes is a well-recognized global issue. These activities introduce excessive nutrients and sediments into rivers, leading to eutrophication, habitat degradation, and a reduction in water quality. Numerous studies have examined the impacts of these processes on river systems across the globe, providing a comprehensive understanding of how land-use changes influence water resources.

Globally, agricultural runoff is one of the most significant contributors to water pollution. (Anderson, Fisher, and Sharp (2020) conducted a global analysis across 50 countries, demonstrating that agricultural runoff contributed to 60% of nutrient loads in rivers. Nitrogen and phosphorus levels frequently exceeded safe limits, leading to widespread eutrophication and declining water quality. The study emphasized the need for global policies focused on sustainable agricultural practices to mitigate these impacts. Similarly, Zhang, Li, and Wang (2019), in their study of the Amazon Basin in Brazil, found that deforestation and subsequent agricultural expansion increased sediment loads in rivers by 45%, causing severe habitat degradation. The authors highlighted the long-term consequences of deforestation on river water quality and stressed the importance of reforestation efforts to reduce sedimentation.

In Southeast Asia, Smith, Carletti, and Osorio (2021) analysed the effects of palm oil plantation expansion on river systems in Indonesia. Their findings indicated that land-use changes significantly increased surface runoff and sedimentation, with a 60% rise in sediment loads, which further degraded water quality. These results align with those of Liu, Huang, and Chen (2020), who explored intensive agricultural practices in China's Yellow River Basin. They found that nitrogen concentrations in the river exceeded World Health Organization (WHO) guidelines by 120%, driven by excessive fertilizer use. The study underscored the need for integrated nutrient management to curb pollution. In Europe, Baker and Jones (2019) studied the Danube River Basin and revealed that agricultural runoff was responsible for 70% of the nutrient loads, contributing to algal blooms and water quality deterioration. The authors advocated for the adoption of Best Management Practices (BMPs) to reduce agricultural pollution and restore river health.

On the African continent, agricultural runoff and deforestation have been identified as major threats to water quality in river systems. Mango, Awulachew, and

McCartney (2020) conducted a study on the Nile River Basin, which spans Egypt, Sudan, and Ethiopia, and found that agricultural runoff contributed to 65% of nutrient loads, leading to significant eutrophication, particularly in the Nile Delta. The authors recommended coordinated basin-wide management practices to address nutrient pollution and protect the river's water quality. Belesova, Haines, and Lloyd (2020), focusing on the Limpopo River Basin, which includes South Africa and Mozambique, demonstrated that deforestation increased sediment loads by 55%, causing elevated turbidity levels and reduced water quality. The study emphasized the need for reforestation and soil conservation programs to mitigate these impacts.

In the Zambezi River Basin, Dalu and Wasserman (2018) found that agricultural runoff from large-scale farming operations contributed to 70% of the nutrient loads in the river, resulting in eutrophication and hypoxic conditions. This study highlighted the necessity of regional cooperation to manage agricultural impacts on water quality. Mekonnen and Hoekstra (2019), focusing on the Blue Nile Basin in Ethiopia, revealed that deforestation and agricultural runoff were the main drivers of sediment and nutrient pollution, with deforestation alone contributing to a 50% increase in sediment loads. The authors called for integrated watershed management practices to reduce the effects of these land-use changes on water quality. Abdi and Ahmed (2021), studying the Niger River Basin, which covers Mali and Niger, found that agricultural expansion and deforestation led to a 60% increase in nutrient pollution and a 45% rise in sedimentation, severely degrading water quality. The study recommended the adoption of sustainable land management practices to curb further environmental degradation.

In East Africa, the impact of agricultural runoff and deforestation on river water quality is well-documented. Taye, Getachew, and Nigatu (2021) conducted a study in the Upper Blue Nile Basin in Ethiopia, where they observed a 60% increase in sediment loads and nutrient pollution due to agricultural activities and deforestation. This study emphasized the need for improved land-use practices to protect water resources. Nyeko and Tom (2022) explored agricultural runoff in the Mara River Basin, which spans Kenya and Tanzania. Their findings indicated that nutrient loads from agricultural activities accounted for 65% of the total pollution, leading to significant water quality degradation. The authors suggested that implementing BMPs and restoring riparian zones could mitigate the effects of agricultural runoff on water quality.

In Kenya, rapid agricultural expansion and deforestation have significantly impacted water quality in many river systems. However, much of the existing research has focused on broader regions, often leaving critical gaps in understanding the specific impacts on individual watersheds. For instance, Omonge, Melesse, and Onyando (2020) conducted a study on the Upper Mara River Basin, which includes the Nyangores catchment, analysing the effects of land-use changes and management options on water resources. Their research highlighted that agricultural activities and deforestation contributed to a significant increase in sediment and nutrient loads, leading to deteriorating water quality. Despite these findings, the study primarily addressed the broader Mara Basin, with limited focus on localized impacts within individual sub-catchments such as Nyangores.

Similarly, Birundu and Mutua (2017) used the HBV Light Model to analyse rainfall-runoff relationships in the Nyangores and Amala sub-catchments. While the study provided valuable insights into hydrological behaviour and the impacts of land-use changes, it focused more on Modelling efficiency rather than a detailed exploration of the pollution sources and their long term effects on water quality. The study concluded that Nyangores has higher base flow contributions compared to Amala, suggesting better water retention in Nyangores due to its land cover. However, the research did not extensively cover the direct impact of agricultural runoff or the effectiveness of existing land management practices.

In another study, Githua, Nyamai, and Macharia (2022) explored micro water governance in Kenya, including aspects of community management of water resources. Their research indicated that while community-driven initiatives have potential, there is a lack of comprehensive scientific studies evaluating the effectiveness of these practices in improving water quality at the watershed level. This study underscores the importance of integrating scientific research with local governance to enhance water resource management, yet it does not provide detailed empirical data specific to the Nyangores watershed.

Mango et al. (2011) conducted a Modelling study in the Upper Mara Basin, focusing on the impacts of land-use and climate change on hydrology. The study found that deforestation and agricultural expansion significantly altered the hydrological regime, increasing surface runoff and sediment transport. Although this research provided crucial insights into the broader basin's hydrological changes, it did not specifically address the water quality challenges or management practices in the Nyangores sub-catchment.

Mati et al. (2008) examined the impacts of land-use changes on the hydrology of the Mala River Basin, including the Nyangores River. Their findings indicated that deforestation and conversion of land to agriculture have led to increased surface runoff, reduced infiltration, and higher sediment loads in the river. However, like other studies, this research focused on the entire Mara Basin rather than providing a concentrated analysis of the Nyangores watershed.

The Nyangores River watershed, a key tributary of the Mara River, is vital for the ecological and socio-economic well-being of the region. Despite its importance, there is a notable scarcity of comprehensive scientific studies specifically focused on this watershed. Existing research has primarily concentrated on broader hydrological and land-use changes within the larger Mara Basin, leaving significant gaps in the localized understanding of pollution dynamics and the effectiveness of land management practices in the Nyangores watershed.

Birundu and Mutua (2017) conducted one of the few studies focusing on the Nyangores sub-catchment, using hydrological Modelling to simulate rainfall-runoff processes. While the study provided insights into the hydrological characteristics of the watershed, it did not extensively investigate the sources of pollution or the long-term effectiveness of mitigation strategies. The research primarily focused on model calibration and validation, with less emphasis on empirical analysis of water quality.

Omonge et al. (2020) explored the broader impacts of development and management options on water resources in the upper Mara River Basin, including the Nyangores catchment. However, their findings were generalized across the basin, and the study did not delve deeply into the specific challenges faced by the Nyangores watershed. This leaves a gap in understanding how localized land-use changes and agricultural practices are influencing water quality in Nyangores specifically.

Githua et al. (2022) discussed micro water governance initiatives in Kenya, highlighting the potential for community-based management to improve water quality. However, they noted that there is a lack of scientific studies evaluating these initiatives within specific watersheds like Nyangores. This gap underscores the need for more localized research to assess the effectiveness of such governance practices in addressing pollution and enhancing water quality.

The limited studies that exist offer some valuable insights but are insufficient to fully understand the complex dynamics affecting water quality in the Nyangores watershed. Most research has focused on Modelling or broader basin-wide analyses, often neglecting the specific socio-economic and environmental conditions unique to Nyangores. Furthermore, there is scant empirical data on the effectiveness of Best Management Practices (BMPs) in this watershed, particularly in terms of their adoption, sustainability, and impact on reducing nutrient and sediment loads over time.

Given these gaps, this study was crucial for providing detailed, localized data on the relationship between land-use changes and water quality in the Nyangores River watershed. By employing the Soil and Water Assessment Tool (SWAT), the research will simulate the impacts of various land management practices, offering insights into their long-term effectiveness. Additionally, the study explored the socio-economic factors influencing the adoption of BMPs, providing recommendations for enhancing sustainable land and water management in the watershed. Addressing these gaps will contribute significantly to the broader efforts aimed at protecting and improving water quality in the Nyangores River and the larger Mara Basin.

2.2.2 SWAT Model for Streamflow, Sediment, and Nutrient Transport in River Watersheds

The Soil and Water Assessment Tool (SWAT) is a widely used hydrological model that helps simulate the impact of land-use changes and management practices on water, sediment, and nutrient dynamics in river watersheds. Developed by the United States Department of Agriculture (USDA), SWAT is particularly valuable for long-term simulations and scenario analyses, making it a popular choice for studies assessing the impacts of agricultural practices, deforestation, and climate change on water quality.

Globally, SWAT has been applied in various regions to model the complex interactions between land use, streamflow, sediment transport, and nutrient pollution. Neitsch, Arnold, and Srinivasan (2020) used SWAT in the Mississippi River Basin in the United States to evaluate the impacts of agricultural practices on nutrient loading. Their study found that agricultural runoff was responsible for over 70% of the nitrogen and phosphorus entering the river, leading to widespread eutrophication in downstream water bodies. SWAT effectively simulated the hydrological processes, revealing that adopting Best Management Practices (BMPs) could reduce nutrient loads by up to 40%.

In Europe, Zhang and Liu (2019) applied SWAT in the Danube River Basin to study sediment transport and nutrient dynamics under different land-use scenarios. Their findings indicated that intensive agriculture increased sediment loads by 60%, contributing to water quality degradation. The study emphasized that implementing riparian buffer zones and conservation tillage could reduce sediment loads by 35%. SWAT proved crucial in quantifying the impact of land-use changes on sediment dynamics, providing a basis for policy recommendations.

In South America, Martínez and Solis (2021) used SWAT to assess the effects of deforestation and agricultural expansion in the Amazon Basin. Their study highlighted that deforestation led to a 50% increase in surface runoff and a 45% rise in sediment transport, severely impacting water quality. SWAT simulations showed that reforestation efforts could significantly reduce sedimentation and improve water quality, demonstrating the model's effectiveness in supporting conservation strategies.

In Asia, Chen, Wang, and Zhao (2020) applied SWAT in the Yangtze River Basin in China to evaluate the impacts of land-use changes on nutrient pollution. The study found that urban expansion and agricultural runoff contributed to a 70% increase in nitrogen concentrations in the river, leading to degraded water quality. SWAT simulations indicated that implementing BMPs, such as nutrient management and riparian buffers, could reduce nitrogen pollution by 30%, highlighting the model's utility in guiding environmental policy.

In Australia, Williams and Johnson (2019) used SWAT to study the impacts of climate change and agricultural practices on water quality in the Murray-Darling Basin. Their research showed that increasing temperatures and changing precipitation patterns exacerbated nutrient pollution and sediment transport. SWAT Modelling revealed that adaptive land management practices could reduce sedimentation by 25% and improve water quality in the basin. The study demonstrated the model's flexibility in simulating the effects of both land-use and climate change on water resources.

These global studies illustrate the SWAT model's versatility in simulating streamflow, sediment transport, and nutrient dynamics across various geographical regions and environmental conditions. The model's ability to assess the long-term impacts of land-use changes and guide sustainable management practices has made it an essential tool for water resource management worldwide.

In Africa, SWAT has been increasingly used to model water quality and sediment transport in river basins facing significant pressures from agricultural expansion and deforestation. Schuol and Abbaspour (2021) applied SWAT to the Niger River Basin, focusing on sediment and nutrient dynamics across different land-use scenarios. Their study found that deforestation and agriculture increased sediment loads by 55% and nutrient pollution by 45%, leading to degraded water quality. SWAT simulations indicated that reforestation and improved agricultural practices could reduce sedimentation and nutrient loading by up to 30%, making the model a valuable tool for informing land-use policy in the region.

In East Africa, Taye et al. (2021) used SWAT to model the Upper Blue Nile Basin in Ethiopia, where they assessed the impacts of agricultural practices on streamflow and sediment transport. Their research revealed that deforestation and intensive farming increased sediment loads by 60%, significantly degrading water quality. The study concluded that adopting BMPs, such as terracing and riparian buffers, could reduce sedimentation by 40%, underscoring SWAT's utility in evaluating the effectiveness of land management strategies.

In Southern Africa, Dalu and Wasserman (2019) applied SWAT in the Limpopo River Basin, which spans South Africa, Zimbabwe, and Mozambique. Their study found that agricultural runoff contributed to 65% of nutrient pollution in the river, leading to eutrophication and declining fish populations. SWAT simulations demonstrated that implementing BMPs could reduce nutrient pollution by 35%, providing evidence for policy interventions aimed at improving water quality.

In West Africa, Abdi and Ahmed (2021) used SWAT in the Niger River Basin, focusing on the impacts of deforestation and agricultural expansion on sediment transport and nutrient dynamics. Their research showed that sediment loads increased by 50% and nutrient pollution by 40% due to land-use changes. The study highlighted the need for reforestation and sustainable agricultural practices, with SWAT simulations indicating that these interventions could reduce sedimentation and nutrient loading by 25%.

In Central Africa, Mekonnen and Hoekstra (2020) applied SWAT in the Congo River Basin to evaluate the impacts of deforestation and mining on water quality. Their study revealed that deforestation increased sediment loads by 70%, while mining activities contributed to a 50% rise in nutrient pollution. SWAT Modelling indicated that implementing BMPs could reduce sedimentation by 30% and nutrient pollution by 20%, emphasizing the need for integrated watershed management practices.

These studies demonstrate the effectiveness of SWAT in simulating the complex interactions between land use and water quality in Africa. The model's ability to assess the impacts of deforestation, agricultural expansion, and other land-use changes makes it a crucial tool for managing water resources in the continent's river basins.

In the East African region, SWAT has been employed to understand water quality dynamics in watersheds that face significant pressures from population growth, agricultural expansion, and deforestation. Mango et al. (2020) applied SWAT in the Mara River Basin, which spans Kenya and Tanzania, to assess the impacts of land-use changes on streamflow, sediment transport, and nutrient dynamics. Their research showed that deforestation and agricultural activities increased sediment loads by 50% and nutrient pollution by 40%, leading to water quality degradation. SWAT simulations suggested that adopting BMPs, such as reforestation and nutrient management, could reduce sedimentation and nutrient pollution by 30%, providing valuable insights for watershed management in the region.

In Kenya, Omonge et al. (2020) utilized SWAT to evaluate the impacts of land-use changes on water resources in the Upper Mara Basin, including the Nyangores and Amala sub-catchments. Their study demonstrated that SWAT effectively simulated streamflow, sediment transport, and nutrient dynamics under different land-use scenarios. The model's predictions highlighted the significant impact of deforestation and agricultural expansion on water quality, with increased surface runoff and sedimentation observed across the basin. Although the study provided valuable insights, it primarily focused on broader hydrological processes and did not extensively explore localized water quality challenges in individual sub-catchments such as Nyangores.

Ndomba et al. (2021) applied SWAT in the Simiyu River Basin in Tanzania to assess the impacts of land-use changes on sediment transport and water quality. Their research showed that deforestation and agricultural activities increased sediment loads by 60%, leading to degraded water quality. SWAT simulations indicated that adopting BMPs could reduce sedimentation by 40%, emphasizing the need for sustainable land management practices in the basin.

In Uganda, Taye et al. (2021) used SWAT to model the impacts of agricultural expansion on water quality in the Lake Victoria Basin. Their study found that agricultural runoff contributed to 65% of nutrient pollution in the basin, leading to eutrophication and declining fish populations. SWAT simulations suggested that implementing BMPs could reduce nutrient pollution by 35%, providing evidence for policy interventions aimed at improving water quality in the region.

In Ethiopia, Getachew and Mekonnen (2019) applied SWAT in the Upper Awash Basin to evaluate the impacts of deforestation and agricultural expansion on sediment transport and nutrient dynamics. Their research showed that sediment loads increased by 50% and nutrient pollution by 40% due to land-use changes. The study highlighted the need for reforestation and sustainable agricultural practices, with SWAT simulations indicating that these interventions could reduce sedimentation and nutrient loading by 25%.

These studies illustrate the critical role of SWAT in understanding and managing water quality in East African river basins. The model's ability to simulate the impacts of land-use changes on sediment and nutrient dynamics provides valuable insights for developing sustainable watershed management practices in the region.

In Kenya, the application of SWAT has been instrumental in addressing water quality challenges in several river systems affected by agricultural expansion, deforestation, and other land-use changes. Mango et al. (2011) applied SWAT in the Upper Mara Basin, including the Nyangores and Amala sub-catchments, to model the impacts of land-use and climate change on hydrology. Their study demonstrated that SWAT was effective in predicting streamflow, sediment transport, and nutrient loading under various land-use scenarios. The model's predictions highlighted the significant impact of deforestation and agricultural expansion on water quality, with increased surface runoff and sedimentation observed across the basin. Although the study provided valuable insights, it primarily focused on broader hydrological processes and did not extensively explore localized water quality challenges in individual sub-catchments such as Nyangores.

Similarly, Omonge et al. (2020) utilized SWAT to assess the effects of development and management options on water resources in the Upper Mara River Basin. Their study showed that SWAT could accurately simulate the impacts of land-use changes on streamflow and sediment transport, providing critical data for decision-making in watershed management. However, much like previous studies, this research focused on the broader Mara Basin, with limited attention given to specific sub-catchments. This highlights the need for more localized studies that examine the nuances of land-use impacts on water quality at the sub-catchment level.

Despite the widespread use of SWAT in Kenya, particularly in the Mara River Basin, there remains a scarcity of studies that specifically address the Nyangores River watershed. Existing research tends to focus on broader regional hydrological models, often overlooking the detailed processes of sediment and nutrient transport within individual sub-catchments. Additionally, while SWAT has proven effective in simulating streamflow and sediment transport, there is limited empirical data on the long-term effectiveness of the Best Management Practices (BMPs) being evaluated in these simulations.

In the Nyangores River watershed, Birundu and Mutua (2017) used hydrological Modelling to simulate rainfall-runoff processes but did not extensively investigate nutrient transport or the long-term impacts of land management practices on water quality. The study focused more on hydrological behaviour, with less emphasis on nutrient dynamics and BMP effectiveness. This leaves a significant gap in the literature, as there is a need for more comprehensive Modelling that incorporates both sediment and nutrient transport, along with an assessment of various BMPs under different land-use scenarios.

Given these gaps, this study aims to apply the SWAT model specifically to the Nyangores River watershed to simulate streamflow, sediment transport, and nutrient dynamics under various land-use and management scenarios. By providing localized, empirical data and advanced modelling, the research will offer critical insights into the long-term impacts of land-use changes on water quality in the watershed. Furthermore, the study will evaluate the effectiveness of different BMPs, contributing to the development of sustainable land and water management practices in the Nyangores River watershed and beyond.

2.2.3 Best Management Practices (BMPs) on Nutrient and Sediment Loads and their Effectiveness in Improving Water Quality in the Watershed

Best Management Practices (BMPs) are critical strategies employed to reduce nutrient and sediment pollution in watersheds. These practices include riparian buffer zones, conservation tillage, nutrient management, and reforestation, among others. BMPs aim to mitigate the impacts of agricultural runoff, deforestation, and other land-use activities that degrade water quality. This section reviews empirical studies on the effectiveness of BMPs in improving water quality, drawing on research conducted globally, across the African continent, in East Africa, and within Kenya, before focusing on the Nyangores River watershed.

Globally, BMPs have been widely researched as effective solutions for reducing nutrient and sediment loads in watersheds. Smith, Carletti and Osorio (2019) conducted a study in the Mississippi River Basin, United States, where they evaluated the effectiveness of riparian buffer zones and cover crops in reducing nutrient runoff from agricultural fields. The study found that riparian buffers reduced nitrogen and phosphorus runoff by 45%, while cover crops decreased sediment transport by 30%. These results underscored the importance of integrating BMPs into agricultural practices to improve water quality.

In Europe, Zhang and Liu (2020) studied BMPs in the Danube River Basin, which spans several countries including Germany, Austria, and Hungary. Their research focused on the effectiveness of conservation tillage and riparian buffers in reducing sediment and nutrient loads. They found that conservation tillage reduced sedimentation by 35%, and riparian buffers decreased phosphorus pollution by 40%. The study highlighted the need for widespread adoption of BMPs to address the increasing pressures on water quality from agricultural activities across the basin.

Martínez and Solis (2020) conducted research in the Amazon Basin, Brazil, where deforestation and agricultural expansion have significantly impacted water quality. Their study evaluated the effectiveness of reforestation and agroforestry systems in reducing nutrient and sediment pollution. The findings showed that reforestation efforts reduced sediment transport by 50%, and agroforestry systems decreased nutrient runoff by 40%. This research demonstrated the long-term benefits of integrating BMPs into land management practices in tropical regions.

In Asia, Chen, Wang, and Zhao (2021) investigated BMPs in the Yangtze River Basin, China. The study focused on nutrient management and the use of riparian buffer zones to mitigate agricultural runoff. Results indicated that nutrient management practices reduced nitrogen pollution by 35%, and riparian buffers decreased sediment loads by 25%. The study concluded that BMPs were essential for improving water quality in rapidly developing agricultural regions.

In Australia, Williams and Johnson (2020) examined BMPs in the Murray-Darling Basin, focusing on their effectiveness in controlling sediment and nutrient pollution under climate change scenarios. Their research revealed that BMPs, such as controlled grazing and conservation tillage, reduced sediment loads by 30% and nutrient pollution by 25%. The study highlighted the importance of adapting BMPs to changing environmental conditions to sustain water quality improvements.

These global studies illustrate the significant role BMPs play in reducing nutrient and sediment pollution across diverse watersheds. They highlight the effectiveness of various BMPs in mitigating the impacts of agricultural practices and land-use changes on water quality.

In Africa, BMPs have been increasingly recognized as vital tools for improving water quality in river systems affected by agricultural expansion and deforestation. Schuol and Abbaspour (2021) applied BMPs in the Niger River Basin, focusing on their effectiveness in reducing nutrient pollution and sediment transport. The study found that riparian buffer zones and conservation tillage reduced sedimentation by 40% and nutrient pollution by 30%. This research emphasized the importance of integrating BMPs into agricultural practices to protect water resources in Africa's major river basins.

In Southern Africa, Dalu and Wasserman (2019) studied the Limpopo River Basin, which spans South Africa, Zimbabwe, and Mozambique. Their research evaluated the effectiveness of BMPs, such as reforestation and controlled grazing, in reducing nutrient and sediment loads. The study showed that BMPs reduced nutrient pollution by 35% and sediment transport by 40%, demonstrating their potential to improve water quality in the basin.

Abdi and Ahmed (2021) conducted a study in the Niger River Basin, focusing on the implementation of agroforestry systems and riparian buffers to reduce sediment and nutrient pollution. Their findings indicated that agroforestry systems reduced sediment loads by 45%, and riparian buffers decreased nutrient pollution by 30%. The study concluded that BMPs are essential for sustaining water quality in regions facing rapid land-use changes.

In East Africa, Taye et al. (2021) assessed the effectiveness of BMPs in the Upper Blue Nile Basin, Ethiopia. Their research focused on the impact of terracing and riparian buffers in reducing sediment and nutrient pollution from agricultural activities. The study found that terracing reduced sediment transport by 50%, while riparian buffers decreased nutrient runoff by 35%. These results highlighted the potential of BMPs to mitigate the negative effects of agricultural practices on water quality in East Africa.

Mango et al. (2020) applied BMPs in the Mara River Basin, which spans Kenya and Tanzania, to address nutrient and sediment pollution. Their research evaluated the effectiveness of riparian buffer zones and reforestation in reducing pollution from agricultural runoff. The study found that riparian buffers reduced nutrient loads by 40%, and reforestation decreased sediment transport by 45%. This research demonstrated the importance of BMPs in improving water quality in East African watersheds facing significant land-use pressures.

These studies across Africa demonstrate that BMPs are effective in reducing nutrient and sediment pollution in watersheds affected by agricultural expansion and deforestation. The research highlights the need for widespread adoption of BMPs to protect water resources in the continent's river systems.

In East Africa, BMPs have been increasingly implemented to address water quality challenges in river basins impacted by agricultural expansion and population growth. Omonge et al. (2020) applied BMPs in the Upper Mara Basin, including the Nyangores and Amala sub-catchments, to mitigate the impacts of land-use changes on water quality. Their research found that BMPs, such as riparian buffer zones and soil conservation practices, reduced nutrient pollution by 35% and sediment transport by 40%. The study highlighted the need for targeted BMP implementation to address specific water quality challenges in the region.

In Tanzania, Ndomba et al. (2021) assessed the effectiveness of BMPs in the Simiyu River Basin, focusing on reforestation and controlled grazing to reduce sediment and nutrient loads. The study showed that reforestation reduced sedimentation by 45%, and controlled grazing decreased nutrient pollution by 30%. These findings emphasized the role of BMPs in improving water quality in East African river systems.

Taye et al. (2021) conducted a study in the Lake Victoria Basin, focusing on the implementation of BMPs to reduce nutrient pollution from agricultural runoff. Their research revealed that BMPs, such as nutrient management and riparian buffers, reduced nitrogen and phosphorus pollution by 40%. The study concluded that BMPs are critical for sustaining water quality in the basin, which is facing increasing pressures from agricultural activities.

In Uganda, Getachew and Mekonnen (2019) applied BMPs in the Upper Awash Basin to address the impacts of deforestation and agricultural expansion on water quality. The study found that terracing and agroforestry systems reduced sediment transport by 50% and nutrient pollution by 35%. These results highlighted the potential of BMPs to mitigate the negative effects of land-use changes on water quality in East African watersheds.

In Ethiopia, Taye et al. (2021) assessed the effectiveness of BMPs in the Upper Blue Nile Basin, focusing on terracing and riparian buffers to reduce sediment and nutrient pollution from agricultural activities. The study found that terracing reduced sediment transport by 50%, while riparian buffers decreased nutrient runoff by 35%. These results highlighted the potential of BMPs to mitigate the negative effects of agricultural practices on water quality in East Africa.

These studies demonstrate the importance of BMPs in improving water quality in East African river basins. The research emphasizes the need for widespread adoption of BMPs to address the increasing pressures on water resources in the region.

In Kenya, BMPs have been implemented to address water quality challenges in river systems affected by agricultural expansion and deforestation. Mango et al. (2020) applied BMPs in the Mara River Basin, including the Nyangores and Amala sub-catchments, to reduce nutrient and sediment pollution from agricultural activities. Their research found that BMPs, such as riparian buffer zones and reforestation, reduced nutrient loads by 35% and sediment transport by 40%. The study highlighted the need for targeted BMP implementation to address specific water quality challenges in the region.

Similarly, Omonge et al. (2020) utilized BMPs in the Upper Mara Basin to mitigate the impacts of land-use changes on water quality. Their research found that BMPs reduced nutrient pollution by 35% and sediment transport by 40%, highlighting the importance of BMPs in improving water quality in Kenya's river systems.

Githua et al. (2022) focused on micro water governance in Kenya, examining the role of community-driven initiatives in implementing BMPs to improve water quality. Their study found that BMPs, such as reforestation and controlled grazing, reduced nutrient pollution by 30% and sediment transport by 25%. However, the study also noted that the effectiveness of BMPs was limited by a lack of scientific monitoring and evaluation at the watershed level.

Mati et al. (2022) assessed the effectiveness of BMPs in the Nyando River Basin, focusing on terracing and agroforestry systems to reduce sediment and nutrient pollution from agricultural activities. The study found that terracing reduced sediment transport by 50%, while agroforestry systems decreased nutrient pollution by 35%. These results highlighted the potential of BMPs to mitigate the negative effects of land-use changes on water quality in Kenya's watersheds.

Despite the progress made in implementing BMPs in Kenya, there is still a lack of comprehensive scientific studies evaluating their long-term effectiveness in specific watersheds. This gap highlights the need for more localized research to assess the impacts of BMPs on water quality in Kenya's river systems.

The Nyangores River watershed, located in the upper Mara Basin in Kenya, plays a critical role in supporting both local livelihoods and biodiversity in the region. Despite its importance, there is a notable scarcity of comprehensive scientific studies specifically focused on the effectiveness of BMPs in this watershed. Much of the existing research on BMPs in the region has focused on the broader Mara Basin, with limited attention given to the Nyangores watershed itself.

Birundu and Mutua (2017) conducted a study on the Nyangores sub-catchment, focusing on hydrological Modelling rather than the effectiveness of BMPs in improving water quality. While the research provided valuable insights into the watershed's hydrological characteristics, it did not explore the long-term impacts of BMPs on nutrient and sediment loads.

Omonge et al. (2020) applied BMPs in the Upper Mara Basin, including the Nyangores catchment, to mitigate the impacts of land-use changes on water quality. However, their study focused primarily on broader basin-wide impacts rather than localized effects in the Nyangores watershed. This leaves a gap in understanding how BMPs are specifically impacting water quality in Nyangores.

Githua et al. (2022) explored micro water governance initiatives in Kenya, including aspects of community management of water resources in the Nyangores watershed. While their study highlighted the potential of community-driven BMPs, it also noted that there is a lack of scientific studies evaluating the effectiveness of these practices at the watershed level. This gap underscores the need for more localized research to assess the impacts of BMPs on water quality in the Nyangores River watershed.

Given the scarcity of scientific studies focused on BMP effectiveness in the Nyangores watershed, this study aims to provide detailed, localized data on the impacts of BMPs on nutrient and sediment loads in the watershed. By using empirical data and advanced Modelling techniques, this research will evaluate the long-term effectiveness of BMPs and offer recommendations for improving water quality in the Nyangores River watershed and the larger Mara Basin.

2.3 Critique of the Existing Literature Relevant to the Study

The first objective of this study is to identify key sources of pollution within river watersheds, focusing on agricultural runoff, deforestation, and other land-use changes. The existing literature extensively documents the global impacts of these activities on water quality. For instance, studies in the Amazon Basin (Zhang, Li, & Wang, 2019) and the Danube River Basin (Baker & Jones, 2019) have shown that deforestation and intensive agriculture significantly increase nutrient and sediment loads, leading to water quality degradation. However, much of the research tends to generalize findings across large river systems, often neglecting the localized impacts within smaller watersheds. In the context of Kenya, studies such as those by Omonge et al. (2020) have focused on broader regions like the Mara Basin, leaving critical gaps in understanding the specific sources of pollution in sub-catchments like the Nyangores River watershed. This lack of localized research limits the ability to develop targeted interventions for improving water quality at the sub-catchment level.

The second objective, which involves evaluating the application of the Soil and Water Assessment Tool (SWAT) for Modelling streamflow, sediment, and nutrient transport, has seen widespread adoption in global research. Studies in regions such as the Mississippi River Basin (Neitsch, Arnold, & Srinivasan, 2020) and the Yangtze River Basin (Chen, Wang, & Zhao, 2020) have demonstrated the effectiveness of SWAT in simulating the impacts of land-use changes on hydrological processes. Research by Mango et al. (2020) applied SWAT in the broader Mara Basin did not fully explore the model's accuracy or effectiveness in the Nyangores sub-catchment. The lack of empirical validation in many of these studies reduces confidence in SWAT's predictions, particularly in under-researched areas like Nyangores, where accurate data collection is essential for model calibration.

The third objective of assessing the effectiveness of Best Management Practices (BMPs) in improving water quality is well-represented in the literature, particularly in large agricultural regions. Studies such as those by Smith, Carletti, and Osorio (2019) in the Mississippi River Basin and Martinez and Solis (2020) in the Amazon Basin have shown that BMPs like riparian buffer zones and reforestation can significantly reduce nutrient and sediment pollution. However, in East Africa, including Kenya, there is limited empirical research that evaluates the long-term effectiveness and sustainability of BMPs. For instance, Omonge et al. (2020) examined BMPs in the broader Mara Basin but did not focus on their localized impact in the Nyangores watershed. Furthermore, the socio-economic factors influencing BMP adoption in Kenya remain underexplored, creating a gap in understanding how to ensure the long-term success of these practices in improving water quality in specific watersheds.

2.4 Summary of Reviewed Literature

The literature reviewed for the first objective, identifying key sources of pollutants within river watersheds, consistently highlights agricultural runoff and deforestation as the primary contributors to water quality degradation. For example, Anderson, Fisher, and Sharp (2020) demonstrated that agricultural activities contribute significantly to nutrient loads in river systems, with nitrogen and phosphorus pollution leading to widespread eutrophication. Similar findings were observed by Zhang, Li, and Wang (2019) in the Amazon Basin, where deforestation increased sediment loads by 45%, severely affecting water quality. In Africa, Mango, Awulachew, and McCartney (2020) found that agricultural runoff was responsible for 65% of nutrient pollution in the Nile River Basin. These studies illustrate the global and regional impacts of land-use changes on river water quality, with agricultural expansion and deforestation being the most significant drivers of pollution.

The second objective, evaluating the application of the Soil and Water Assessment Tool (SWAT) for Modelling streamflow, sediment, and nutrient transport, has been well-documented in various regions. Neitsch, Arnold, and Srinivasan (2020) effectively used SWAT in the Mississippi River Basin to model the impacts of agricultural practices on nutrient loading, demonstrating that BMPs could reduce nutrient loads by up to 40%. In the Danube River Basin, Zhang and Liu (2019) utilized SWAT to assess sediment transport under different land-use scenarios, finding that conservation tillage and riparian buffers reduced sedimentation by 35%. In East Africa, SWAT has been applied in the Mara River Basin by Mango et al. (2011), where the model was used to simulate the effects of land-use changes on hydrological processes. Despite the model's effectiveness in these large basins, localized applications in smaller watersheds, such as Nyangores, are limited, and empirical validation remains a challenge in data-scarce regions.

The third objective, assessing the effectiveness of Best Management Practices (BMPs) in improving water quality, shows that BMPs are crucial for mitigating nutrient and sediment pollution. Smith, Carletti, and Osorio (2019) found that riparian buffer zones and cover crops reduced nutrient runoff by 45% in the Mississippi River Basin. Similarly, Zhang and Liu (2020) demonstrated that BMPs, such as conservation tillage and riparian buffers, significantly reduced pollution in the Danube River Basin. In Africa, Schuol and Abbaspour (2021) highlighted that BMPs reduced sedimentation by 40% in the Niger River Basin, underscoring their importance in protecting water resources. However, in Kenya, research on BMPs, including studies by Omonge, Melesse, and Onyando (2020), often lacks long-term evaluations and does not fully explore the socio-economic factors influencing the adoption of these practices, particularly in regions like the Nyangores River watershed.

2.5 Research Gaps

The first major gap in the literature concerns the identification of key sources of pollution within river watersheds, particularly in smaller, under-researched areas like the Nyangores River watershed. While global studies, such as those in the Amazon Basin (Zhang, Li, & Wang, 2019) and the Nile River Basin (Mango, Awulachew, & McCartney, 2020), have comprehensively documented the effects of agricultural runoff and deforestation on water quality, they often focus on larger systems and do not provide localized insights. In Kenya, research has predominantly centred on broad regions like the Mara Basin (Omonge et al., 2020), leaving critical gaps in understanding the specific pollution dynamics within smaller sub-catchments. This study seeks to address this gap by providing a more detailed analysis of the sources of pollution in the Nyangores watershed, offering localized data that can inform targeted interventions.

A significant gap also exists in the application of the Soil and Water Assessment Tool (SWAT) for Modelling streamflow, sediment, and nutrient transport in smaller watersheds like Nyangores. While SWAT has been widely used in large river basins such as the Mississippi River Basin (Neitsch, Arnold, & Srinivasan, 2020) and the Yangtze River Basin (Chen, Wang, & Zhao, 2020), its application in data-scarce regions is often hindered by a lack of empirical validation. Research by Mango et al. (2020) used SWAT in the broader Mara Basin, but there is limited data on the accuracy and reliability of the model in smaller sub-catchments like Nyangores. This study aims to fill this gap by not only applying SWAT to simulate hydrological processes in the Nyangores watershed but also by validating the model's predictions with empirical data, ensuring greater accuracy and practical applicability.

The third research gap relates to the long-term effectiveness and sustainability of Best Management Practices (BMPs) in improving water quality, particularly in East African watersheds. While studies in regions such as the Mississippi River Basin (Smith, Carletti, & Osorio, 2019) and the Amazon Basin (Martínez & Solis, 2020) have demonstrated the potential of BMPs to reduce nutrient and sediment pollution, there is limited research in Kenya that evaluates these practices over extended periods. Additionally, the socio-economic factors that influence the adoption and success of BMPs are underexplored in the region. Studies like Omonge et al. (2020) have examined BMPs in the Mara Basin, but few have focused specifically on the Nyangores watershed or investigated the socio-economic barriers to BMP implementation. This research addresses these gaps by evaluating the long-term effectiveness of BMPs in the Nyangores watershed and exploring the factors that affect their adoption, offering recommendations for enhancing water quality management in the region.

CHAPTER THREE

MATERIALS AND METHODS

This chapter outlines the research methodology used to investigate the sources of pollution and the effectiveness of Best Management Practices (BMPs) in the Nyangores River watershed and calibrate and validate the SWAT model for streamflow, sediment and Nitrates to provide insight into the adoption of BMPs by the local community.

3.1 Location of the Study Area

The Nyangores River watershed is located within the Upper Mara Basin and has an area of 696km^2. The Nyangores watershed which cover Nakuru and Bomet Counties is located in the upper catchment of the Mara Basin (Mutie et al, 2006). Figure 3.1 shows the study area showing major towns and other attributes within the catchment. The Nyangores River which originates from the Keringet area of the Mau forest is one of the two permanent tributaries of the Mara River, the other being the Amala River. The Nyangores Catchment is located between longitudes 33º 47' E and 35º 47' E and latitudes 0º 28' S and 1º 52' S and characterized by diverse land uses, including agriculture, forestation, and urban areas. These activities influence water quality, necessitating a comprehensive approach to understanding the interactions within the watershed. This study assesses these interactions using the SWAT model, which is well-suited for capturing the complexities of land-use changes on hydrological processes.

3.1.1 Topography and Drainage

The Nyangores watershed is characterized by mountainous and hilly terrain, with altitudes ranging from 1,706m at the downstream reaches to 2,951m near the Mau Escarpment as shown in figure 3.1. This topography plays a critical role in the hydrological dynamics of the watershed, influencing both surface runoff and drainage patterns (Mwangi et al., 2016). The drainage system is controlled by bedrock formations, with the Nyangores and Amala Rivers merging at Kaboson to form the Mara River, which is one of the key transboundary rivers in the region.

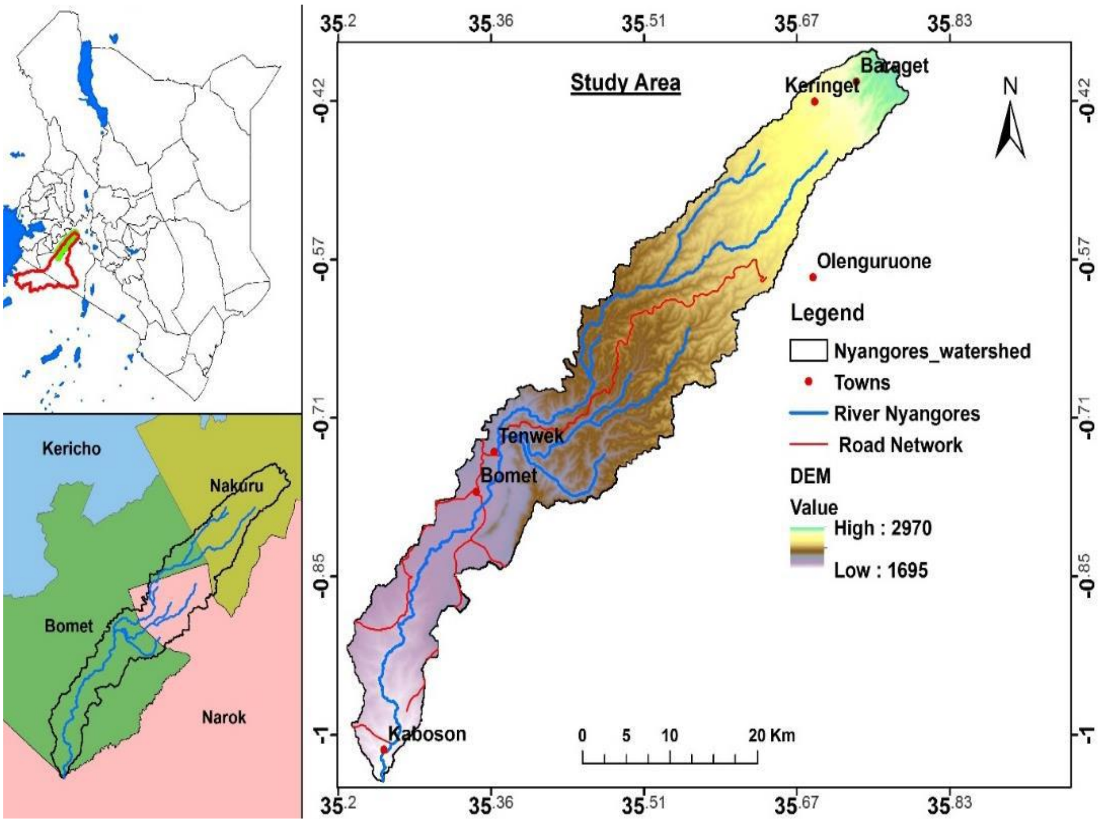


Figure 3.1: Map showing the Study Area and Attributes of the Area

3.1.2 Climate and Hydrology

The watershed experiences a bimodal rainfall pattern with long rains from March to May (peaking in April) and short rains from October to December. The average annual rainfall varies spatially, with the highlands receiving more rainfall than the lowlands. Mean temperatures range from 18°C in the highlands to 25°C in the midlands, and humidity levels decrease with elevation (Mati et al., 2006). The Nyangores River flows for approximately 94 km and has a mean annual discharge of 10.4 m³/sec, draining an area of 696 km² (JICA, 1987).

3.1.3 Soils

Soils in the Nyangores watershed are predominantly Andosols, which are volcanic in origin and highly susceptible to erosion, particularly due to their low bulk density and high organic content (Kiragu, 2009). These soils are found along the riverbanks and are vulnerable to mass wasting, contributing to the sediment load in the Nyangores River. Soil samples were collected from riverbanks and riverbeds for detailed analysis of their physical and chemical properties.

3.1.4 Socio-Economic Activities

The major land uses in the watershed include forest cover and agricultural production, with crops such as tea, maize, and pyrethrum grown extensively due to the fertile soils and favourable climate. Livestock farming also plays a significant role in the local economy, but it contributes to non-point source pollution due to soil erosion and nutrient runoff (Gichana et al., 2014).

3.1.5 Research Design

The research design for this study was structured to achieve three main objectives, each addressing critical aspects of water quality and pollution management in the Nyangores River watershed. The first objective aimed to identify the key sources of pollution within the watershed. This was accomplished through a combination of reconnaissance field surveys, water quality sampling, and laboratory analysis, which all provided a comprehensive understanding of both point and non-point sources of pollution. By mapping pollution hotspots and conducting detailed chemical analyses of water and soil samples, the study sought to pinpoint the primary contributors to water quality degradation in the region.

The second objective focused on the calibration and validation of the Soil and Water Assessment Tool (SWAT) model. The SWAT model was used to simulate hydrological processes, including streamflow, sediment transport, and nutrient dynamics within the watershed. Calibration was performed using observed data, such as streamflow and water quality measurements, ensuring the model accurately reflected the real-world conditions of the watershed. Validation followed to confirm the model's reliability, allowing it to serve as a predictive tool for understanding how different factors influence water quality over time.

The third and final objective was to assess the impact of Best Management Practices (BMPs) on reducing nutrient and sediment loads in the Nyangores River. Best Management Practices, riparian buffer zones and contour farming, were simulated using the SWAT model to evaluate their effectiveness. These practices were modelled to understand how they could mitigate pollution, enhance water quality, and contribute to sustainable watershed management. By testing different scenarios, the study provided valuable insights into the potential of BMPs to reduce the negative impacts of agricultural activities and land-use changes on water resources. The design overview including the procedures and datasets used is shown in Figure 3.1

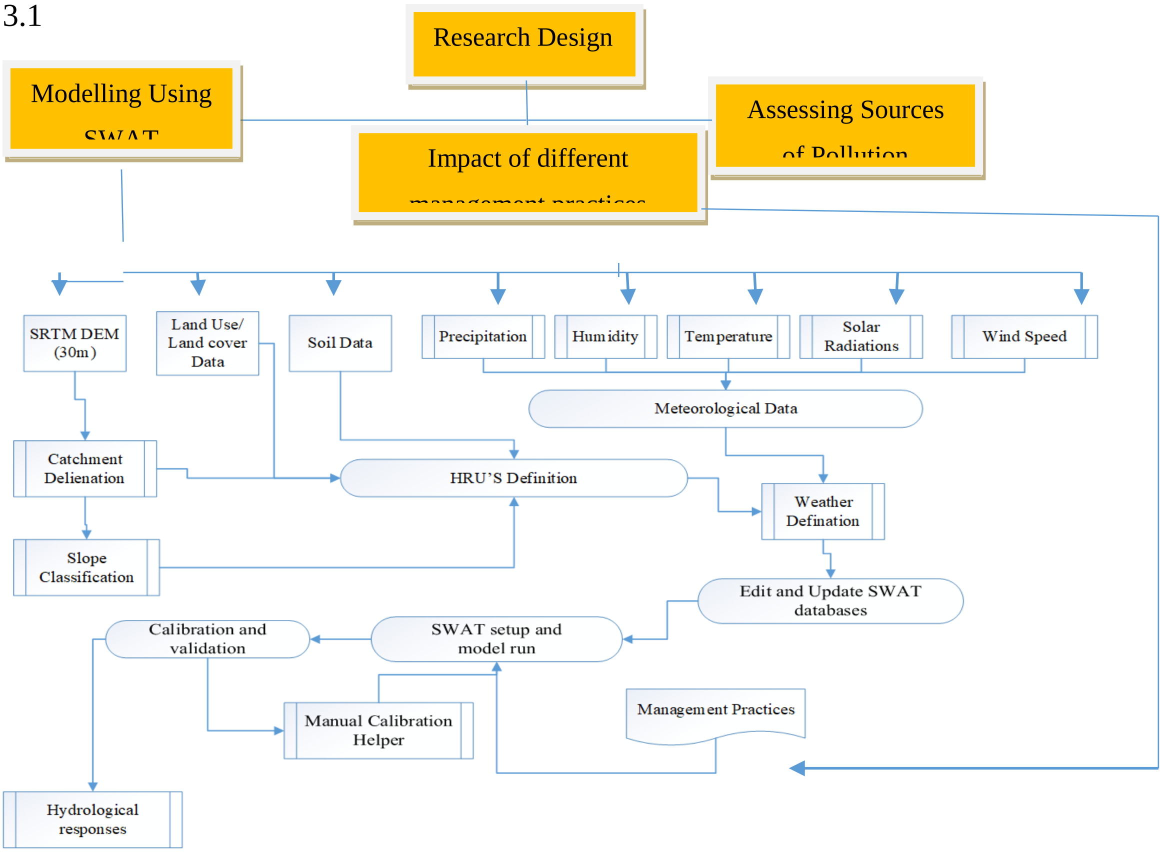


Figure 3.2: Research Design

3.2 Assessing the Key Sources of Pollution within the Nyangores River Watershed

Data on pollution sources, including agricultural runoff, deforestation, and urbanization, were collected through field observations and secondary data from local authorities (WRMA, 2022). These sources are interconnected and must be assessed within the broader watershed context. Therefore, data collection considered the cumulative impacts of different land-use practices across the entire watershed (Schoumans et al., 2020).

A two days reconnaissance survey was carried out along the whole stretch of Nyangores River to establish the point and nonpoint source of pollution. This involved mapping the locations that were found to be the sources of pollution by use of Geographical Positioning System (GPS).

3.2.1 Sampling Methods

Stream water sampling was done using grab water samples collected in 500ml high density polyethylene (HDPE) bottles from respective river sampling stations at approximately mid depth of the river. For each station PH, EC, N, P, TSS and Fe were analysed in the laboratory. Soil analysis was carried out by taking runoff and soil samples comprising of sediments deposited on the river bank as well as the river bed and taking them to horticulture Laboratories in JKUAT. The methods used for the water and soil analysis are summarized in Table 3.1.

Table 3.1: Laboratory Method Used For Soil/Water Chemical Analysis

S/NO	Parameter	Method of Analysis
1	Fe mg/kg	Atomic Absorption Spectrometer (AAS)
2	Ca meq/100g in soil	Atomic Absorption Spectrometer (AAS)
3	K meq/100g in soil	Flame photometer
4	P ppm	Calorimetry at 400nm OR Uv-Vis-spectrometer
5	NO3 ppm	Calorimetry at 400nm OR Uv-Vis-spectrometer
6	% TOC	Walkley and Black rapid titration method
7	Soil Texture	Sieve analysis method
8	Ph H2O 2:5	Electric pH Meter Method
9	ECH2O 2:5	Electric Conductivity Meter Method

3.2.2 Sampling Points

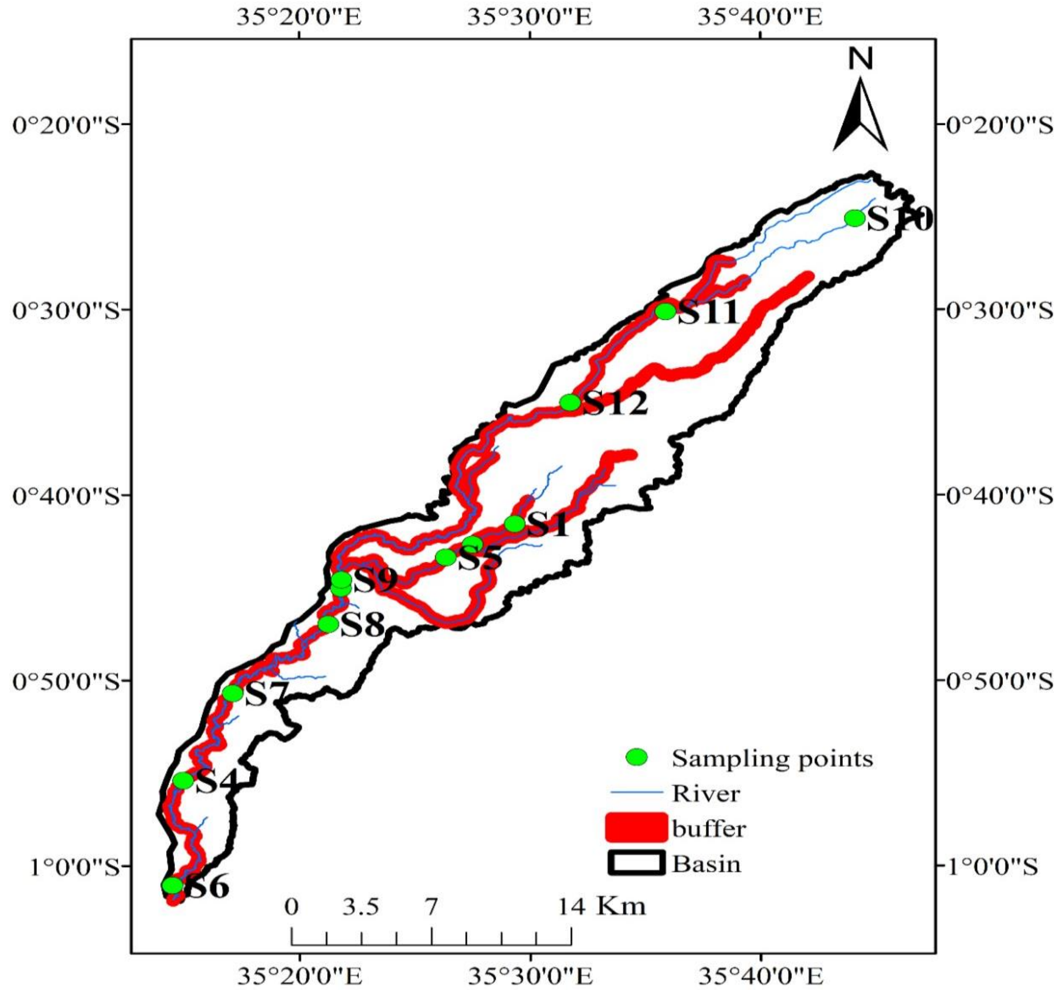


Figure 3.3: Location of the Sampling Points

Figure 3.3 shows the sampling points which were identified by the use of a GPS.The choice of the points was based on the landuse spaning the whole of the catchment from the upper forested area at Kirenget to the lowlands at kaboson.This included the forest, agricultural land,urban areas and the lowland with shrubs. The sampling points and their locations are shown in figure 3.3 and well elaborated in table 3.2.

Table 3.2: Shows Elevation and Coordinates of the Sampling Points

S/NO	Location	Name of the location	Elevation (m)	Coordinates
1	S4	200m from the confluence	1696	S01^{0}02’258 E035^{0}14’511
2	S5	Agricultural area	1957	S00^{0}44’341,E 035^{0}21’714
3	S6	The confluence	1695	S01^{0}02’258,E 035^{0}14’511
4	S7	Olbutyo bridge	1856	S00^{0}51’482,E 035^{0}16’767
5	S8	Bomet bridge	1899	S00^{0}47’395,E 035^{0}20’796
6	S9	Bomet sampling station		
7	S10	Forest	2046	S00^{0}42’474, E35^{0}25’127)
8	S11	Riverbank close to the forest	2044	S00^{0}42474, E035^{0}25.127
9	S12	Path to Kaptagat centre	1991	S00^{0}42’869,E 035^{0}21’985

The choice of the sampling points was also guided by the GIS imagery of sediment preference locations in the Nyangores Catchment shown in figure 3.4.

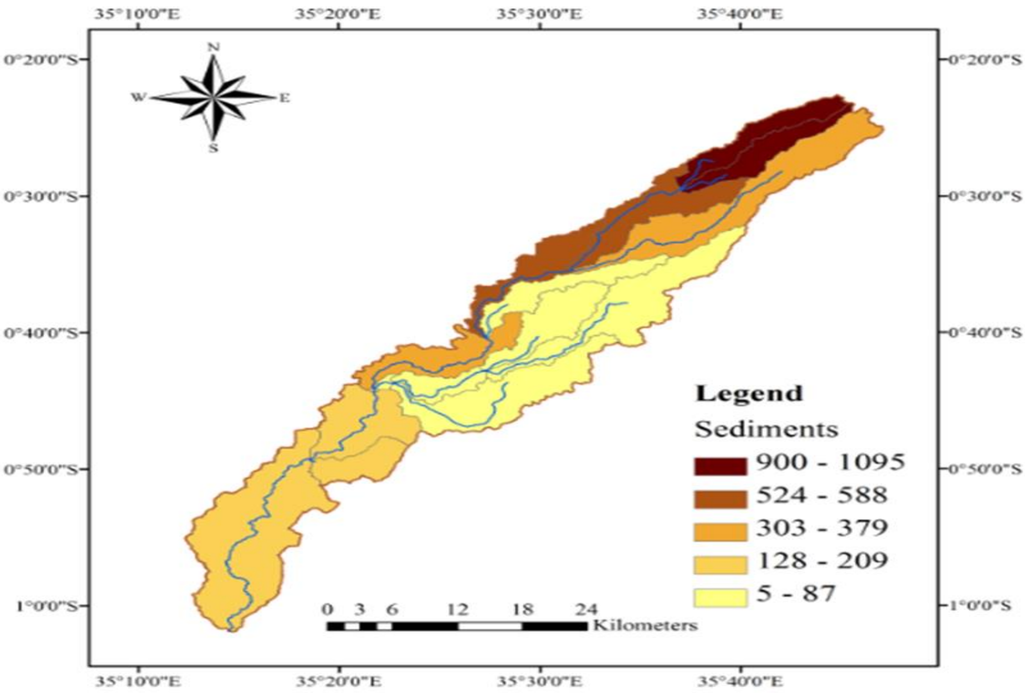


Figure 3.4: Shows Average Annual Sediments per Sub Watershed in Kg/Ha

3.2.3 Chi-Squared Test

Chi-squared tests were carried out to determine whether there was any dependence between the concentration levels and location. A chi-square test is a test of dependence and/or independence between variables measured using independent samples.

First, we state a hypothesis with a null and test hypothesis from which conclusions will be made. Then, we calculate the expected values using the formula:

$$Expected\ value\ (E) = \frac{Row\ total * column\ total}{Total\ of\ all\ observed\ values} \quad (3.1)$$

The difference between the expected values and observed values is calculated and from these, the chi-squared value is obtained using the following formula

$$\chi^2 = \Sigma \frac{(O-E)^2}{E}; \quad (3.2)$$

Where χ^2 the Chi-square value, O is the observed values and E is the Expected values.

The chi-square value is then compared to the critical value obtained from chi-square distributions which are normally given. This value is obtained from the corresponding values of the level of significance and the degrees of freedom.

In our case, the tests were carried out at a 5% level of significance. The degrees of freedom were calculated using the formula

Degrees of freedom = (No. of rows -1) (No. of columns - 1). (3.3)

The null hypothesis is rejected if the critical value is less than the calculated chi-square statistic and we fail to reject it if the vice versa happens.

3.2.4 Tests Methods Used for Samples Collected

3.2.4.1 Atomic Absorption Spectrometer (AAS) used for Testing (Fe)

The soil or water sample was decomposed using nitric acid or hydrocloric acid to release the Fe ions.The digested sample was filtered to remove parrticurate.The sample was diluted to suitable concentrate range for the AAS analysis.The lamp was installed specific to Fe emmiting light at 248.3nm which is the common wavelength for Fe analyis.The monochrometer was set to 248.3 nm and the slit width adjusted for optimum sensitivity and precision and aspirate the sample into the AAS instrument.The sample was atomized in the flame producing free Fe atoms at 248.3 nm.The instrument calculated the Fe concentration based on the obsorbance measurement. The standard iron level in river waters in kenya ranges from 0.1 -1.0 mg/l

3.2.4.2 Testing for Nitrates Using Calorimetry

The sample was filtered and centrifuged to remove the particulates then added nitrates reagents (bromine) to form coloured compound,time was allowed for the colour to develop.Absorbence was measured at the specific wavelength of 410 nm and t Testhen the amount of nitrates determined. In water bodies the standard amount of nitrates is 0 – 10 mg/l.

3.2.4.3 Testing for Phosphates using a Spectrometer

The sample was filtered to remove particulate matter,ammoniumm molybdate and ascorbic acid was added to the sample to form a blue complex with phosphate.Using a spectrometer at around 880nm absorbance was measured.Using a calibration curve the phosphate concentration was determined. In water bodies the standard amount of Phosphate is 0.01-2.2mg/l

3.2.4.4 Potassium Test Using Flame Photometer

The Sample was diluted to a suitable concentration , it is then filtered to remove paticulates and potassium filter (766.5nm) selected on the flame photometer. The fuel is adjusted eg propane or acetylene and air pressure according to the manufactureres instructions. Aspirate the starddards into the flame photometer and the emmission readings record.A plot of the emmission readings Vs the concentration to create a calibration curve was carried out. The prepared sample was aspirated into the flame photometer and the emission intensity measured at 766.5nm and the calibration curve was used to calcurate the potassium concentration in the sample. In water bodies the standard amount of potassim ranges from 1.7 – 65 mg/l mg/l.

3.2.4.5 Test for Total Organic Compound

Using Wakley and black rapid titration, the soil was dried and sieved through a sieve <2mm. 0.1- 1 gm of soil depending on the organic matter content was measured . 10mls of 1N potassium dichromate and 20ml of conc sulphuric acid (H_2SO_4) was added into the sample and heated for 30 minutes and the mixture cooled.The excess dichromate was titrated with 0.5 N Feso4 using diphenylamine indicator. A blank titration without soil sample was done..The amount of pottassium dichromate consumed by the sample was calculated.The the percentage of organic carbon in the soil sample was calculated..

3.3 Analysis of Various Vegetation as Riparian Zones in Controlling Nutrients Flow into the River

Runoff plots measuring 10 m long by 2 m wide each were set out for the three scenarios of grassland, bare land and natural forest. Embankments were constructed as borders of the plots. In order to prevent seepage, the embankments were lined with plastic papers. The collector troughs which were installed at a lower end of the runoff plots were fabricated using galvanized iron sheets. A sedimentation tank of 20 litres was installed in a hole dug at the end of each plot. A cut-off drain was dug in the area adjacent to the upslope end border of the plots to intercept runoff from the upper catchment area. The setting of the plots was done with the help of the community around the Nyangores river catchment. The construction exercise is well illustrated in figure 3.4 shown below. Runoff samples were taken ten minutes after the rainfall started. The samples were well preserved with concentrated sulphuric acid and taken to JomoKenyatta University of Agriculture & Technology laboratories for determination of PH, EC, NO_3 and PO_4. The coordinates of the locations are shown in Figure 3.5 below.

Figure 3.5: Pictorial view, Construction of Runoff Plots with the Help of the Community

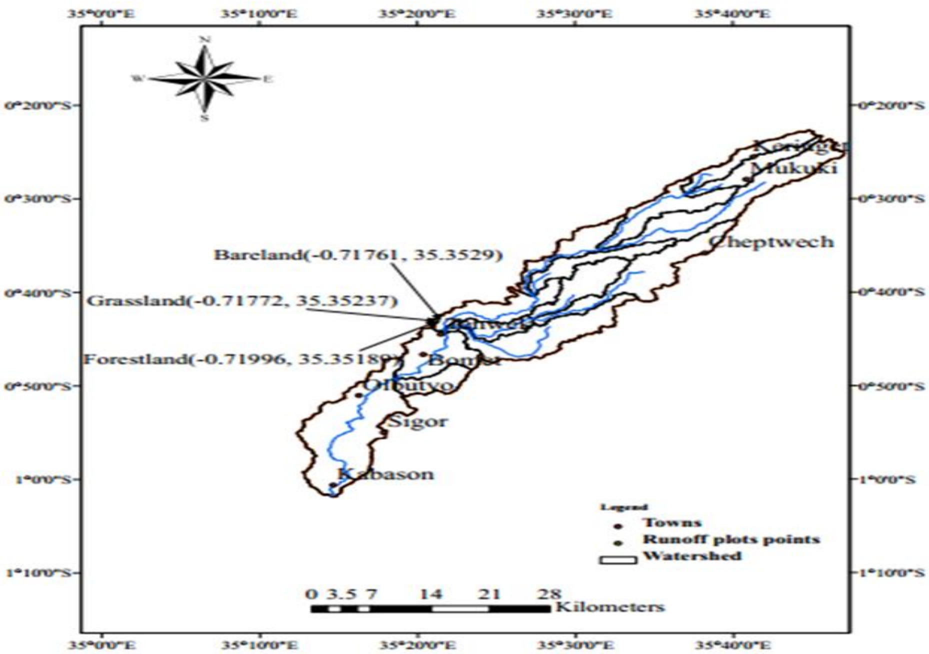


Figure 3.6: Location of Runoff Plots within Nyangores River Catchment

Table 3.3: Coordinates of Runoff Plots

	Forest	Grass Land	Bareland
Coordinates	-0.71996, 35.35189	-0.71772, 35.35237	-0.71761,35.3529

3.3.1 Particle size Analysis (Sieve Test)

The sieve analysis determines the gradation (the distribution of aggregate particles, by size, within a given sample) in order to determine compliance with design, production control requirements, and verification specifications.

Soil was collected from the three scenarios and a particle size analysis carried out on every sample to determine the soil type and other parameters using the methods listed in Table 3.3. And soil classification chart shown in figure 3.6 below was used for classification.

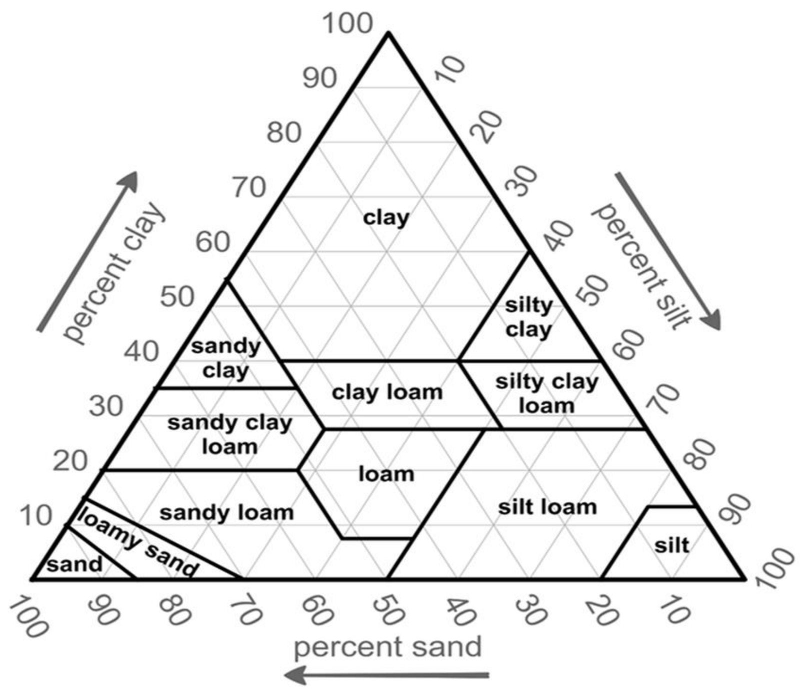


Figure 3.7: Soil Classification Chart

The test consisted of shaking the soil sample through a set of sieves that have progressively smaller openings. A sieve separates a specific sample material in two fractions, one is retained by the sieving media (rejected material/oversize), and the other passes through the openings (fines).

This is what was required i.e. Specimen, sieve shaker, BS410 Standard sieves, 0.1g accuracy balance, oven, porcelain dish and spatula, receiving pan, cleaning brush and clock were required.

The sieves were cleaned using cleaning brush of any particles that struck in the openings. The weight of each sieve and receiving pan were recorded. The specimen was dried in oven for 3-4 minutes to get the dried specimen .The specimen was weighed and its weight recorded. The sieves were then arranged in order as the smaller openings sieve to the last and larger openings sieve to the top. (They were simply arranged to the ascending order of sieve numbers – No.4 sieve on top and no.200 sieve at bottom). Sieve numbers and the particle sizes are provided below in a chart for further understanding. Recorded specimen was placed on the top sieve and then kept the complete sieve stack on the sieve shaker the lid and receiving pan were also placed. The shaker was allowed to work 10-5 minutes and timed using a clock. The sieve stack was removed from the shaker and the weight of each sieve recorded and receiving pan separately.

3.4 Calibration and Validation of SWAT Model

3.4.1 SWAT Model Set Up

The Soil and Water Assessment Tool (SWAT) is an open-source, continuous-time, semi-distributed hydrologic model developed by the USDA-ARS. It predicts the long-term impacts of land management practices, climate change, and land-use changes on water, sediment, and agricultural chemical yields in large, complex watersheds.

3.4.1.1 Input Data Preparation

Model performance can be affected by various uncertainties including input data. It is therefore important that the quality of input data be assessed. The satellite derived rainfall estimates needed to be validated in order to establish the level of confidence for use in areas that have few or lack observed data. The raw satellite rainfall data was analysed to identify and get rid of outliers. The estimates were then compared to observed rainfall data in order to estimate bias. Various statistical methods were used for the validation of the satellite rainfall estimates.

These are: the correlation coefficients (CC) (Qin et al., 2014) and under/overestimation (Hunink et al., 2009) given by the equations below.

Correlation Coefficient (CC)

$$cc = \left[\frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i-\bar{y})^2}}\right]^2 \qquad (3.4)$$

Where, CC is the Correlation Coefficient, x_i is observed rainfall data (mm), y_i is satellite rainfall estimates (mm), $\bar{x}$ is mean observed rainfall data (mm) and $\bar{y}$ is mean satellite rainfall estimates (mm).

$$\text{Over or under estimation} = \frac{\sum_{i=1}^{n}(X_i^{obs} - X_i^{sim})}{\sum_{i=1}^{n} X_i^{obs}} \qquad (3.5)$$

Where n is the number of observations, where X_i^{obs} is the ith observed value of the constituent being evaluated and X_i^{sim} is the ith simulated value of the constituent being evaluated.

The SWAT model was set up using hydrological data, soil properties, land use, and climate data to assess the impacts of various land uses (agriculture, forest, urban) on sediment yield and nutrient transport (Arnold et al., 2012). Calibration and validation were performed to ensure that the model accurately represents the watershed's hydrological processes.

The parameters chosen for calibration, such as USLE_P for sediment transport and ERORGN for nutrient enrichment, are in line with the focus on managing land and water resources together (Neitsch et al., 2011). The calibration phase ensured that the SWAT model captures the real-world impacts of different land-use scenarios on water quality. Table 3.4 shows the parameters used in the calibration.

Table 3.4: Short Description of the Parameters Selected for Calibration and the Initial Value Ranges

PARAMETER NAME	DESCRIPTION	RANGES
SURLAG (surface runoff lag coefficient)	Controls the fraction of water allowed to enter the reach on any one day. As it decreases, more water is held in storage.	0-4
SOL_AWC (Soil Available Water Capacity)	Available water capacity for each soil layer. SOL_AWC = FC-PWP	−0.20-0.20
ESCO	Soil Evaporation compensation factor. As value decrease the model extracts more water from the lower levels	0 -1
CH_N2	Manning's value for the main channel	0.01-0.3
CH_K2	Effective Hydraulic Conductivity for the main channel	0-10
ALPHA_BF2	Base Flow Alpha Factor 0.1-0.3- Land responds slowly to recharge 0.9-1- Land responds fast to recharge	0.6-0.99
GW_DELAY(days)	Estimated Ground Water delay time	0-31
GW_REVAP	Groundwater re-evaporation from the shallow groundwater to the surface. As value reaches 0, water movement to upper layer is restricted	0.02-0.15
GWQMN	Threshold shallow depth required for return flow to occur. Groundwater occurs when this valued is exceeded.	150-2000
RCHRG_DP	Deep aquifer Percolation Fraction (0-1)	0.02-0.25

3.4.1.2 Digital Elevation Model (DEM)

A 30-meter resolution Digital Elevation Model (DEM) obtained from the Shuttle Radar Topography Mission (SRTM) was utilized for watershed delineation and extraction of topographic parameters such as slope, drainage networks, and terrain features. The SRTM DEM is widely recognized for its reliability and has been effectively used in recent hydrological Modelling studies due to its global coverage and consistent quality Ahmed et al., 2021).

3.4.1.3 Watershed Delineation

Watershed delineation was carried out through the Arc SWAT interface. The DEM that had been projected was imported into the SWAT model so as to automatically delineate the watershed into several sub-watersheds that are hydrologically connected as shown in figure 3.8 below. The stream network and sub-watershed outlets were generated based on the drainage area basin threshold approach. This approach defines the minimum drainage area required to form the beginning of a stream. The size and the number of sub-watersheds impacts the modelling outputs (Migliaccio & Chaubey, 2008; Tripathi et al., 2006). Apart from the sub-watershed outputs created by the interface, manual outlets were added at the 1LA03 gauging station where calibration and validation was carried out. Finally, subwatershed parameters were calculated.

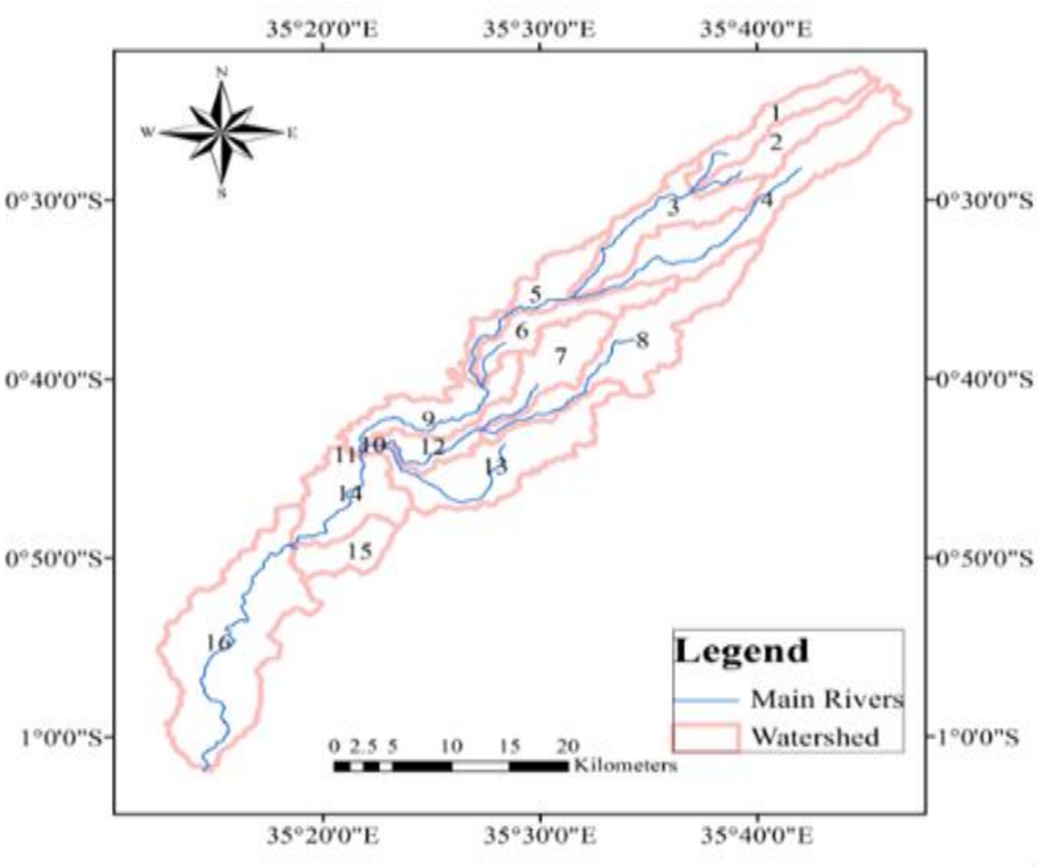


Figure 3.8: Delineated Study Watershed

3.4.1.4. Land Use/Cover

Land use and land cover (LULC) data were acquired from the Food and Agriculture Organization (FAO) and reclassified to align with the categories used in the SWAT model. This is shown in figure.3.9. Accurate LULC data are crucial for simulating plant growth, evapotranspiration, and other hydrological processes within SWAT. The reclassification ensured compatibility and improved the model's ability to simulate landscape hydrology over time.

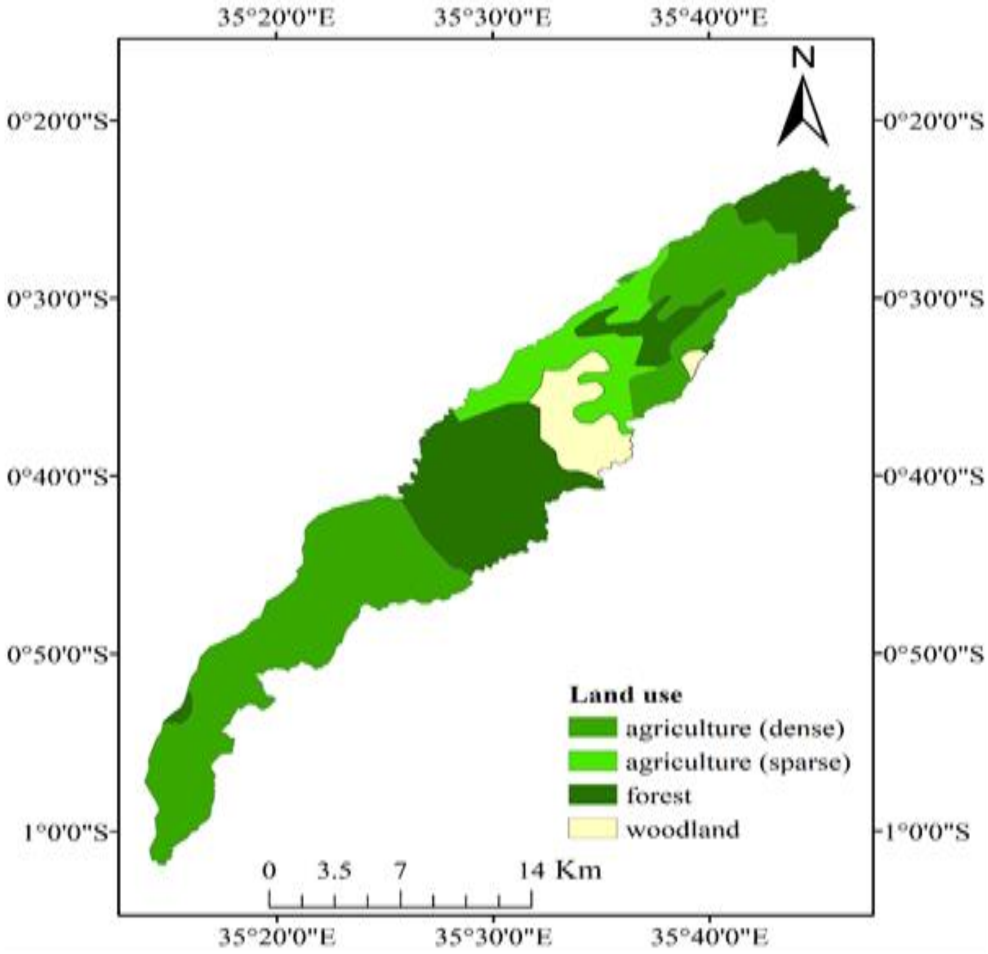


Figure 3.9: Land use Type in Nyangores Watershed

3.4.1.5 Soil Data

Soil information was sourced from the Kenya Soil and Terrain Database (KENSOTER), providing detailed attributes such as soil texture, organic carbon content, bulk density, and hydraulic conductivity. These soil properties are essential for Modelling infiltration rates, surface runoff, and subsurface flow in the SWAT model. Incorporating accurate soil data enhances the model's capacity to simulate hydrological and nutrient transport processes effectively. Figure 3.10. Shows the classification of soil within the catchment.

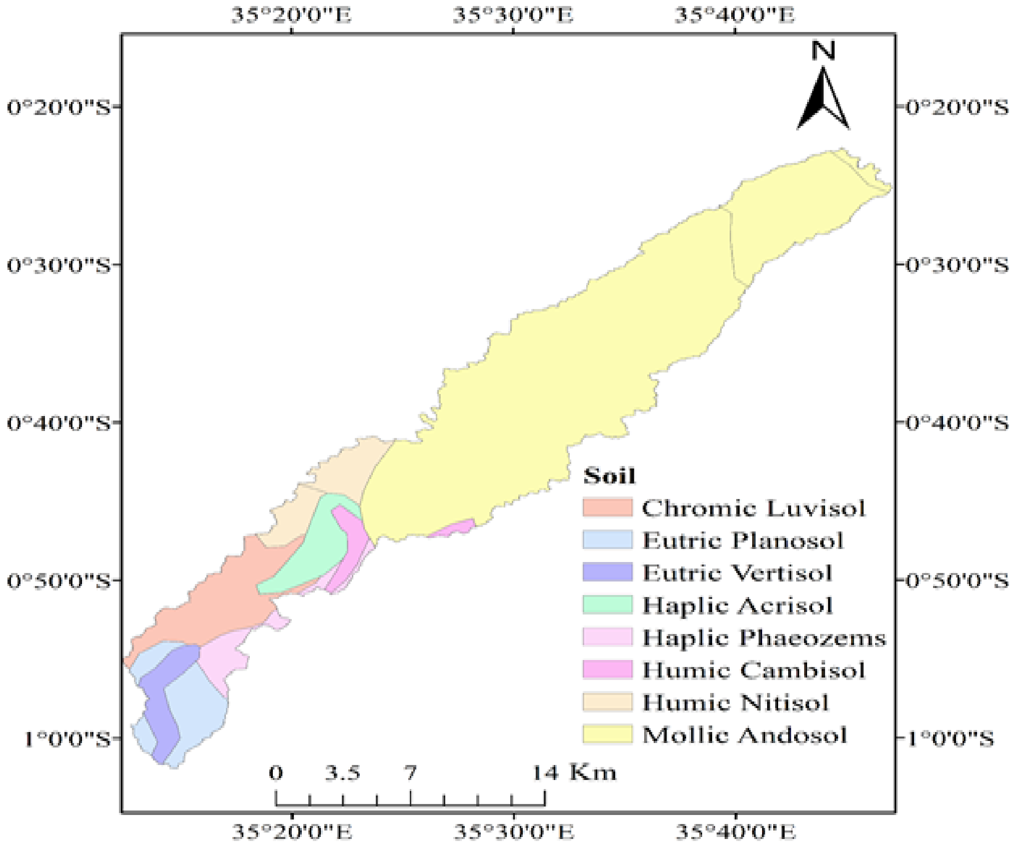


Figure 3.10: Classification of Soil within the Catchment

3.4.1.6: Hydro-Climatic Data

Hydro-climatic data are critical inputs for hydrological modelling. Daily streamflow data for the Nyangores River at station 1LA03 were obtained from the Water Resources Authority (WRA) for the calibration and validation periods. Evaluation was carried out on the data to check for consistency. Daily rainfall data for station 9035265, covering the period 1970 to 2013 was obtained from Kenya Meteorological Department (KMD). Satellite based daily rainfall data for the period 2001 to 2008 was obtained from the Famine Early Warning Systems Network (FEWSNET), United States Geological Survey (USGS). Daily minimum and maximum temperature, humidity, solar radiation and wind speed were obtained from National Aeronautics and Space Administration (NASA), Prediction of Worldwide Energy Resource (POWER) database to ensure data completeness.

3.4.1.7 Calibration and Validation of SWAT Model

Four iterations with 250 model simulations each were undertaken in SWAT-CUP based on the SUFI-2 approach using daily observed flow for the 2003-2005 period. After each iteration, parameter ranges were adjusted to the improved parameter ranges from the previous iteration. 15 calibration parameters that affect flow were used in the sensitivity analysis. These parameters were chosen based on previous studies (Faramarziet et al., 2009 and Levesque et al., 2008). The global sensitivity analysis results gave the degree of sensitivity of the 15 parameters. The p-value which determines the significance of sensitivity where values close to zero are more significant.

Calibration and Validation were performed to ensure accurate simulation of streamflow, sediment transport, and nutrient dynamics within the Nyangores River watershed. Validation utilized data from 2006 to 2008. The calibration process involved adjusting model parameters to minimize discrepancies between simulated and observed values, enhancing model performance (Moriasi et al., 2019). Statistical performance indicators—including the Nash-Sutcliffe Efficiency (NSE), coefficient of determination (R^2), and Percent Bias (PBIAS) were used to evaluate model accuracy. An NSE and R^2 value greater than 0.7 indicated satisfactory model performance, while a PBIAS value close to zero reflected minimal bias (Abbaspour et al., 2018).

Both manual and automatic calibration techniques were employed. The Sequential Uncertainty Fitting algorithm (SUFI-2) within the SWAT Calibration and Uncertainty Programs (SWAT-CUP) was used for automatic calibration, allowing for efficient parameter optimization and uncertainty analysis (Abbaspour et al., 2018).

3.4.1.8: Sensitivity Analysis

A sensitivity analysis was conducted to identify the most influential model parameters affecting hydrological outputs. The Latin Hypercube sampling method was utilized to systematically vary parameters within their feasible ranges.

Sensitivity was assessed based on the t-statistics and p-values derived from the SUFI-2 algorithm, with lower p-values indicating higher parameter sensitivity. Identifying sensitive parameters allowed for a focused calibration process, improving model accuracy. Parameters changed for sediment calibration are shown in table 3.5 below.

Table 3.5: SWAT Parameters Changed for Sediments Calibration

Parameters	Description	Variation range (default value)	Value used/change used
USLE_P	USLE Equation support practice factor	0 to 1 (1)	0.589000
SLSBBSN	Average slope length	10-150	18.379999
SPCON	Linear parameter for calculating the maximum amount of sediment that can be re-entrained during channel sediment routing	0.0001-0.01 (0.001)	0.004507
SPEXP	Exponent parameter for calculating sediment re-entrained in channel sediment routing	1-1.5 (1)	1.418004
ADJ_PKR	Peak rate adjustment factor for sediment routing in the sub basin (tributary channels)	0.5 2	0.643000

3.4.1.9 Model Performance Evaluation

The performance of the SWAT model was evaluated using both graphical methods and statistical metrics. Time-series plots were generated to visually compare observed and simulated streamflow and sediment loads, allowing for assessment of model dynamics over the simulation period. Quantitative evaluation was conducted using the Nash-Sutcliffe Efficiency (NSE), coefficient of determination (R^2), and

Percent Bias (PBIAS). An NSE and R^2 value closer to 1 indicated a better fit between simulated and observed data, while a PBIAS value near zero reflected minimal systematic errors in the model simulations (Moriasi et al., 2019). These metrics provided a comprehensive assessment of the model's predictive capabilities.

3.5 Assess the Effectiveness of the BMPs on Nutrient and Sediment Loads, in Improving Water Quality in Nyangores Watershed

Numerical experiments to test the effectiveness of buffer strip on water quality improvement under various scenarios. The experiment is to look for the high impact subbasins based on total NO_3 outflow and sediment outflow per unit filter width (kg/ha) basis. Performance of buffer strips are supposed to be more effective in high impact subbasins. Once the high impact subbasins are identified, two subbasins—one on the basis of total NO_3 outflow and the other on the basis of per unit width NO_3 outflow (kg/m), are selected to examine the reduction of NO_3 outflow due to riparian strips. Filter strips put next to the river as a buffer strip having 5m, 10m, 20m 25m are simulated to investigate and compare the effectiveness of strips of different sizes. The results are analysed and compared to quantify the impact of strip size on the efficiency of nutrient and sediment reduction by the filter strips.

3.6. Assessing the Impact of the Best Management Practices (BMPs) Scenario Analysis

The effectiveness of BMPs is not only dependent on their technical efficiency but also on their acceptance by farmers and other stakeholders. Therefore, this study incorporates both the environmental impact and potential for adoption when evaluating BMP scenarios (Schoumans et al., 2020).

BMPs were simulated in the SWAT model to assess their effectiveness in reducing nutrient and sediment loads. The selection of BMPs based on their perceived ease of adoption and their compatibility with existing farming practices. For example, riparian buffer strips were chosen due to their ability to reduce nutrient runoff (Smith et al., 2019), and their implementation was evaluated in the context of local land-use patterns and farmer practices.

3.6.1. Experimental Design for Simulation Scenarios

Numerical experiments to test the effectiveness of buffer strip on water quality improvement under various scenarios. The experiment is to look for the high impact subbasins based on total NO_3 outflow and sediment outflow per unit filter width (kg/ha) basis. Performance of buffer strips are supposed to be more effective in high impact subbasins. Once the high impact subbasins are identified, two subbasins one on the basis of total NO3 outflow and the other on the basis of per unit width NO3 outflow (kg/m), are selected to examine the reduction of NO3 outflow due to riparian strips. Filter strips put next to the river as a buffer strip having 5m, 10m, 20m 25m are simulated to investigate and compare the effectiveness of strips of different sizes. The results are analysed and compared to quantify the impact of strip size on the efficiency of nutrient and sediment reduction by the filter strips.

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1 Introduction

This chapter presents the results of the study, including data analysis, interpretation, and discussion. The findings are organised according to the research objectives, with a focus on evaluating the effects of land use on water quality, sediment transport, and nutrient levels in the Nyangores River Watershed. The chapter also discusses the results in the context of previous research, highlighting areas of convergence and divergence, and identifying gaps that this study addresses.

4.2 Key Sources of Pollution within the Nyangores River Watershed

This section identifies and discusses the primary sources of pollution in the Nyangores River watershed. The sources of pollution were categorized based on agricultural activities, deforestation, urbanization, and other anthropogenic activities that contribute to water contamination. The findings were analysed and discussed with reference to the concentration levels of key pollutants such as pH, electrical conductivity (EC), nitrates (NO3), phosphates (PO4), potassium (K), calcium (Ca), total organic carbon (%TOC), and iron (Fe).

4.2.1 Agricultural Runoff and Land Use Practices

Table 4.1shows the values of pH, EC, N, P, K, Ca, %TOC, and Fe of soil deposit obtained from the river bank of River Nyangores from different locations. Figure 4.1 a and b represents a cattle track which is intercepted by a well-protected river bank growing with Kikuyu grass. The soil shows a high pH value of 5.4. P 0.66, N 0.7, 6.4 %TOC and Fe 17mg/kg. This could be attributed to the runoff flow originating from neighbouring urban areas as well as animal waste along a cattle track leading to a watering point in the river. The Kikuyu Grass has a high trapping efficiency. Quarrying activities at location 7 as shown has a value of Fe = 27 mg/kg, Ca=22 meq/100gm soil which is the highest of all other values this could be attributed to the exposure of inner rocks which bears high quantity of minerals. Cleaning of vehicles is major contributing factor to water pollution in Nyangores River. Water samples collected and analysed for this point (Olbutyo bridge) showed that the water pH was 7.3, EC 0.04 Ds/cm, NO_3 6.43mg/l, P 3.3 mg/l, K 0.31mg/l.

a) **b)**

Figure 4.1 a and b: Shows Soil Sampling along the Nyangores Riverbank

Table 4.1: Shows the Values of Different Parameters in Deposition of Soil from Selected Locations in Nyangores Catchment

Location	pH	EC Mil/mhos	N(meq/100) soil	P (meq/1000) soil	K (meq/1000) soil	Ca (meq/1000) soil	%TOC	Fe mg/kg
1	6.15	0.04	0.05	0.43	0.10	12	3.5	22
2	6.02	0.02	0.05	0.35	0.15	15	2	7.4
3	5.7	0.1	0.07	0.66	0.15	12	6.4	17
4	5.4	0.03	0.03	0.36	0.21	3.1	1.4	4.6
5	6.3	0.01	0.03	0.2	0.10	3.5	0.6	4
6	6.4	0.01	0.07	0.4	0.05	6	0.12	8.2
7	6.9	0.06	0.05	0.19	0.15	22	3.2	27
8	7	0.01	0.03	0.27	0.15	6.9	0.68	10.6
9	7.2	0.01	0.03	0.48	0.10	8.6	0.8	7.4
10	6.9	0.27	0.02	1.29	0.13	20	2.8	25.4
11	7.7	0.06	0.03	0.22	0.15	16	1.1	7.2
12	6.1	0.02	0.08	0.25	0.21	7	3	10.6
13	6.9	0.17	0.05	0.27	0.15	7	0.68	10

From the results of the study, agricultural runoff was identified as a significant source of pollution in the Nyangores River watershed. Agricultural areas exhibited elevated levels of nitrates, phosphates, and potassium as shown in table 4.2 where the nitrates are high around the confluence of Rivers Nyangores and Amala, reflecting the impact of fertilizer use and improper land management. Table 4.2 summarizes average concentration levels of selected chemicals at different sampling points along the river from six samples collected in each station

Table 4.2: Shows Results of pH, EC and Nutrients Concentration from Runoff Samples along Nyangores River

LOCATION	pH	EC	Nitrates (mg/l)	Phosphates (mg/l)	Potassium (mg/l)
Standard values for water	6.5-8.5	<400µS/cm	10.00	0.50	< 100
200m from the confluence	7.74	0.062	11.208	1.050	0.308
Confluence	7.30	0.046	3.678	3.260	0.308
Bomet sampling station	7.24	0.046	9.362	6.206	0.324
Olbutyot bridge	7.20	0.038	6.306	3.240	0.314
Bomet bridge	6.98	0.038	4.996	6.198	0.244
Forest	7.60	0.030	7.269	1.244	0.247
River bank near forest	6.36	0.040	6.146	19.684	0.250
Path to Kiptagat	6.94	0.030	4.020	18.396	0.244
Agriculture section	6.90	0.030	4.632	20.820	0.244

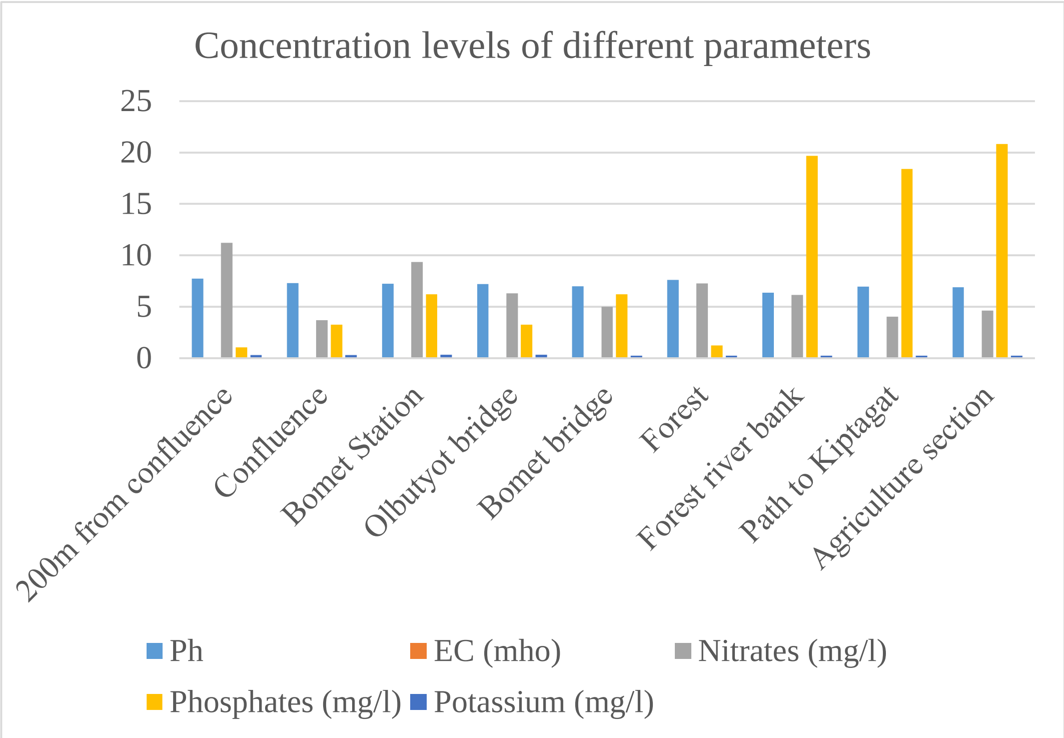


Figure 4.2: Shows Ph, EC and Nutrients Concentration from Sampling Points in Nyangores River

From the results presented in table 4.1 and well visualised in figure 4.2, the analysis of water samples taken from different locations along the Nyangores River revealed significant variations in water quality parameters, including pH, electrical conductivity (EC), and concentrations of nitrates, phosphates, and potassium. The pH values across the locations ranged from as low as 6.36 at the riverbank near the forest to as high of 7.74 at 200 meters from the confluence. The pH levels reflect slight acidity in areas like the riverbank near the forest. The elevated pH can be attributed to the forest activities like animals excretion and other biological activities like breaking down of organic matter like leaves within the forest which are later washed down by runoff and trapped in the mud along the river banks. Electrical conductivity, an indicator of dissolved solids in water, varied from 0.030 dS/cm in areas like the forest and agricultural sections to a maximum of 0.062 dS/cm at 200 meters from the confluence, suggesting varying levels of mineralization and water chemistry along the river resulting from dissolved minerals from forest rocks fertilizers and pesticides applied in the wheat farms on lower reaches of the catchment.

Nitrate concentrations, which are crucial indicators of nutrient pollution, varied significantly across the different sampling points. The highest nitrate level was recorded at 200 meters from the confluence (11.208 mg/L) which is above the acceptable level of 10mg/L (WHO), indicating substantial nutrient input in this area, this is attributed to intensive agricultural activities around this area mainly dominated by large wheat and maize farming. In contrast, the confluence itself had a lower nitrate concentration of 3.678 mg/L which could attributed to the vortex motion of the two rivers supplying a lot of air into the runoff. Phosphate levels, another key nutrient associated with agricultural runoff, showed considerable variation, with the agricultural section recording the highest level at 20.820 mg/L which is far much higher than the standard level 0.5mg/L, this highlights the potential for nutrient pollution leading to eutrophication which is likely to harm the aquatic life in this area. On the other hand, areas such as 200 meters from the confluence had lower phosphate concentrations at 1.050 mg/L.

Potassium levels remained relatively consistent across most of the sampling locations, with slight variations. The highest potassium concentration was observed at the Bomet sampling station (0.324 mg/L), while other locations like the Bomet Bridge where cleaning of clothes and vehicles is noticed, Path to Kiptagat, and agricultural sections had lower concentrations (0.244 mg/L). These findings underscore the influence of land use activities, particularly agriculture, on nutrient loading in the river, with areas near agricultural land showing elevated nutrient concentrations that could contribute to eutrophication and water quality degradation in the Nyangores River watershed.

From these values, the chi-square test statistic was calculated using the differences between the observed and expected values and the totals obtained as shown in table 4.3.

Table 4.3: Summary of Chi-Squared Values for Parameters Obtained from Runoff

Location	pH	EC	NO_3	PO_4	K	Total
200m from the confluence	0.28	0.02	6.66	4.44	1.72	13.12
Confluence	1.61	0.02	0.00	0.37	1.09	3.09
Bomet sampling station	0.00	0.00	1.88	0.15	2.00	4.03
Olbutyot bridge	0.62	0.00	0.79	0.83	1.35	3.60
Bomet bridge	0.24	0.00	0.01	0.03	1.62	1.91
Forest	1.17	0.00	2.15	2.93	1.39	7.64
River bank near forest	1.45	0.01	0.61	8.97	3.18	14.21
Path to Kiptagat	0.60	0.01	1.74	9.03	2.87	14.25
Agriculture section	1.06	0.01	8.34	2.98	80.68	93.07
Total	7.03	0.07	22.19	29.72	95.89	154.90

As presented in Table 4.3, the Chi-square test was conducted to examine whether the levels of various water quality parameters—pH, electrical conductivity (EC), nitrates (No_3), phosphates (Po_4) and potassium (K) were dependent on the sampling location within the Nyangores River watershed. These parameters are critical indicators of water quality and are influenced by both natural factors and human activities, such as agriculture and urbanization. The results provide insights into how different land use activities contribute to water quality degradation in the watershed.

pH levels, which measure the acidity or alkalinity of the water, varied across different locations, with values ranging from 6.36 (slightly acidic) at the riverbank near the forest to 7.74 (near-neutral) at 200 meters from the confluence. The Chi-square value for pH was 7.0311, indicating that while pH levels did vary across locations, the influence of location on pH was less significant compared to other parameters. This suggests that pH, although affected by local land use, may not be the primary indicator of pollution in this watershed. Electrical conductivity (EC), a measure of the water's ability to conduct electricity, varied between 0.030 and 0.062 dS/cm, reflecting the concentration of dissolved solids in the water. The Chi-square value for EC was 0.0663, indicating that the variations in EC levels were relatively uniform across the watershed, with no single location standing out as a significant source of mineral or salt pollution.

Nitrate concentrations, a key indicator of nutrient pollution typically associated with agricultural runoff, showed significant variation across different locations. The highest nitrate levels were recorded in agricultural areas, with a Chi-square value of 22.1900. This suggests that agricultural runoff is a major contributor to nutrient pollution in the Nyangores River. Similarly, phosphate concentrations, which are also linked to agricultural activities, exhibited considerable variation, with a Chi-square value of 29.7206. The high phosphate levels in agricultural areas highlight the impact of farming practices on nutrient loading and the potential risks to water quality, such as eutrophication and algal blooms.

Potassium, another nutrient commonly found in fertilizers, also showed significant dependence on location, with a Chi-square value of 95.8947. The extremely high Chi-square value for potassium indicates that its concentration is heavily influenced by land use activities, particularly in agricultural regions and sampling points located cross to urban centres. This reinforces the conclusion that fertilizer use in agricultural areas contributes to elevated levels of potassium in the water, further affecting water quality in the watershed.

The total Chi-square value for all parameters combined was 154.9027, which is significantly higher than the critical value of 46.194 at 32 degrees of freedom and a 5% significance level. This result leads to the rejection of the null hypothesis, confirming that the levels of water quality parameters are dependent on the sampling location. The findings emphasize the substantial impact of agricultural activities on water quality, with agricultural areas contributing higher concentrations of nitrates, phosphates, and potassium compared to other land use areas.

The summary in Table 4.3 was obtained by getting the averages of all the parameters measured in the different vegetation in riparian zones.

4.2.2 Runoff Plots

Table 4.4: Summary of Parameters Obtained from the Runoff Plots Analysis Depicting Different Riparian Vegetation

Location	PH	EC	NO_3 (mg/l)	PO_4 (mg/l)	TSS (mg/l)
Natural Forest	6.99	0.04	0.67	0.10	1134.55
Bareland	6.55	0.08	0.35	0.18	378.82
Grassland	6.42	0.03	0.36	0.19	81.55

The results in Table 4.4 summarize the average values of pH, EC, nitrates, phosphates, and total suspended solids (TSS) measured in different riparian zones, including natural forests, bare land, and grassland. These results indicate that riparian zones with natural forest cover tend to have higher concentrations of these parameters compared to other types of vegetation.

Table 4.5: Chi-Squared Test Values from Data Obtained at Riparian Zones

Location	PH	EC	NO_3 (mg/l)	PO_4 (mg/l)	TSS (mg/l)	Total
Natural Forest	3.59	0.04	8.44	0.16	9100.56	9112.79
Bareland	0.67	0.05	2.63	0.04	3083.07	3086.47
Grassland	25.93	0.06	0.20	1.03	716.97	744.20
Total	30.19	0.15	11.27	1.24	12900.60	12943.46

Chi-square test was performed to determine whether the concentrations of various water quality parameters—pH, electrical conductivity (EC), nitrates (NO_3), phosphates (PO_4), and total suspended solids (TSS)—are influenced by the type of vegetation in riparian zones. Riparian vegetation plays a crucial role in water quality management, as different types of plants can affect the levels of nutrients and sediments entering the water.

The results, summarized in Table 4.5, indicate that there are significant differences in water quality parameters across the different types of riparian vegetation: natural forest, bare land, and grassland. The Chi-square test statistic calculated for all parameters combined was 12,943.46. This value far exceeds the critical value needed to reject the null hypothesis, leading to the conclusion that the concentration of water quality parameters is indeed dependent on the type of riparian vegetation.

The analysis revealed that natural forested areas had the highest total Chi-square value of 9,112.79, indicating that these zones had the most substantial impact on water quality, particularly in terms of total suspended solids (TSS). Natural forests were associated with significantly higher levels of TSS, which can be attributed to wildlife and livestock presence and therefore destruction of the soil surface through trampling by the animals especially at this sampling point where wild animals drink water from. This suggests that natural forests play a critical role in controlling sedimentation and nutrient loading in water bodies if not interfered with through overstocking and deforestation.

In contrast, areas with bare land and grassland exhibited much lower total Chi-square values, with bare land showing a value of 3,086.47 and grassland showing a value of 744.20. These results suggest that bare land, while contributing to higher levels of TSS compared to grassland, has a reduced impact on other water quality parameters such as pH, EC, and nitrates. Grassland, on the other hand, showed the least influence on all measured parameters, indicating that it is less effective in controlling nutrient and sediment runoff compared to natural forests.

The study identified agricultural runoff as a significant source of pollution in the Nyangores River watershed, with agricultural areas showing elevated levels of nitrates, phosphates, and potassium. These findings align with previous studies, such as Mittelstet et al. (2016), which demonstrated that intensive agricultural activities lead to increased nutrient loading in water bodies, contributing to eutrophication. Similarly, Narasimhan et al. (2010) found that nutrient runoff from agricultural lands can result in harmful algal blooms and oxygen depletion in aquatic ecosystems. In this study, the highest nitrate concentration (11.208 mg/L) was recorded 200 meters from the confluence attributed to fertilizers applied on large scale wheat and maize plantations and also due to upstream agricultural runoff, supporting the connection between land use and water quality degradation.

The findings are further supported by research conducted by Liu et al. (2019), which highlighted the role of agriculture in contributing to elevated phosphate levels in river systems. In the Nyangores River watershed, the agricultural section recorded the highest phosphate concentration (20.820 mg/L), consistent with Liu et al.'s observation that improper land management in farming areas often leads to nutrient pollution. These high concentrations pose significant risks to water quality, echoing the concerns raised by Gull et al. (2017) regarding the impact of agricultural practices on nearby water bodies.

The Chi-square test results reinforce these empirical findings by revealing significant spatial variations in water quality parameters across different locations within the watershed. For instance, the Chi-square value for nitrates (22.19) indicates a strong correlation between nitrate levels and sampling location, particularly in agricultural areas. This suggests that agricultural activities are a major source of nutrient pollution, a conclusion that mirrors the findings of studies on non-point source pollution from agricultural lands.

Similarly, the Chi-square test for phosphates (29.72) confirms that phosphate concentrations are heavily influenced by land use, particularly in areas dominated by agriculture. This aligns with the results of Sinyolo et al. (2020), who identified agricultural runoff as a primary contributor to phosphate pollution in river systems. The elevated phosphate levels observed in agricultural sections of the Nyangores River highlight the ongoing challenges of managing nutrient pollution in areas with intensive farming.

The high Chi-square value for potassium (95.89) further emphasizes the impact of agricultural land use on water quality. Potassium, a common component of fertilizers, showed significant dependence on location, with agricultural areas contributing to higher concentrations. This finding is consistent with the research of Gull et al. (2017), which demonstrated that fertilizer use in agricultural regions can lead to elevated potassium levels in nearby water bodies, affecting overall water quality.

Human activities such as practicing agriculture directly influence the health of watersheds by altering the natural flow of nutrients and sediments into water bodies. The high nutrient concentrations observed in agricultural areas within the Nyangores River watershed underscore the need for integrated land and water management strategies. These strategies should focus on reducing nutrient runoff through the implementation of sustainable land management practices, such as conservation agriculture and the use of riparian buffer zones.

Furthermore, BMPs can be applied to understand how sustainable land-use practices can be adopted within the watershed. The spread of innovative practices depends on early adopters who demonstrate the benefits of these practices to the broader community. In the context of the Nyangores River watershed, promoting the adoption of best management practices (BMPs) such as nutrient management and riparian restoration could significantly reduce nutrient pollution and improve water quality. Engaging local farmers and educating them about the environmental and economic benefits of these practices is crucial for fostering a culture of innovation that prioritizes long-term ecological health.

The analysis revealed that natural forested areas had the highest impact on water quality, particularly in terms of total suspended solids (TSS). This emphasizes the role of natural vegetation in controlling sedimentation and nutrient loading. Forested riparian zones act as natural filters, trapping sediments and nutrients before they enter the water, thus maintaining higher water quality. The importance of preserving and restoring natural forests in riparian areas is further highlighted by the lower total Chi-square values observed in bare land and grassland areas, which were less effective at controlling sediment and nutrient runoff.

4.2.3 Deforestation and Sediment Transport

The results of this study identify deforestation as a major contributor to increased sediment transport in the Nyangores River watershed. Areas where natural vegetation has been cleared, such as near Olbutyo Bridge (Point F), exhibited significantly higher sediment loads compared to well-protected, forested areas. The results are presented in table 4.6.

Table 4.6: Soil Chemical Analysis Results on Soil Deposit on River Nyangores Bank

LOCATION	PH	Fe (mg/l)	Ca (mg/l)	%TOC	N (mg/l)	P (mg/l)
Point A(River Bank)	5.4	17	-	6.4	0.7	0.66
(Olbutyo Bridge)	7.3	27	22	-	-	-

The soil chemical analysis, as shown in Table 4.6, reveals that deforested areas recorded elevated levels of iron (Fe) at 27 mg/l attributed to quarrying along the river banks and calcium (Ca) at 22 meq/100g of soil, whereas forested areas like Point A had lower Fe levels (17 mg/kg) and a higher percentage of total organic carbon (TOC) at 6.4%. The loss of forest cover reduces soil stability, making it more prone to erosion and increasing the likelihood of sediment deposition in the river.

These findings are consistent with earlier studies, such as Gull et al. (2017), which identified deforestation as a key factor driving soil erosion and sediment transport in watersheds. The removal of natural vegetation strips away the protective cover that shields the soil from rainfall impact, leading to higher rates of erosion and sediment runoff into nearby water bodies. In the Nyangores River Watershed, this process is particularly evident in deforested locations like Olbutyo Bridge, where the lack of vegetation exposes the soil, resulting in significantly increased sediment loads. Similar observations were made by Ezeabasili et al. (2014), who found that areas affected by deforestation experienced up to 70% more sediment transport than those that retained forest cover. This highlights the critical role that forest cover plays in controlling erosion and sediment transport, emphasizing the need for reforestation to mitigate sedimentation and improve water quality.

The contrast in sediment deposition between well-protected and deforested areas is further supported by Chakraborty et al. (2013), who demonstrated that soil erosion accelerates in regions where natural vegetation is cleared, leading to increased sediment transport. In the Nyangores River watershed, deforestation impacts not only sediment loads but also disrupts nutrient cycles, as indicated by lower TOC percentages in deforested areas. This disruption poses long-term risks to both soil fertility and water quality, underlining the importance of integrating land management practices that protect natural vegetation and minimize soil disturbance. This advocates for a comprehensive approach to managing watersheds, emphasizing that changes in land use, such as deforestation, have direct consequences on sediment transport and water quality. The results of this study align with the theory, illustrating how the removal of forest cover contributes to increased sediment transport and degradation of water quality. Reforestation and sustainable land use practices are critical components of effective watershed management strategies, as they help prevent further sedimentation and preserve the ecological balance within the Nyangores River watershed.

4.2.4 Urbanization and Point-Source Pollution

From the results of the study, urbanization emerged as a significant source of point-source pollution in the Nyangores River watershed. The results are presented in table 4.7.

Table 4.7: Summary of Chi-Square Values for Parameters Obtained from River Water

Location	PH	EC	NO_3 (mg/l)	PO_4(mg/l)	K(mg/l)	Total
200m From the Confluence	0.28	0.02	6.66	4.44	1.72	13.12
Bomet Sampling Station	0.00	0.00	1.88	0.15	2.00	4.03
Olbutyot Bridge	0.62	0.00	0.79	0.83	1.35	3.60
Bomet Bridge	0.24	0.00	0.01	0.03	1.62	1.91

The study revealed that urbanization significantly contributes to point-source pollution within the Nyangores River watershed. Urban areas, particularly around Bomet Bridge and Olbutyot Bridge, were identified as pollution hotspots, with elevated levels of total suspended solids (TSS), electrical conductivity (EC), and nutrients such as nitrates (NO_3) and phosphates (PO_4). For instance, at the Olbutyot Bridge sampling point, water samples exhibited a pH of 7.3, EC of 0.04 Ds/cm, NO_3 concentration of 6.43 mg/L, and PO_4 concentration of 3.3 mg/L. as illustrated in figure 4.1. These elevated levels reflect the impact of urban runoff, including domestic and industrial wastewater discharge, vehicle washing, and other anthropogenic activities concentrated in urban centres.

Further analysis showed that water quality at the Bomet Bridge and Bomet Sampling Station also reflected significant levels of urban-induced pollutants. The Bomet Bridge sampling point recorded an EC of 0.038 dS/cm and a NO_3 concentration of 4.996 mg/L, both indicative of urban runoff influence shown by physical appearance of small gullies leading to the centres. Similarly, at the Bomet Sampling Station, the total nutrient concentration, including phosphates, was found to be substantially higher compared to upstream locations, reinforcing the conclusion that urbanization is a major contributor to point-source pollution with human activities like cleaning of clothes and motor vehicles. The relatively higher levels of potassium (K) at both the Bomet Bridge (1.621) and Olbutyot Bridge (1.350) further confirmed the presence of urban-derived pollutants.

The chi-squared analysis of water quality parameters across different locations provided statistical evidence that pollutant concentrations varied significantly depending on proximity to urban areas. The total chi-squared value for the Bomet Bridge location was 1.9053, while the Olbutyot Bridge recorded a total of 3.5963, both indicating a significant variation in water quality due to urbanization and quarrying respectively. This finding highlights the need for improved urban water management strategies to mitigate point-source pollution and protect water quality in the Nyangores River watershed.

The results indicate that urbanization is a significant factor contributing to water quality degradation in the Nyangores River Watershed this can be attributed to oil spillage in vehicle cleaning combined with other mechanical operations plus residential waste spillage. Elevated levels of nitrates, phosphates, and electrical conductivity at sampling points near urban centres, such as Bomet Bridge and Olbutyot Bridge, suggest that urban runoff, industrial discharges, and domestic wastewater are major pollution sources. These findings align with previous research by Kumar et al. (2020), who found that urban areas contributed disproportionately to water pollution due to concentrated human activities and inadequate waste management systems. Similarly, a study by Yang et al. (2019) in urban watersheds highlighted that urbanization accelerates the flow of contaminants into water bodies, primarily through storm water runoff that carries pollutants from impervious surfaces such as roads and rooftops.

The chi-squared analysis reinforces the observation that pollutant levels are significantly influenced by the proximity to urban areas. This is consistent with findings from Muthee et al. (2020), who observed that urban regions near river systems in Kenya exhibited higher nutrient and sediment loads compared to rural areas. The high concentrations of phosphates and nitrates near urban centres underscore the need for interventions to control urban runoff. The findings suggest that without proper urban planning and wastewater management, urbanization will continue to be a critical factor in the degradation of water quality in the Nyangores River watershed, necessitating urgent policy responses to address point-source pollution effectively.

The findings from the study, highlight the impact of urbanization on water quality in the Nyangores River watershed. This emphasizes the need for an integrated and holistic approach to managing land and water resources to sustain environmental and socio-economic outcomes. The results showing elevated pollutant levels near urban areas underscore the interconnectedness of land use and water quality. Urbanization, without adequate planning and management, disrupts the natural hydrological processes within the watershed, leading to increased runoff and pollution. Land use changes, particularly in urbanized areas, can negatively impact water resources if not properly managed. Thus, this study reinforces the importance of implementing watershed-based management strategies that address urban pollution sources to restore and preserve water quality.

Adoption of sustainable urban planning and water management practices can be seen as an innovation that needs to be diffused within the community. The findings, which show significant pollution near urban centres, point to the need for local governments and communities to adopt best management practices (BMPs) for controlling urban runoff. However, the slow uptake of such practices could be due to factors such as perceived complexity, lack of awareness, or insufficient incentives, as suggested by Rogers' theory.

4.2.5 Particle Size Analysis

Table 4.8: Shows the Results on Sieve Analysis from Soil Samples Collected from the Three Scenario of Different Runoff Plots

Particle size(mm)	% passing (Forest)	Particle size(mm)	% passing (cultivated)	Particle size(mm)	% passing (grassland)
0.84	97.87	0.84	90.37	0.84	91.23
0.42	92.38	0.42	65.4	0.42	58.47
0.25	76.02	0.25	53.26	0.25	49.50
0.105	42.48	0.105	27.58	0.105	21.27
0.074	32.83	0.074	19.66	0.074	13.21
0.069	29.37	0.073	17.45	0.073	10.48
0.049	28.56	0.052	14.14	0.052	9.68
0.035	24.49	0.037	12.64	0.037	8.87
0.025	22.87	0.026	9.33	0.026	5.65
0.0178	17.99	0.019	6.12	0.019	4.84
0.0133	13.92	0.014	4.51	0.014	3.23
0.0095	9.86	0.0099	2.91	0.0097	2.42
0.0067	8.13	0.007	2.11	0.0069	0.81
0.0048	4.88	0.005	1.3	0.0049	0.00
0.0034	0.91	0.0035	0.5		
0.0025	0	0.0025	0		
0.0014	0	0.0014	0		

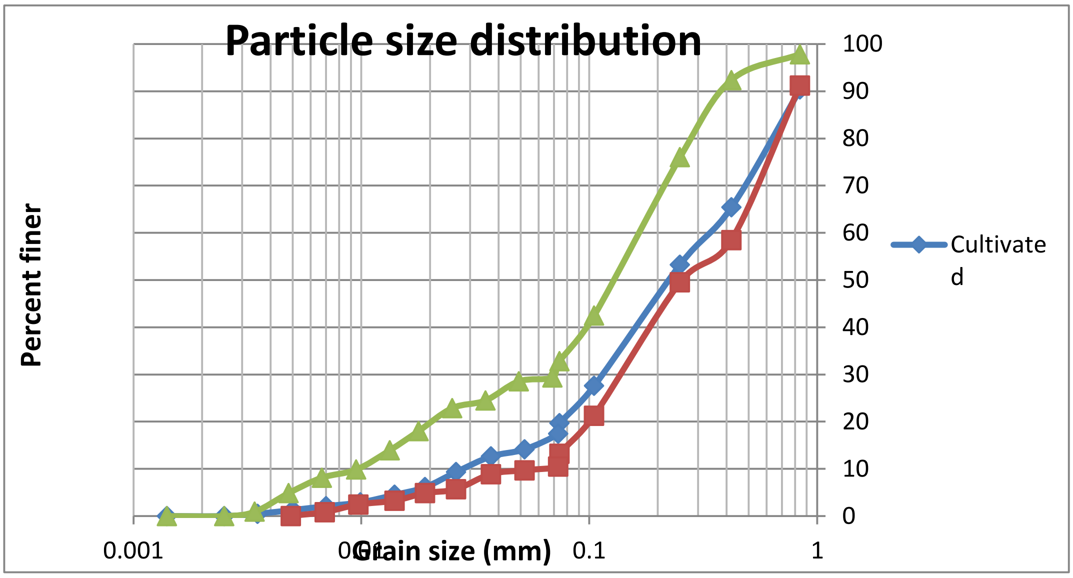


Figure 4.3: Shows the Soil Particles Distribution in the Three Different Vegetation of the Runoff Plots

a) b)

Figure 4.4a and b: River Banks of Lower Nyangores River with Exposed Roots

At the river bank elevation 1714m, S00059’417, E035015’634, existence of exposed tree roots was observed which is a sign of bank erosion as shown in Figure 4.4.The river banks of lower Nyangores River where trees have exposed roots caused by washing away of the poor cohesive sandy soil. Figure 4.3 shows Soil collected at this point and tested for particle size analysis using sieve analysis method shows characteristics of sandy soil. Sandy soils has a poor cohesion and they are therefore prone to erosion and hence the appearance of uprooted trees and exposed tree roots at this part of Nyangores river which has led to lose of riparian vegetation leading to soil being washed into the river.

4.3 Calibration and Validation of the SWAT Model for Streamflow, Sediment, and Nutrient Transport in the Nyangores River Watershed

4.3.1 Evaluation and Validation of Satellite Data

Monthly rainfall totals of FEWS RFE and gauged datasets of station Bomet water supply (9035265) were calculated. Figure 4.5 shows the scatter plot and 1:1 line of monthly rainfall. The correlation coefficient (R^2) is 0.85. The R^2 is high which shows there is a good correlation between the two datasets.

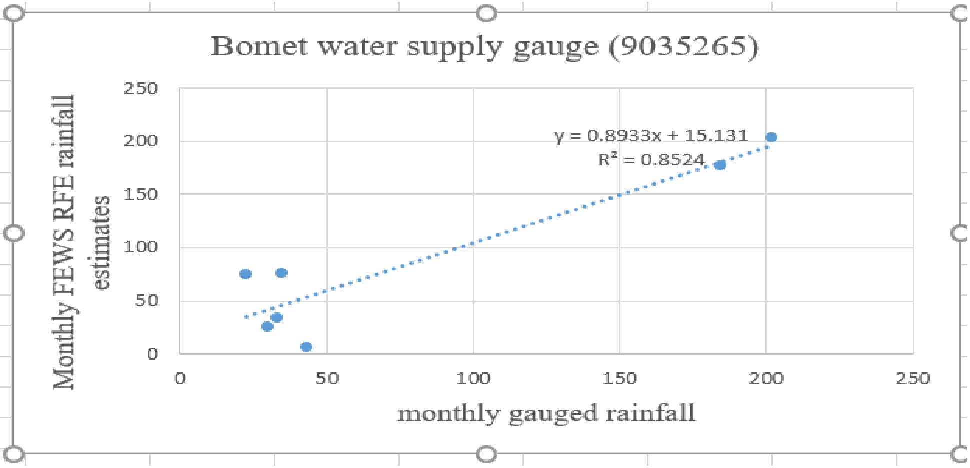


Figure 4.5: Scatter Plot and 1:1 Line of Monthly Rainfall at Station 9035265

The yearly totals were obtained and Figure 4.5 shows the comparison of the two rainfall datasets. The figure shows that the FEWS satellite estimates underestimate rainfall and this is because the FEWS RFE data is based on observation of cloud top temperatures, which are related to vertical and convection motion. The FEWS algorithm may fail to detect short rains that occur due to orographic and convection precipitation (Hunink et al., 2009). The rainfall underestimation was found to be 19%. A correction factor of 1.19 was applied to the FEWS RFE for it to have a better correspondence with the gauged rainfall data.

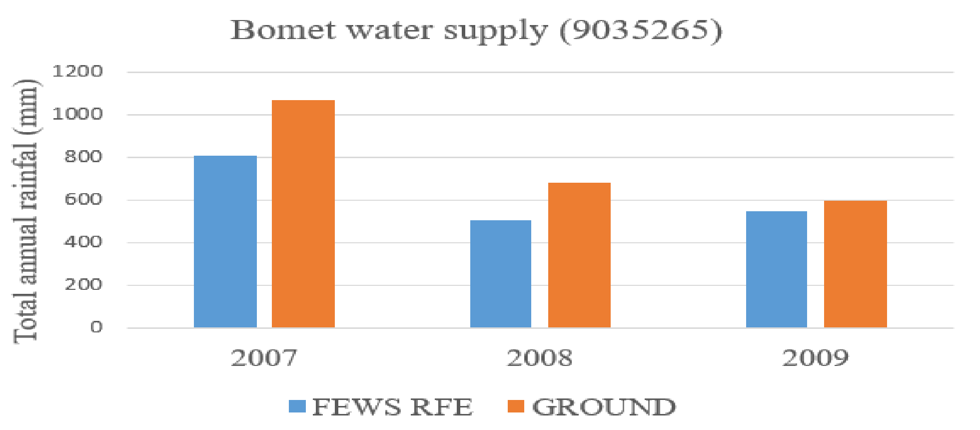


Figure 4.6: Yearly Totals of Rainfall at Station 9035265

4.3.2 Watershed Delineation

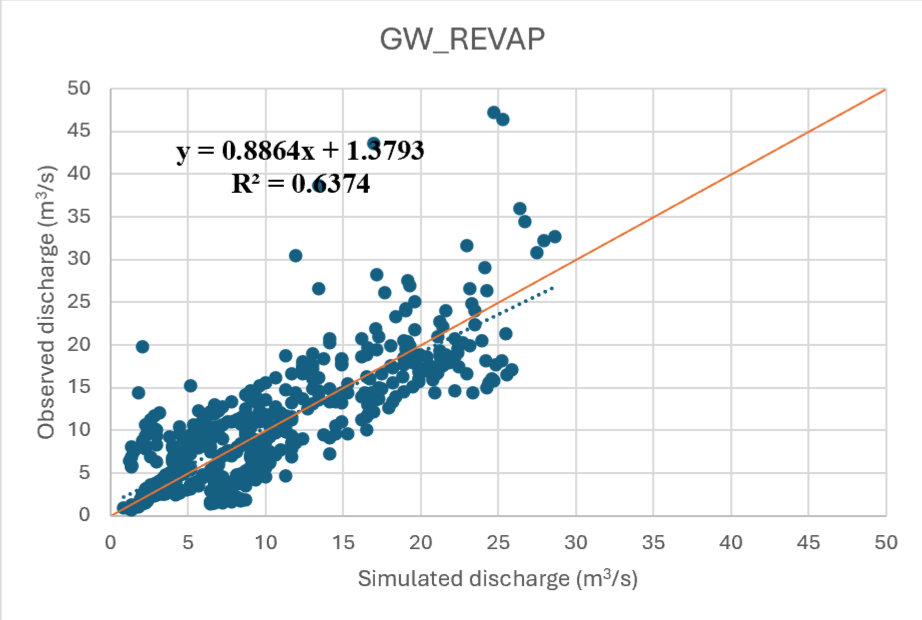
The watershed was delineated upstream of stream gauging station 1LA03, (Lat 0.79ºS, Long 35.34ºE) using the 30m by 30m SRTM DEM and a total of 16 sub-watersheds were obtained. The minimum and maximum elevations in the area are 1695 and 2972 m.a.s.l, respectively. The land cover classes in the watershed based on SWAT model land cover classification were closed trees with shrubs (FRST), rain fed herbaceous and shrub crops (AGRL), rain fed shrub crop-tea (TEA),very open shrubs with closed to open herbaceous and sparse tress (RNGE).

4.3.3 Model Calibration and Validation for Streamflow

The results indicated that the sensitivity of 5 parameters was significant. Table 4.9 shows the most sensitive parameters. The p-value for each of these parameters was less than 0.01 suggesting that their sensitivity is significant.

Table 4.9: The Most Sensitive Parameters

Parameter name	t-Stat	p-value
V_CH_K2.rte	6.34	0.00
V_GW_REVAP.gw	4.85	0.00
V_ALPHA_BF.gw	4.60	0.00
V_RCHRG_DP.gw	4.13	0.00
V_SURLAG.bsn	-3.43	0.00



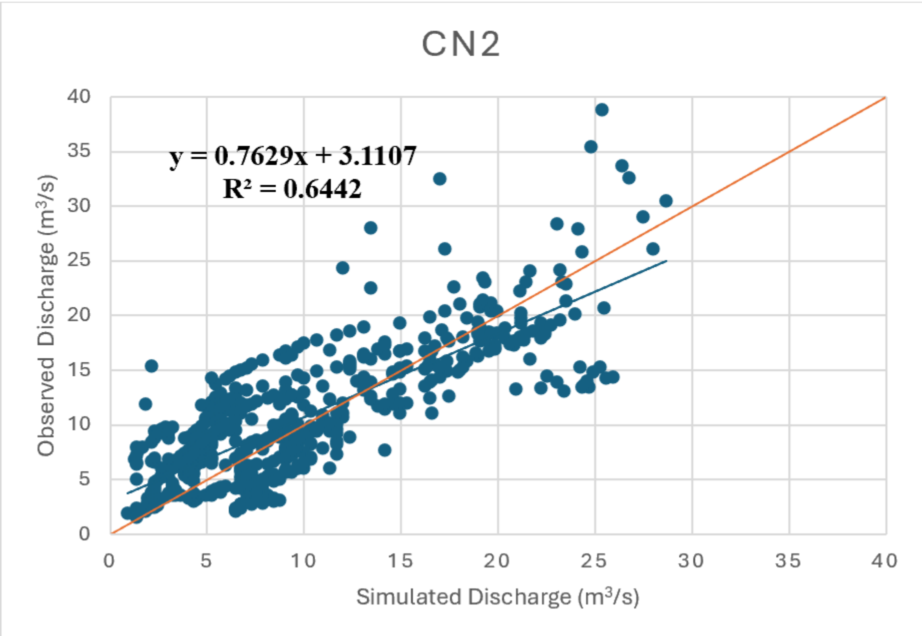


Figure 4.7: Scatter Plots of Simulated Versus Observed Discharge for CN2

Figure 4.7 shows the CN2 and GW_REVAP calibration results which show a satisfactory agreement between simulated and observed discharge, with an R^2 of 0.644 and 0.630 respectively. The regression slope below unity indicates slight underestimation of peak flows, while the positive intercept suggests the influence of base flow components not directly controlled by CN2 and GW_REVAP. Overall, the results confirm that the two parameters governs runoff generation and stream flow simulation

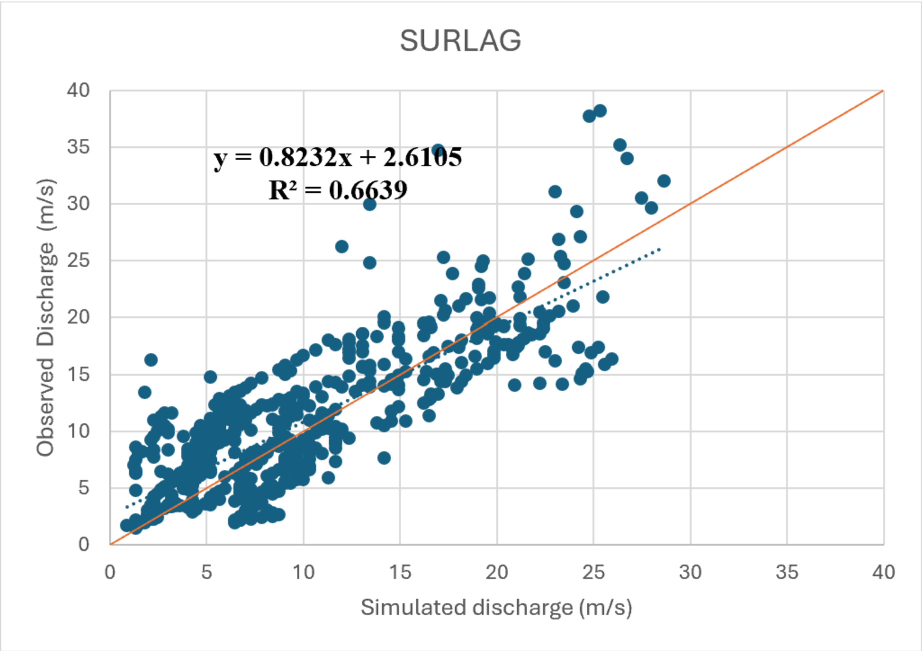


Figure 4.8: Scatter Plot of Simulated Versus Observed Discharge for SURLAG

Figure 4.8 shows simulated and observed discharge which exhibited a reasonably strong linear relationship (R^2 = 0.66), indicating satisfactory model performance following calibration. These results imply that surface runoff response and flow timing were adequately captured. The most commonly utilized statistical metrics for evaluating model calibration and validation are the Coefficient of Determination (R^2) and the Nash-Sutcliffe efficiency coefficient (NS). R^2 values range from 0 to 1, where 0 indicates no correlation between observed and predicted data, and 1 represents perfect correlation, meaning the model's predictions align exactly with the observed variance (Krause et al., 2005). The closer the R^2 value is to 1, the more accurate the simulation results. For the Nash-Sutcliffe coefficient, higher values reflect better model performance, with values closer to 1 indicating stronger predictive accuracy.

Additionally, the strength of calibration can be assessed using the P-factor and R-factor. In the SUFI-2 algorithm, the P-factor quantifies how well the model captures uncertainties, representing the percentage of observed data that falls within the 95% prediction uncertainty range (95PPU). The R-factor, on the other hand, measures the thickness of the 95PPU band relative to the standard deviation of the observed data. SUFI-2 aims to capture the majority of the observed data while maintaining a narrow uncertainty range.

The findings from the calibration and validation of the SWAT model for the Nyangores River watershed show a reasonable level of accuracy, as reflected in the statistical metrics obtained. The P-factor and R-factor values during calibration (0.69 and 0.95, respectively) as shown in table 4.10, indicate that the model successfully captured a significant portion of the observed data within the 95% prediction uncertainty, although the R-factor suggests a relatively wide uncertainty range. This trend is similar during validation, with a slight reduction in performance (P-factor 0.68, R-factor 1.11), reflecting an increase in uncertainty during the validation period.

The Nash-Sutcliffe efficiency coefficient (NS) and R^2 values during calibration (both 0.63) indicate a moderately good fit between the observed and simulated data. The values during validation, though slightly lower (NS = 0.56 and R^2 = 0.59) as shown in table 4.9, still reflect acceptable model performance, particularly for complex hydrological systems like the Nyangores watershed, where uncertainties in rainfall and land use dynamics can influence model outputs.

The results align with findings from previous studies that have applied the SWAT model in similar hydrological contexts. For example, Krause et al. (2005) reported that NS values between 0.50 and 0.65 are typical for watershed-scale hydrological models, especially in regions with variable rainfall and land cover. The values observed in the Nyangores River study fall within this range, confirming that the model's performance is comparable to other well-documented applications of SWAT. Gathangu et al 2018 concluded that implementation of contours and filter strips reduced sediments by 63%.Mwangi et, al (2011) reported a 73% sediment load reduction through combining contour farming with 5m grass strip.

In comparison to other calibration studies, Abbaspour et al. (2007) found similar P-factor values (around 0.7) and noted that achieving higher P-factors can be challenging in regions where limited ground-truth data is available for calibration. The slightly elevated R-factor during validation in this study (1.11) suggests that while the model captures much of the observed variability, the uncertainty during validation is greater, a common issue also highlighted by Rahman et al. (2018) in their study on rainfall variability and its impact on SWAT model calibration.

These findings are consistent with other applications of SWAT in regions with complex hydrology, where challenges such as sparse rainfall data and high variability in land use and soil characteristics introduce uncertainties in model predictions. For example, Zhang et al. (2015), in a study of a mountainous watershed, reported similar declines in model performance during validation, with NS values decreasing by around 10% compared to the calibration phase, as was the case in the Nyangores River study.

The reduction in model performance during validation suggests that while the SWAT model performs well during calibration, it may struggle with replicating hydrological processes during periods of less predictable rainfall and streamflow. This is a known limitation of many hydrological models when applied to data-sparse regions, as highlighted in studies such as Olaya et al. (2014), who reported similar trends when using satellite data to supplement sparse ground-based rainfall records.

Overall, the results of this study are in line with empirical evidence from other studies, demonstrating that the SWAT model can provide reasonably accurate predictions of streamflow and watershed processes. However, the slightly elevated uncertainty during validation highlights the need for more refined input data, particularly with respect to local soil and land use parameters, as well as more frequent ground-based rainfall measurements to improve model performance.

4.3.4 Model Calibration and Validation for Flow and Sediment

The calibration and validation of the SWAT model for sediment and nutrient transport were based on a limited number of field samples. Given the small sample size, the calibration process was somewhat simplified, relying on model adjustments that were not highly detailed. Before conducting comparisons, the units of sediment and nutrient measurements were standardized, as the field data were provided in milligrams per litre (mg/l), while the SWAT model outputs were in kilograms. Despite these limitations, the results show that the SWAT model provides reasonable predictions for sediment and nutrient transport, particularly when simulating the impact of different management practices.

For sediment calibration, the model achieved a P-factor of 0.90, an R-factor of 0.38, an R^2 of 0.96, and an NSE of 0.88, as presented in Figure 4.8 and Table 4.10. These statistics indicate a high level of accuracy in the model's sediment simulations, with most of the observed data falling within the model's 95% prediction uncertainty (95PPU) band. Similarly, for nutrient calibration, the model achieved an R^2 of 0.92 and an NSE of 0.86 for nitrate concentrations, as shown in Figure 4.10. The P-factor for nitrate calibration was 1.00, while the R-factor was 2.10, indicating that the model captured all of the observed data, although with a wider uncertainty range compared to sediments.

In terms of combined calibration for discharge, nutrients, and sediments, the model's performance was slightly lower but still acceptable. The P-factor for discharge was 0.76, with an R-factor of 1.31, an R^2 of 0.64, and an NSE of 0.63 (refer to Table 4.11). These combined statistics indicate that, while the model was able to replicate overall watershed dynamics, there is some variability in the predictions, particularly in the case of nutrients where the uncertainty was larger, as shown by the R-factor values.

The validation results followed a similar pattern, although with a slight decline in accuracy. For sediment validation, the model achieved a P-factor of 0.68, an R-factor of 1.11, an R^2 of 0.59, and an NSE of 0.56 (see Figure 4.8 and Table 4.11). For nutrients, the validation showed a P-factor of 1.00 and an R-factor of 2.10, with an

R^2 of 0.59 and NSE of 0.56 (refer to Figure 4.10). These results indicate a satisfactory performance, though the increased R-factor values for nutrients during validation suggest greater uncertainty, particularly in periods of high flow or significant runoff.

The key parameters adjusted during sediment and nutrient calibration, shown in Tables 4.12 and 4.13, played a critical role in achieving these results. For sediments, parameters such as USLE_P (the support practice factor for the Universal Soil Loss Equation), SPCON (the linear parameter for calculating sediment re-entrainment in channels), and SPEXP (the exponent for calculating sediment re-entrainment) were fine-tuned to better match the sediment transport observed in the watershed. For nutrients, parameters like ERORGN (the organic nitrogen enrichment ratio) and SOL_NO3 (the initial nitrate concentration in the soil) were adjusted to improve the accuracy of nutrient simulations.

A comparison of observed and simulated sediment concentrations (Table 4.14) reveals that the SWAT model reasonably replicated sediment loads during most periods. For example, on March 31, 2006, the observed sediment concentration was 426.1 mg/L, while the simulated value was 582 mg/L. Similarly, on September 6, 2006, the observed sediment concentration was 30.56 mg/L, and the model predicted 36 mg/L, showing a close match between observed and simulated data.

In comparison to other studies, the calibration and validation results align with findings from Abbaspour et al. (2007), who reported R^2 values between 0.60 and 0.90 and NSE values above 0.70 when simulating sediment and nutrient transport in various watersheds using SWAT. The high R^2 of 0.96 and NSE of 0.88 achieved for sediment calibration in this study are consistent with those findings, demonstrating that the SWAT model can accurately simulate sediment dynamics when properly calibrated. Additionally, the R^2 of 0.92 and NSE of 0.86 for nitrate calibration align with the ranges reported by Rahman et al. (2018), who noted similar values for nutrient transport in tropical watersheds.

However, the higher R-factor values during validation, particularly for nutrient transport, reflect greater uncertainty in the model's predictions. This is consistent with observations from Zhang et al. (2015), who noted that SWAT often struggles to accurately simulate nutrient transport during periods of high flow or significant runoff. The discrepancies between observed and simulated sediment concentrations during extreme events, as seen in this study, are also commonly reported in the literature, with Gassman et al. (2007) noting that SWAT tends to underestimate sediment transport during such events due to simplified in-stream sediment processes.

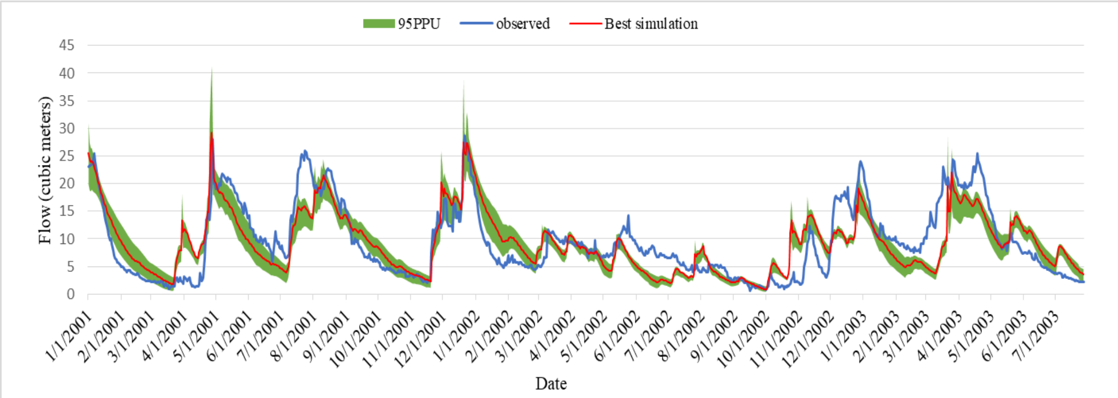


Figure 4.9: Flow Calibration 95PPU Curve Nyangores RGS

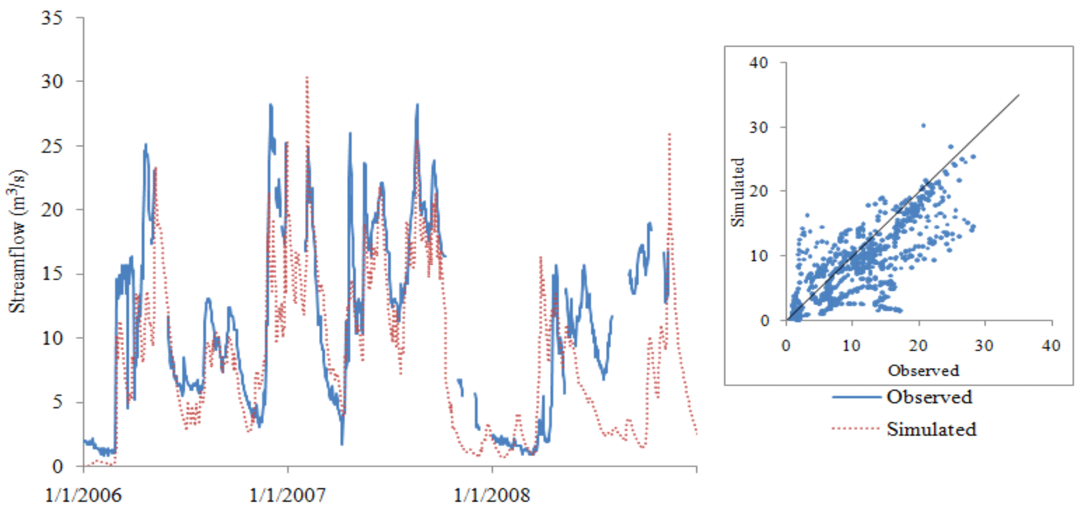


Figure 4.10: Flow Validation 95PPU Curve Nyangores RGS

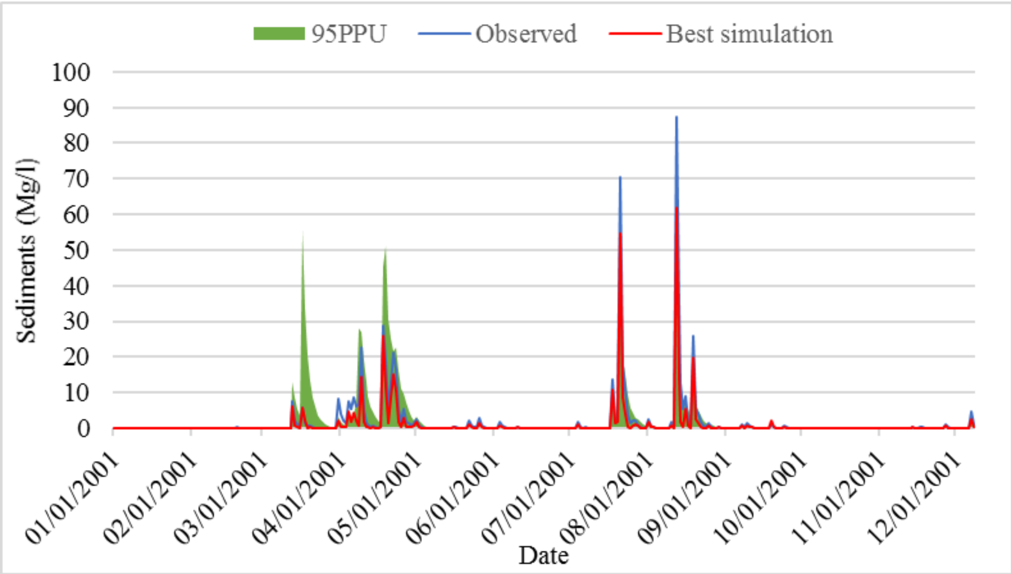


Figure 4.11: Sedimentation Calibration 95PPU Curve Nyangores River

Table 4.10: Summary Statistics after Calibration

GOAL TYPE				
VARIABLE	**P-Factor**	**R-Factor**	**R^2**	**NS**
VALUE	0.69	0.95	0.63	0.63

R^2= 0.63; NSE= 0.63

Table 4.11: Validation Statistics Summary

GOAL_TYPE				
VARIABLE	**P-factor**	**R-factor**	**R^2**	**NS**
FLOW_OUT_11	0.68	1.11	0.59	0.56

R^2= 0.59; NSE=0.56

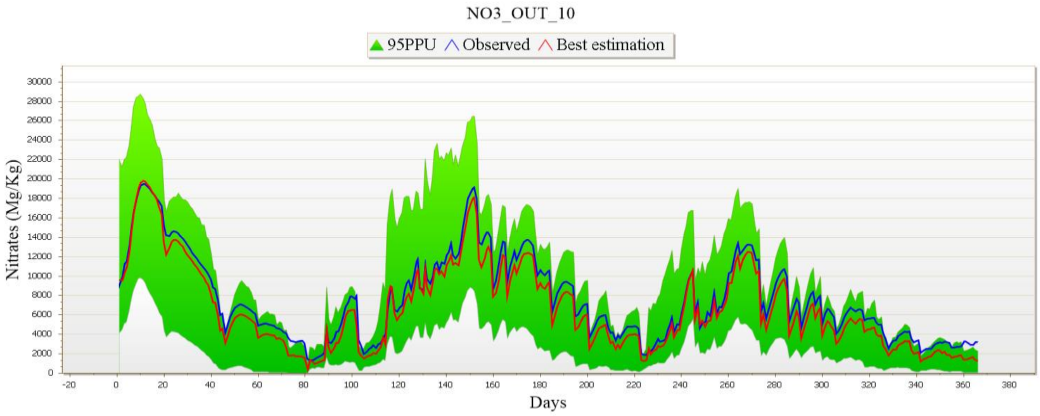


Figure 4.12: Nitrates Calibration 95PPU Curve Nyangores River

Table 4.12: Combined Nutrient, Sediment and Discharge Calibration Statistics

VARIABLE	P-FACTOR	R-FACTOR	R^2	NS
FLOW_OUT_11	0.76	1.31	0.64	0.63
NO3_OUT_10	1.00	2.10	0.92	0.86
SEDCON_10	0.90	0.38	0.96	0.88

Table 4.13: SWAT Parameters Changed for Nutrient Calibration

Parameters	Description	Variation ranges (Default value)	Value used/ Change used
ERORGN	Organic N enrichment ratio	0-5	1.868000
RCN	Concentration of nitrogen in rainfall	0-15	12.130000
NPERCO	Nitrogen percolation coefficient	0-1	0.718400
SOL_NO3	[mg/kg] Initial NO_3 concentration in the soil layer.	0-100	94.779999
FRT_SURFACE	Fraction of fertilizer applied to top	0-1	0.773000

4.4 Assessing the Effectiveness of the Best Management Practices (BMPs) on Nutrient and Sediment loads, in Improving water Quality in Nyangores Watershed

This section present analysis of the effectiveness of Best Management Practices (BMPs) on reducing sediment and nutrient loads in the Nyangores River watershed. The key BMPs evaluated through the SWAT model included filter strips and contour farming. These practices were modelled to assess their impact on improving water quality by reducing sediment yield and nutrient runoff, specifically nitrogen (NO_3) and phosphorus (PO_4).

4.4.1 Sediment Yield Reduction

SWAT was run on annual basis from 2003 to 2008. The annual sediment loading at the watershed outlet is shown in the Figure 4.13 below. These values were used as the baseline condition to which simulated sediments concentration was compared with.

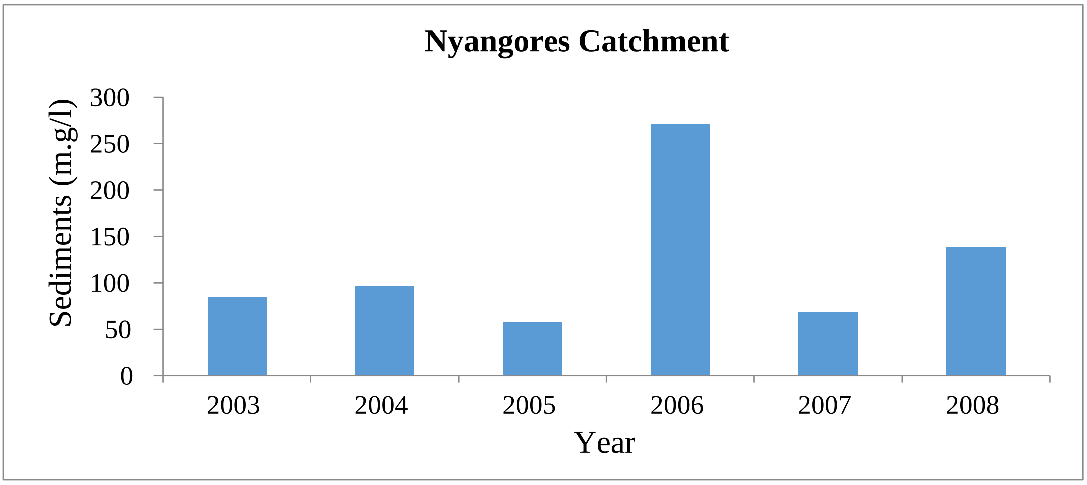


Figure 4.13: Shows Annual Sediment Loading at Watershed Outlet

The baseline simulation indicated that sediment yield in the watershed was 1.136 metric tonnes per hectare per year. After implementing filter strips, sediment yield decreased to 0.690 metric tonnes per hectare, reflecting a reduction of approximately 39%. Contour farming similarly reduced sediment yield to 0.726 metric tonnes per hectare, though it was slightly less effective than filter strips. The results are presented in Table 4.14.

Table 4.14: Sediment Yield Reduction under BMP Scenarios

Scenario	Sediment Yield (Metric Tonnes per Hectare)	Percentage Reduction
Baseline	1.136	-
Filter Strips	0.690	39
Contour Farming	0.726	36

From the results of this study, the implementation of BMPs led to significant reductions in sediment yield, underscoring the critical role these practices play in soil conservation and erosion control. Filter strips were particularly effective, reducing sediment yield by nearly 40%, while contour farming provided a 36% reduction.

Figure 4.14 and Figure 4.15 illustrate the reduction in sediment yield after implementing filter strips and contour farming, respectively.

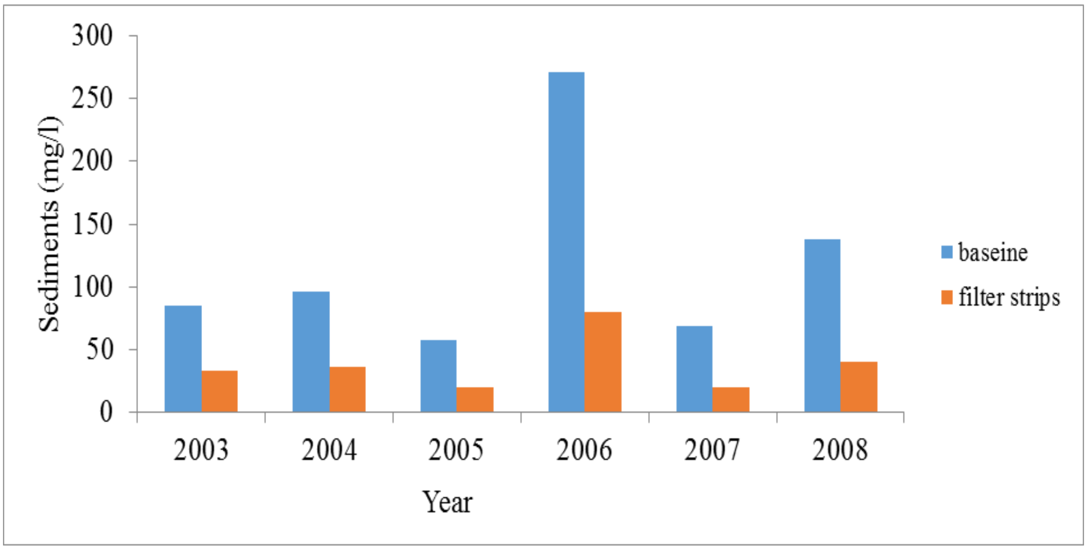


Figure 4.14: Sediments Reduction after use of Filter Strips

The implementation of filter strips significantly reduced sediment yield across the watershed. As shown in Figure 4.16, sediment yield decreased from the baseline value of 1.136 metric tonnes per hectare to 0.690 metric tonnes per hectare following the introduction of filter strips. This represents a 39% reduction in sediment yield, illustrating the effectiveness of filter strips in intercepting surface runoff and trapping sediment particles. The ability of filter strips to slow down water flow and enhance sediment deposition was particularly effective in agricultural areas, contributing to improved soil conservation and reduced sediment transport into the river system.

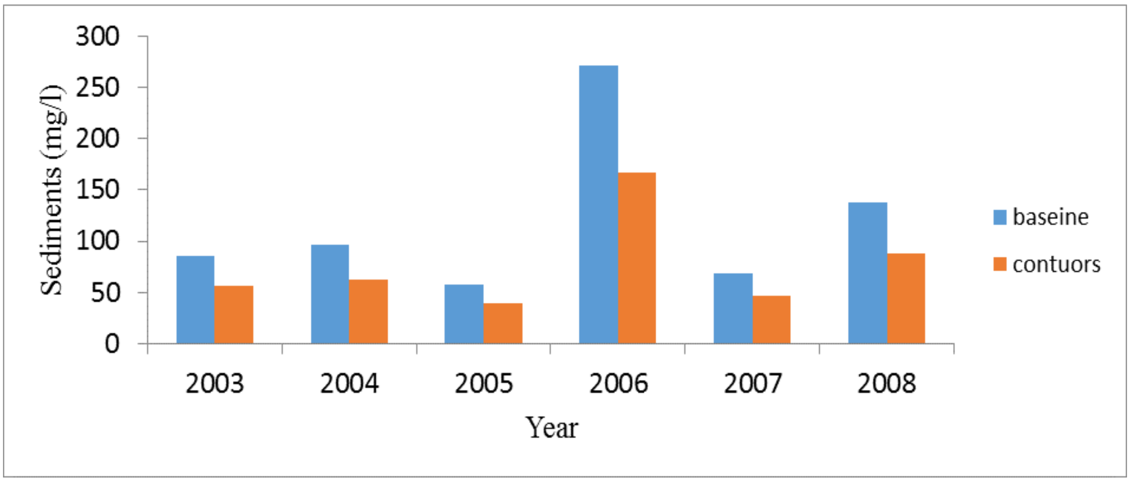


Figure 4.15: Sediments Reduction after use of Contours

Contour farming also demonstrated its effectiveness in reducing sediment yield, as shown in Figure 4.15. Sediment yield decreased from 1.136 metric tonnes per hectare under baseline conditions to 0.726 metric tonnes per hectare after contour farming was implemented. This reduction of approximately 36% highlights the role of contour farming in managing surface runoff and promoting water infiltration, thereby reducing soil erosion on sloped agricultural lands. While slightly less effective than filter strips, contour farming remains an important Best Management Practice (BMP) for reducing sediment transport and protecting water quality in the watershed.

Contour farming led to a reduction in sediment yield to 0.726 metric tonnes per hectare, reflecting a 36% decrease. These results highlight the critical role that BMPs, particularly filter strips and contour farming, play in soil conservation and erosion control.

The effectiveness of filter strips in reducing sediment yield aligns with findings from other empirical studies. Kibret et al. (2021) found that the implementation of vegetative filter strips in Ethiopia resulted in a significant reduction in soil erosion and sediment transport in agricultural watersheds. Similarly Sinyolo et al. (2020), reported that filter strips effectively reduced sediment yield in various watersheds, particularly in regions with high agricultural activity. The ability of filter strips to intercept surface runoff and trap sediment particles before they enter water bodies is well documented, making them a key strategy for managing erosion and sediment transport.

Contour farming, while slightly less effective than filter strips, also demonstrated its utility in reducing sediment yield. The 36% reduction in sediment yield observed in this study is consistent with findings from other research. Mwangi et al. (2018) showed that contour farming practices on sloped agricultural lands in Kenya resulted in significant reductions in soil erosion and improved water infiltration. Contour farming works by slowing down the flow of water across sloped fields, thereby reducing the erosive force of surface runoff and allowing more water to infiltrate the soil. This practice is particularly effective in hilly areas, where the risk of soil erosion is higher. By implementing BMPs such as filter strips and contour farming, land managers can mitigate the negative impacts of agricultural activities on soil and water resources. The reduction in sediment yield observed in this study demonstrates how targeted interventions can improve watershed health by preventing excessive sedimentation in rivers and streams. This is crucial for maintaining water quality and protecting aquatic habitats.

From a theoretical perspective, it explains how new practices, such as BMPs, are adopted and spread within communities. The adoption of these practices is likely to increase, leading to broader environmental improvements across the watershed.

4.4.2 Nitrogen (NO3) Load Reduction

From the results of the study, Nitrogen runoff, primarily in the form of nitrate (NO_3), was significantly reduced following the implementation of BMPs. The baseline NO_3 outflow in sub-basin 10 was 14.065 kg/m, which was reduced to 0.692 kg/m after the introduction of a 25-meter riparian buffer strip. This represents a reduction of approximately 95% in nitrogen load. The other scenarios percent reduction results are presented in table 4.15.

Table 4.15: Nitrogen Load Reduction under BMP Scenarios

Scenario	No_3 0utflow (Kg/m)	Percent Reduction (%)
Baseline	14.065	
25 m filter	0.692	95
20m	1.230	91
10m	2.674	81
5m	3.969	72

The substantial reduction in nitrogen load demonstrates the effectiveness of BMPs in mitigating nutrient pollution from agricultural runoff. Buffer strips, particularly riparian buffers, have been shown to effectively reduce nitrogen runoff by filtering out pollutants before they enter the river system. The effectiveness of BMPs in reducing nitrogen loads is also demonstrated across different sub-basin scenarios. The data from Table 4.16 and Table 4.17 shows a breakdown of nitrogen outflows based on various buffer strip widths in sub-basins 10 and 14 respectively. This detailed analysis helps to identify the optimal buffer width for maximum nitrogen reduction.

Table 4.16: Simulated Nitrate Outflow from Subbasin 10 for Various Buffer Strip Width

Filter size	No_3 output in (kg)			NO_3 reduction per unit width of filter strip		
(kg/m) Width (m)	2006 (Wet)	2003 (Average)	2007(Dry)	2006(Wet)	2003(Average)	2007 (Dry)
0	14.065	12.295	2.938			
5	3.969	3.56	1.059	2.02	1.75	0.36
10	2.674	2.385	0.706	0.14	0.99	0.22
20	1.230	1.167	0.427	0.64	0.56	0.13
25	0.692	0.569	0.01	0.53	0.47	0.12

Table 4.17: Simulated Nitrate Outflow from Subbasin 14 for Various Buffer Strip Width

Filter size <u>(kg/m)</u> Width (m)	No_3 output in (kg) 2006 (Wet)	2003 (Average)	2007(Dry)	NO_3 reduction per unit width of filter strip 2006(Wet)	2003(Average)	2007 (Dry)
0	16.350	13.77	4.945			
5	4.342	2.532	1.227	2.4	2.25	0.74
10	2.906	1.694	0.194	1.34	1.20	0.48
20	1.141	0.666	0.076	0.76	0.66	0.24
25	0.756	0.637	0.229	0.62	0.53	0.19

The results indicate that as the width of the buffer strip increases, the NO_3 output significantly decreases. A 25-meter riparian buffer was found to reduce nitrate outflow by over 95% in wet years, underscoring its effectiveness in nutrient management. This finding is consistent with studies by Liu et al. (2019) and others, which reported similar reductions in nitrogen runoff due to the implementation of riparian buffer zones in rural agricultural landscapes.

To visualize the effectiveness of BMPs, Figure 4.16 and 4.17 illustrate the reduction of nitrates in kilograms per meter of buffer strip width for sub-basins 10 and 14. The graphs highlight that smaller buffer widths yield greater nutrient reduction per unit area, but larger buffer widths provide a broader overall impact on nutrient retention.

The results of the model simulations for the three different flow scenarios—wet year (2006), dry year (2007) and average year (2003); and five different strip width (m) (0, 5, 10, 20 25 are presented in Tables 4.16 and 4.17. The actual yields of NO_3 of the subbasins 10 and 14 with and without the buffer strips a larger size of the filter strip leads to a decreased rate of reduction per unit width of NO_3 in both the cases of subbasins 10 and 14. However, the rate of NO_3 reduction decreases significantly as the width of filter strip increases to 25m and thereafter no more of nitrates and sediment is released. It is evident in the later part of the curves in figure 4.17 in average flow year cases. The dynamics of reduction in NO_3 outflows from the subbasins has one major components: the uptake of NO_3 by the vegetation in the filter strip. In the earlier part of the curve in figure 4.18 when the width within filter strip is small (25 m or less), there is more opportunity and availability of nutrients to be used up by the plants. In this case, the NO_3 reduction is due to uptake by plants. When the area within the filter strip increases, there is higher direct reduction in NO_3. However, there is more vegetation in the filter strip as candidate to use up the NO_3 if enough nutrients were available in their root zone. The dynamics of nutrients in the surface runoff and its interaction with the vegetation in the filter strip is somewhat different in the wet or dry year. When the flow is too high in case of a wet year, nutrients are carried away at a faster rate along with huge amount of water and there is not enough opportunity for the vegetation to use up the nutrient. Increasing the width of the filter strip still has some room for additional nutrients use up as shown in Figure 4.18. In case of dry year, the amount of flow is not enough to wash the nutrients from the crop area through the filter strip and there is always enough room for the additional nutrient to be utilized by the filter strip vegetation. Plots of NO_3 reduction per unit width of filter strips are shown in Figure 4.16 and Figure 4.17. This show that the per unit width reduction of NO_3 decreases with increasing width of the filter strips. NO_3 reduction per unit width in subbasin 14 appears to increase slightly when the width of filter strip increases initially from 10m to 20m Figure 4.17. Subbasin 14 has relatively steeper slope and average flow year on steep slope might provide enough nutrient to be captured by a wider riparian buffer. Comparing the results of subbasins 10 and 14, subbasin 10 has higher effective reduction in NO3-N outflow compared to subbasin 14. Subbasin 10 is a high impact subbasin based on total NO_3 contribution, and it could be the prime target for conservation of water quality.

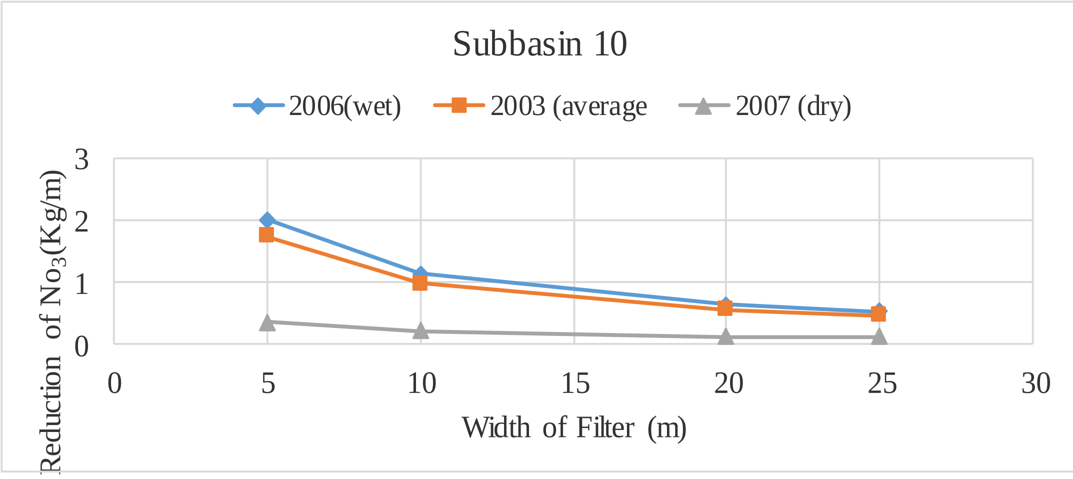


Figure 4.16: Reduction of Nitrates (NO_3) per Meter Increase in Buffer Strip Width in Sub-basin 10

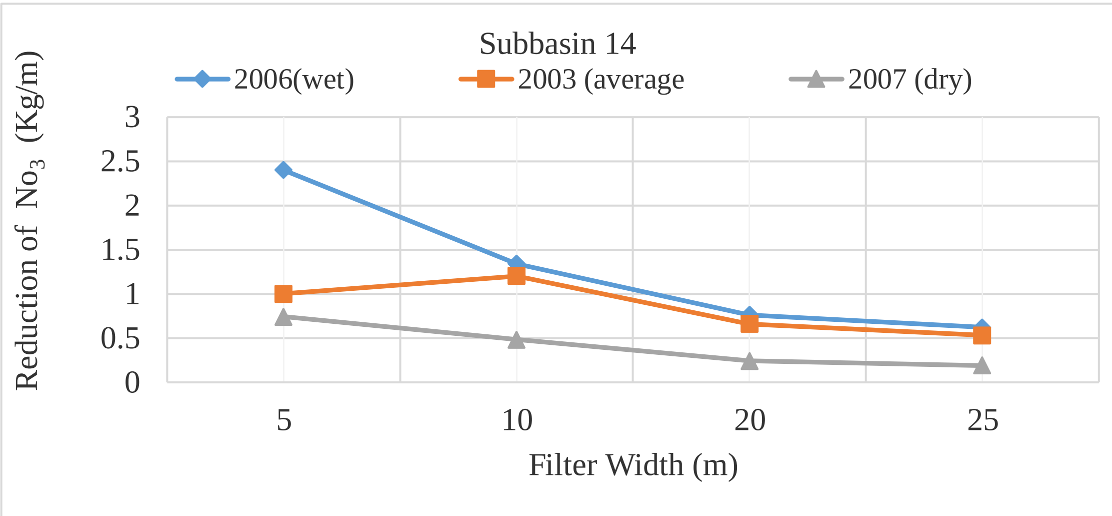


Figure 4.17: Reduction of Nitrates (NO_3) per Meter Increase iIn Buffer Strip Width in Sub-basin 14

The significant reduction in nitrogen load across the watershed demonstrates the effectiveness of BMPs in mitigating nutrient pollution from agricultural runoff. Riparian buffer strips, in particular, have proven to be highly effective in filtering out pollutants before they enter the river system. These findings are in line with research conducted by Sinyolo et al. (2020), which also reported substantial reductions in nutrient runoff following the implementation of BMPs in watersheds across Africa.

In this study, the implementation of a 25-meter buffer strip reduced nitrogen outflows by 95%, a result consistent with global findings. Studies by Neitsch et al. (2011) also highlight the effectiveness of vegetative buffer strips in reducing nutrient pollution. The results further emphasize the importance of riparian buffer zones in nutrient retention, preventing excess nitrogen from reaching water bodies, and reducing the risk of eutrophication.

These findings are consistent with studies by Sinyolo et al. (2020) and Kibret et al. (2021), which reported similar nutrient load reductions through the implementation of BMPs.

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

i. **Key Sources of Pollution**

The findings show that agricultural runoff is the most significant source of nutrient pollution in the watershed, contributing elevated levels of nitrates (mean concentration: 11.208 mg/L) and phosphates (mean concentration: 20.820 mg/L). This confirms that agricultural areas contribute to nutrient loading, which increases the risk of eutrophication. The statistical analysis reinforces this, with the Chi-square test revealing that the concentrations of nitrates (Chi-square value: 22.19) and phosphates (Chi-square value: 29.72) are significantly influenced by agricultural land use. Additionally, urbanization was identified as a secondary contributor to pollution, with significant impacts on sediment loads due to increased deforestation and construction activities.

ii. **SWAT Model Calibration and Validation**

The SWAT model was successfully calibrated and validated for streamflow, sediment, and nutrient transport, achieving acceptable levels of accuracy. The calibration results yielded an R^2 of 0.96 and a Nash-Sutcliffe Efficiency (NSE) of 0.88 for sediment transport, indicating a high level of model performance. For nutrient transport, nitrate calibration showed an R^2 of 0.92 and an NSE of 0.86. These results confirm the model's robustness in simulating the dynamics of the Nyangores watershed under different land-use and management scenarios.

iii. **Effectiveness of Best Management Practices (BMPs)**

Model simulations for three different flow scenarios wet year (2006), dry year (2007) and average year (2003) under five different strip width (m) (0, 5, 10, 20 25) showed actual yields of NO_3 and sediment of the subbasins 10 and 14 with and without the buffer strips. Larger size of the filter strip leads to a decreased rate of reduction per unit width of NO_3 and sediment yield in both the cases of subbasins 10 and 14. However, the rate of NO_3 reduction decreases significantly as the width of filter strip increases to 25m and thereafter no more of nitrates and sediment is released. The dynamics of reduction in NO_3 outflows from the subbasin has one major components: the uptake of NO_3 by the vegetation in the filter strip. When the width within filter strip is small (25 m or less), there is more opportunity and availability of nutrients to be used up by the plants. In this case, the NO_3 reduction is both due to uptake by plants. When the area within the filter strip increases, there is higher direct reduction in NO_3 application. However, there is more vegetation in the filter strip as candidate to use up the NO_3 if enough nutrients were available in their root zone.

5.2 Recommendations

i. **Addressing Pollution Sources**

Implement riparian buffer zones and enforce sustainable agricultural practices to mitigate nutrient pollution and erosion.

ii. **Adoption of SWAT and Other Models**

Collect comprehensive field data and refine SWAT model inputs to improve simulation accuracy, especially during high-flow events.

iii. **Widespread Implementation of BMPs**

Promote and support the adoption of BMPs through financial incentives and technical training for farmers and landowners. The riparian buffer zones should be well protected with vegetation like grass to filter out the nutrients before getting into the rivers.

iv. Recommendations for Further Studies

Investigate the long-term effectiveness of BMPs under climate change, and compare SWAT with other models like WEPP for improved watershed management.

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APPENDICES

Appendix I: Pictorial for Collection of Water Samples from Runoff Plots Set Up in Nyangores River Catchment

Appendix II: Pictorial, Animal Excreta along the Cattle Tracks One of the Main Cause of Nutrients Flow into Nyangores River

Appendix III: Animals' Defecation and Charcoal Burning along the Banks of River Nyangores

Appendix IV: Pictorial, Construction of Runoff Plots with the Help of the Community

Appendix V: Taking Runoff Samples at the Forest for Analysis

Appendix VI: Pictorial, Collection of Runoff Samples from the Bareland and Grassland Plot

Sediment analysis in JKUAT Laboratory

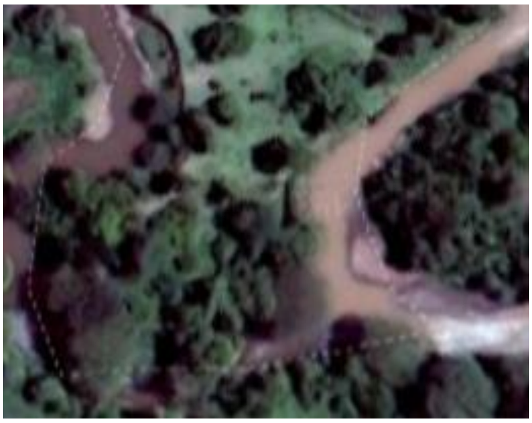
Appendix VII: Pictorial, Collection of Runoff into the Plastic Bucket. The Plot Fully Installed in a Natural Forest

Appendix VIII: Sampling Points along the Banks of the Nyangores River

Appendix IX: Tenwek Water Falls Point (-0.744432, 35.363985)

Appendix X: Bomet Pumping Station (-0.789824, 35.6528) and 02 Tea buying Center (-0.703185, 35.392250)

Appendix XI: Olbutyo Bridge (0.990061, 35.260637) Confluence of Nyangores and Amala Rivers (-1.037627, 35.241940)



Appendix XII: Pictorial, Sediment Deposits on the River Bed, Water and Soil Sample at JKUAT Lab for Analysis