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IMPACT OF LAND USE/COVER CHANGE ON SOIL EROSION AND SURFACE WATER QUALITY:

A case of Upper Lilongwe River Catchment, Central, Malawi.

By

Idrissa Shamsdeen Nkwanda

A thesis submitted to the African Centre of Excellence for Water Management (ACEWM) in partial fulfilment of the requirement for Master’s Degree in Water Management (Water Supply& Sanitation) of Addis Ababa University

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Supervisor: Dr Gudina Legese Feyisa

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This is to certify that we the undersigned, have examined this MSc Thesis entitled **"IMPACT OF LAND USE /COVER CHANGE ON SOIL EROSION AND SURFACE WATER QUALITY: A case of Upper Lilongwe River Catchment, Central, Malawi"** and that in our opinion; it is fully adequate, in scope and quality, as a MSc thesis for the Degree of Master of Science in Water Management (Water Supply and Sanitation).

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ii

Statement of the author

Statement of the author

I, **Idrissa Shamsdeen Nkwanda**, declare that this research report is my original effort and work and to the best of my knowledge, the findings have never been previously presented to the Addis Ababa University or elsewhere for the award of any academic qualification. Where assistance was sought, it has been accordingly acknowledged. The findings, interpretations and conclusions expressed in this study neither reflect the views of the Addis Ababa, African Centre of Excellence for Water Management (ACEWM), nor those of the individual members of the MSc Examination Committee.

Signature: ……………………………………………

Date: 13/07/2020……………………………………………

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Abstract

Safe drinking water, hygiene and good sanitation are important for good health, human survival and development. However anthropogenic activities such as land use have affected water quality in many river catchments worldwide. The adverse effect of water pollution has attracted management attention and research interest in both developed and developing countries. However, there is very limited knowledge on the influence of land use and land cover on water quality in Malawi's catchments. Therefore, this paper aimed at assessing the impact of Land use on Soil erosion and Water quality in upper Lilongwe river which is very important for drinking, irrigation and recreation of Malawi's capital city. The study first assessed the land use patterns between 1989 and 2019 and results showed that forest land has decreased from 66727 ha to 33594 ha from 1989 to 2019 indicating a forest loss of 46.65%. Grass/shrubs/bare land has also declined by 11.49% and water body by 25.32% within the same period. On the other hand, cultivated land has increased by 26.06% and built up by 56.68%. The land use maps indicate that Lilongwe River catchment has experienced declines in forest land with conversion into shrubs and grasslands then cultivated and built-up. Water bodies such as wetlands have also been converted into cultivated lands. The impact has been water resources depletion and watershed degradation that include accelerated rate of soil erosion and water quality degradation. Soil erosion was assessed by using MUSLE model and revealed that about 83% of the area was classified to not have any soil erosion risk (< 1 ton/ha/yr) and 16 % light risk (1-10 tons/ha/yr). For assessment of water quality, nine water monitoring points across the upper, middle and lower catchment were sampled during the rainy season in February 2020. Turbidity, SS, TDS, EC, nitrates, phosphates, pH and faecal coliform were analysed according to standard methods and compared with MBS drinking water standards. The results showed significant ($p>0.05$) spatial variability of nitrates, phosphate and faecal coliform between the upper section and the middle and lower section. Furthermore, the study found a positive correlation between cultivated land, Built-up with nitrate and phosphate while forest and grassland had an inverse relationship with nitrate and phosphate. This study suggests that the implementation of integrated watershed management, promoting afforestation, enforcement of buffer zones along the river banks can assist in improving the state of the catchment and improving water quality and quantity within the catchment.

Keywords: Catchment, Land use napping, MBS, MUSLE

Table of Contents

LIST OF FIGURES

List of Tables

Abbreviations and Acronyms

AGNPS	Agricultural non-point Source Pollution Model
AnnAGNPS	Annualized AGNPS
EC	Electric Conductivity
GIS	Geographical Information System
LWB	Lilongwe Water Board
LULC	Land Use/ Land Cover
MUSLE	Modified Soil Loss Equation
MBS	Malawi Bureau of Standards
RS	Remote Sensing
RUSLE	Revised Universal Soil Loss Equation
ToC	Total Organic Carbon
USLE	Universal Soil Loss Equation
USDA	United States Department of Agriculture
USDA-ARS	USDA-Agricultural Research Service
SADC	Southern Africa Development Commission

1. INTRODUCTION

1.1. Background of the study

Water is the most abundant environmental resource on earth but its accessibility is based on quality and quantity, as well as space and time. This implies that water may be available in various forms and quantity but its use for various purposes is the subject of quality. Despite water being a basic requirement for human survival, the global water crisis is visible when it has been found that about 1.2 billion people worldwide were unable to access basic water in 2017 (WHO/UNICEF, 2017). That big population under water stress at present warns a bitter future for the world. In addition to the already existing water stress problem, it has been estimated that over 700 million people could be displaced by 2030 due to intense water scarcity (UN, 2019). According to UNESCO/UN-Water, (2020) around four billion people currently experience severe physical water scarcity for at least one month per year, a situation that has been exacerbated by the climate crisis. One of the seventeen SDGs aims at ensuring universal and equitable access to safe and affordable drinking water for all the people by 2030. However, there is still a lot of things to be done in order to make this goal a reality.

In most parts of the world, already-scarce freshwater resources are under unprecedented stress from different drivers and pressures, including urbanization, land-use change, population growth, increased food/water demand, and climate change (Dabrowski & De Klerk, 2013; Saraswat, Mishra, & Kumar, 2017). Some researchers have reported that the cumulative effects of both natural and anthropogenic activities have significant impacts on land use, which ultimately affects the services provided by the local ecosystems (Chu, Liu, & Wang, 2013; Gardner & Vogel, 2005). Land-use and land-cover (LULC) change have direct impacts on ecosystems and their associated services, particularly on water yield and water quality (Suxiao Li *et al*., 2018). Quentin *et al*., (2006) defined land-use change as any physical, biological or chemical change attributable to management, which may include conversion of grazing to cropping, change in fertilizer use, drainage improvements, installation and use of irrigation, plantations, building farm dams, pollution and land degradation, vegetation removal, changed fire regime, the spread of weeds and exotic species, and conversion to non-agricultural uses. Deforestation is known as one of the most important elements for changes in land use and landcover. It is recognized as a major driver of the loss of biodiversity and ecosystem services

(Ngwira & Watanabe, 2019). Globally, deforestation has been occurring at an alarming rate of 13 million hectares per year (Arekhi, 2011). Malawi has the highest deforestation rate in the SADC region with a loss of 30,000 to 40,000 hectares of forested land annually (Mauambeta *et al.*, 2010). The high rate of forest loss is mainly attributed to the expansion of agriculture and excessive use of biomass such as wood and charcoal used for cooking and heating (Ngwira & Watanabe, 2019).

Inappropriate use of land for agriculture and poor management of its natural environment leads to environmental problems such as land degradation through soil erosion. Soil erosion in various forms such as sheet, rill, gully bank and bed, river bed and bank and landslides provide sediment to critical water bodies. Nutrients and chemicals from cropland and urban sewage are transported into the water systems. For instance, many reservoirs that have been established for hydroelectric power, urban water supply, and irrigation accumulate an alarmingly higher level of sediment than expected. The consequences of reservoir sedimentation include the loss of storage capacity and its subsequent effects. These effects include water supply shortages for human consumption, irrigation and hydropower, increased hydro-equipment maintenance and repair, a decline in water quality, increase in the cost of removing sediment, blockage of navigational waters and loss of recreation opportunities (Wolancho, 2012).

The adverse effects of land use on water quality have attracted management attention and research interest both in developed and developing countries to understand the relationship between the two that can be instrumental to solve the problems (Faiilagi, 2015). Protecting and restoring water-related ecosystems such as forests, mountains and wetlands are essential to mitigate water scarcity, unsafe water access, and water availability. Protection and restoration of clean water sources such as forests reduce the costs associated with water treatment because water purification is one of the regulating services of ecosystems provided by the ecosystem to human beings (TEEB, 2010).

1.2. Problem Statement

Land use and Land cover changes affect geomorphology, soil properties, hydrological processes and thus water quality and quantity at global, regional and local scales (Wan, et al., 2014). The continued conversion and development of forested land pose a serious threat to the ecosystem's ability to provide key ecosystem services, particularly concerning the provision of drinking water (Vincent, et al., 2016). Deforestation, overgrazing and poor land management accelerate the rate of soil erosion and sedimentation of water reservoirs in developing countries (Conway, 2000). Disturbances in vegetative cover (land use/cover changes due to agriculture, timber and charcoal harvest, construction and others) leave soils vulnerable to erosion.

However, as observed by Han, *et al.*, (2019) where and how much are eroded and transported downstream largely depends on topography and soil hydrological properties. Once eroded, the sediment's journey down the catchment depends significantly on runoff which, over time, reduces in speed resulting in deposition (Han, et al., 2019). Malawi is experiencing a high rate of deforestation due to agricultural land expansion and excessive use of biomass. Deforestation in Malawi is affecting the operations of the semi-public Water Boards in ensuring sustainable water supplies at source water catchments, both in the dry and wet seasons. While there is an important problem of low flows in most source rivers during the dry season, the wet season is full of flooding and sedimentation in rivers affecting pump operations at water abstraction points (Wiyo *et al.*, 2015). Malawi's river catchments, despite being important for its population, have been deteriorating in terms of river channel integrity, ecosystem health and water quality due to human activities (Pullanikkatil *et al.*,2015). The upper Lilongwe river catchment which includes Dzalanyama forest reserve is one of the most threatened natural ecological systems in Malawi due to tobacco curing, brick burning, firewood and charcoal selling that has intensified in the rural communities surrounding it (Katumbi *et al.*, 2015; MUNTHALI, 2013). However, there is little information on the impacts of land use on water quality and soil erosion in the catchment as most of the studies done in the area only focus on the impact of deforestation on the loss of biodiversity and drivers of deforestation in the forest (Katumbi et al., 2015; Munthali & Murayama, 2011). There is a need to establish the relationship between the land-use change and soil erosion and water quality in the catchment.

1.3. Research Objectives

Main Objective

The overarching objective of this study was to analyse the impact of land use/cover changes on soil erosion and water quality in the upper Lilongwe river watershed, Lilongwe, Malawi.

Specific Objectives

The study pursued the following Specific Objectives:

- To assess land use/cover dynamics in the upper Lilongwe River watershed for 1989, 1999, 2014 and 2019.
- To estimate and map the current soil erosion in upper Lilongwe River watershed.
- To analyse the spatial and temporal variability of water quality parameters in the catchment.
- To assess the implication of current land use/cover changes on the specified water quality parameters.

1.4. Research Questions

In pursuing the above objectives, the study strived to answer the following questions:

- To what extent has LULC changed in the upper Lilongwe river Catchment over the past 30 years?
- What is the current rate of annual soil erosion in the watershed and what is the trend of soil erosion in the Upper Lilongwe River watershed?
- What is the quality of water in different seasons and location/sections of the catchment?
- What has been the implication of LULC change on water quality in the catchment?

1.5. Significance of the Study

The study contributes to determining the effects of land-use on water quality which is fundamental in addressing water pollution at the catchment level. This nature of study are scarce in Malawian water basin's hence it contributes to the body of scientific knowledge at the country level. The present study provides baseline data focusing on water quality, soil erosion and observes land use with the intent of identifying the major land-based activities that cause changes in water quality. This information is useful for local government, LWB, and communities in the development of more effective and holistic approaches for improving water quality in the upper Lilongwe river catchment. The study further suggests approaches that can be employed to improve the yields in the catchment area and reduce siltation both in the reservoir and the river. Amare (2005), reports that to increase the life of the reservoir and best achieve the purpose for which it has been constructed for, reducing sediment inflow and removing sediment from the reservoir are substantial activities. Integrated watershed management is one of the mechanisms that can be employed to reduce sediment yield (Wolancho, 2012). The findings of the study also provide baseline information on how the land cover change is affecting the whole catchment and hindering LWB's provision of potable water to the people in the city every day throughout the year. This would enable policymakers to formulate policies that are harmonised that will minimize the undesirable effects of future land cover changes. Using maps and models to identify high priority land for protection and restoration is critical, as funding is always limited and multiple demands are often made upon a valuable piece of land (Ernst, 2004) hence the study has identified high priority land for protection in the catchment.

1.6. Scope and Limitation of the Study

The study aimed at assessing the impact of LULC change on soil erosion and surface water quality of upper Lilongwe river basin, hence the LULC change analysis and soil erosion mapping was only done in the catchment area which is approximately 1,870 Square kilometres. The study estimated average annual soil loss from the watershed and mapped soil erosion risk using MUSLE model which is an event-based model hence long-term soil erosion mapping was not done and the actual rate of sedimentation in the reservoirs and river were not estimated.

Water samples were collected from already existing monitoring points in the watershed and analysed for the following selected parameters: Turbidity (Total dissolved solids, Suspended solids), pH, electric conductivity (EC), Faecal coliform, Nitrate, and Phosphate. Seasonal variability of the selected parameters was evaluated for some of the parameters because the secondary data collected from LWB does not contain all the selected parameters in this research.

The study overlooked the impact of climate change on water quality which is equally important because it was beyond the scope of the study. The study further overlooked the significance of Drivers, Pressures, States, Impacts, Responses (DPSIR) model application though it is a significant tool for generating evidence based on multiple causes -effects relationships which can help to draw a practical recommendation on sustainable management of land and water resources within Lilongwe River catchment. DPSIR was overlooked due to resource constraint which includes lack of data.

Within the aforementioned scope, the study was carried out in a way that the results produced are credible and of great importance to Malawi's (LWB) sustainable development plans.

2. LITERATURE REVIEW

2.1. The Concept of Land Use/ Land Cover Change

The terms land use and land cover are often used interchangeably even though there is a distinction between the two terms. Many authors define land use as; the intended employment of land management strategy placed on the land cover by human agents, or land managers to exploit the land cover and reflects human activities such as industrial zones, residential zones, agricultural fields, grazing, forestry, and mining, just to mention a few (Bello *et al*., 2018; Zubair, 2006). On the other hand; Land cover refers to the surface cover on the ground, whether vegetation, urban infrastructure, water, bare soil, or other. It should be noted that LC does not describe the use of land, and the use of land may be different for lands with the same cover type. In simple terms, land use indicates how people are using the land, whereas land cover indicates the physical attribute of the land. Both types of data (land use/ land cover) are most often obtained from the analysis of either satellite or aerial images. Land cover data shows how much of the region is covered by grass, forest, impervious surfaces and croplands, and water types (wetlands or open water). Land use data shows how people are using the landscape whether for development, agriculture, recreation, conservation, or mixed uses.

Originally Land cover had a different meaning from what it has now. It used to refer to the kind and state of vegetation, such as forest or grass cover but it has broadened in subsequent usage to include other things such as human infrastructures, soil type, biodiversity, surface and groundwater(Meyer 1999)

LULC change can be defined as to be any physical, biological or chemical change attributable to management, which may include conversion of grazing to cropping, change in fertilizer use, drainage improvements, installation and use of irrigation, plantations, building farm dams, pollution and land degradation, vegetation removal, changed fire regime, the spread of weeds and exotic species, and conversion to non-agricultural uses (Quentin *et al.,* 2006). LULC change may further be categorized into two; conversion and modification. Conversion refers to changes from one cover or use type to another, while modification involves maintenance of the broad cover or use type in the face of changes in its attribute (Bello *et al*., 2018).

Anthropogenic and natural factors are responsible for global land cover and land-use change. Although at minimum rate compared with anthropogenic activities, natural activities such as weather, flooding, fire, climate change, global warming, drought, volcanoes, Tsunami and ecosystem dynamics cause the land cover change. The main cause of Land cover change is anthropogenic activities due to the way the land is used by human beings. The anthropogenic activities that alter the land cover are, settlement, expansion of agricultural fields, urbanization and unsustainable development activities, just to mention a few. The LULC change has serious direct and indirect consequences which include the change in water quality and quantity (Kebede *et al*., 2014).

Despite Land use and Land cover change being different, they are normally used interchangeably because a change in the other affects the other. Land use affects land cover and changes in land cover affect land use. However, change in land cover by land use do not necessarily imply a degradation of the land because some land cover change improves the land. For example, planting trees on bare land for recreation purposes improves the land cover. However, many shifting land-use patterns driven by a variety of anthropogenic causes, result in land cover changes that affect biodiversity, water, and radiation budgets.

The use of GIS and remote sensing data and analysis techniques, provide timely, accurate, and detailed information to detect and monitor change in the environment and its implications whether positive or negative impacts (Ban & Yousif, 2016).

2.2. Causes and Drivers of Global Land Use/Land Cover Change

Since time immemorial, humankind has changed landscapes in attempts to improve the amount, quality, and security of natural resources critical to its wellbeing’s, such as food, fresh water, fibre, and medicinal products. With time human beings have been very innovative in finding ways of deriving natural resources from the environment at an increasing rate to meet its ever-growing demand and expand its territory. According to Heistermann *et al.* (2006), a driver of land-use change is defined as causing a change in the total area allocated to a specific land-use type or a change in the spatial distribution of land-use types. The LULC drivers are scale-dependent, as changes in the spatial arrangement of land use may not be detected if the analysis is carried out at a coarse resolution or to a small extent. Also, different drivers can have a dominant influence on the land-use system at different scales of analysis. For instance, at a local level, this can be determined by local policy, while at a regional level this could be attributed to; the distance to market (Verburg *et al.*, 2004). Briassoulis (2006) categorized the drivers of land-use change into two; biophysical and socio-economic drivers. Whereby, the biophysical drivers include characteristic and process of the natural environment such as climate variation, landform, and geomorphic process, plant succession, soil types and process, and drainage pattern, while the socio-economic drivers comprise demographic, social, economic, technological, market, political and institutional factors and their processes. Biophysical drivers in most cases do not 'drive' land-use change directly (Verburg *et al*. 2004), but rather cause land-cover changes, for example, through climate change and influencing land use allocation decisions.

Globalization of food supply and increasing international trade of agricultural supplies has led to the intensification of agricultural production through the usage of greater inputs, such as fertilizer, pesticides, water, and or changes to management practices, and agricultural expansion (Johnson *et al*, 2014; Cossman, 1999). Improvement in agricultural yield has still caused land-use change despite being able to meet the ever-growing demand (FAOSTAT, 2014). Agriculture has been the greatest force of land transformation on this planet. Nearly a third of the Earth's land surface is currently being used for growing crops or grazing cattle. Much of this agricultural land has been created at the expense of natural forests, grasslands, and wetlands that provide valuable habitats for species and valuable services for humankind (Millenium Ecosystem Assessment, 2005). Numerous negative environmental impacts can result from land-use change or agricultural intensification, including greenhouse gas emissions, deteriorating soil quality, use of scarce water resources, and biodiversity loss (Smith *et al*., 2013).

2.3. Drivers of Land Use/Land Cover Change in Malawi

Malawi gained independence in 1964 and since then, agriculture has continued to play a central role in defining Malawian rural livelihoods. It employs over 85 % of the rural population, normally accounts for 35–40 % of Gross Domestic Product (GDP), and contributes over 90 % to total export earnings (GoM, 2007). Livelihood activities are known and believed to cause most of the forest loss in Malawi. According to Katumbi *et al*., (2015), agricultural expansion has a visibly negative impact on forest cover; however, the process of agricultural expansion can only be understood in the context of population growth. Moreover, population fluctuation alone is not evident enough to explain the encroachment into forest land. The situation in Malawi has been linked with a failure to intensify agricultural production on existing land. According to FAOSTAT (2010) in 1975; 47% of the land in Malawi was classified as forest. Nonetheless as of today, the country only has 36 % of the total land categorized as forest. Out of this forest area, 15 % is under natural woodlands on customary lands, 11 % is under national parks and game reserves and only 10 % under forest reserves and protected hill slopes. Malawi registers the highest forest degradation rate in the SADC region, representing a net loss of 30,000 to 40,000 hectares per year of (mostly miombo) woodland (Katumbi *et al*., 2015). Tobacco is the main cash crop in Malawi and many farmers expand their agricultural land to increase earning and profit. The tobacco farmers also extract wood from forests to construct the barns that are used for air curling the tobacco (Ngwira & Watanabe, 2019).

Over-dependence on the use of biomass (such as wood and charcoal), is also one of the leading causes of deforestation in Malawi (Gowela & Masamba, 2002). The biomass accounts for 95.4 per cent (firewood; 77.4 % and Charcoal; 18%) of the nation's energy demand for cooking (NSO, 2019). There is a high demand for charcoal and firewood in urban and suburban communities that make the marketing of fuel-wood products cost-effective. As such, a lot of people in Dzalanyama (just like in any other forest) have abandoned farming and started this business (Katumbi *et al*., 2015).

Infrastructure development is also contributing to land cover change in Malawi. Clay bricks are burned using firewood before being used for the construction of buildings in Malawi. Ngwira and Watanabe (2019), reported that on average each brick-walled house uses 4 metric tons of wood. Sand mining in the rivers is also contributing to the LULC changes.

2.4. Land Use/ Land Cover Change Models

Land-use change is a complex, dynamic process that links together natural and human systems. It has direct impacts on soil, water, and atmosphere (Meyer & Turner, 1994) and is thus directly related to many environmental issues of global importance (Koomen, Stillwell, Bakema, & Scholten, 2007). Models are useful for disentangling the complex suite of socio-economic and biophysical forces that influence the rate and spatial pattern of land-use change and for estimating the impacts of changes in land use. Land-use change models can simply be defined as tools to support the analysis of the causes and consequences of land-use change (Verburg *et al.*, 2004). However, Heistermann *et al.*, (2006) define a land-use model as 'a tool to compute the change of area allocated to at least one specific land-use type.

Land-use models are used to project demand for land for specific purposes and where resulting land-use changes will occur given different boundary conditions. The models help in understanding the drivers of land-use change and which areas are likely to be under the greatest pressure, and can thus provide support to land use and policy decisions. Land-use models can also be used to explore alternative futures using different scenarios; however, not all land-use models can be used for scenario analysis (UNEP-WCMC, 2016).

Many authors have characterized and classified land-use models differently, for example, Lambin *et al.*, (2000), characterized models based on agricultural intensification, while Irwin & Geoghegan, (2001), their classification was based on the degree of spatial explicitness and economic rationale. Furthermore, Briassoulis., (2000), applied the criterion of modelling tradition to distinguish statistical (econometric), spatial interaction, Optimization and integrated models. In this paper Heistermann *et al.*,'s (2006) classification of models will be discussed. The models are categorized into three; geographic, economic and integrated models.

2.4.1. Geographic land-use Models

Geographic land-use models are characterized by the spatial allocation of land-use types, based on biophysical and socioeconomic properties and the resulting suitability of land for specific use (UNEP-WCMC, 2016). Spatially explicit modelling is applied in many disciplines, including both natural and social sciences. These models are promoted by the development of remote sensing and Geographic Information Systems data at local or regional scales (Heistermann *et al.*, 2006). Geographic land-use models are capable of capturing supply-side constraints based on land resources and spatial determination of land use. However, they cannot endogenously treat the interplay between supply, demand, and trade. Geographic land-use models are further classified into three subcategories; empirical statistical models, rule-based/ process-based models and land system models.

The CLUE model framework developed by Veldkamp & Fresco, (1996) is the most well known and most frequently used empirical statistical model globally (UNEP-WCMC, 2016). Over the years, the model has evolved and different versions have been developed (CLUE, CLUE-s, Dyna-CLUE, and CLUE-Scanner). The underlying assumption of the CLUE framework is that observed spatial relations between land-use types and potential explanatory factors represent currently active processes and remain valid in the future. The quantitative relationship between observed land-use distribution and spatial variables is derived through multiple regression. For this reason, the CLUE model is generally referred to as an empirical–statistical model. Nonetheless, statistical analysis is supplemented by a set of transition rules, which additionally control the competition between land-use types. Land-use changes are driven by estimates of national-scale area demands (Heistermann *et al*., 2006). The model uses a 'weights of evidence' method that generates a map of change potential based on several explanatory variables and past trends that involve expert knowledge (UNEP-WCMC, 2016).

In contrast to empirical-statistical models, that are based on statistical relationships between drivers and historical land-use changes, rule or process-based models imitate processes addressing the interaction of various components forming a system (UNEP-WCMC, 2016). The SALU model (Stéphenne & Lambin, 2001) is a zero-dimensional model designed to capture the characteristic processes in the Sahel Zone (Heistermann *et al.*, 2006). It provides an appealingly simple approach to endogenously deal with agricultural intensification by focusing on a sequence of agricultural land-use changes not only typical for the Sahelian region: agricultural expansion at the most extensive technological level is followed by agricultural intensification once a land threshold is reached. Exogenous drivers are human and livestock population, rainfall variability and cereal imports.

More recently, land change modellers have started to use the land systems approach whereby the modelling units are land-use systems that represent human-environmental interactions in mosaic landscapes (Van Asselen & Verburg, 2013). Land systems models are also classed as integrated models as they combine economic and environmental processes. Letourneau *et al*., (2012) developed a land-use system model that is used to model global land change.

2.4.2. Economic land-use Models

In recent years, the rising interest in science-based assessment and treatment of environmental problems has created a new incentive to reintroduce land into standard economic models as a direct link between economy and environment. The economic models are used to study the impact of environmental changes on future economic welfare (Heistermann *et al*., 2006). Most of the global economic models are equilibrium models that explain land allocation by demand and supply structures of the land-intensive sectors, where the main mechanism is to equate demand and supply under exogenously defined constraints (Heistermann *et al.*, 2006). Computable General Equilibrium models (CGEs) attempt to model all markets explicitly and assume these to be in equilibrium in every time-step, whereas Partial Equilibrium models (PEs) only model a subset of the market and ignore or parameterize the remaining markets (UNEP-WCMC, 2016).

One of the big advantages of Economic land-use models is that that they can consistently address demand, supply and trade via price mechanisms. However, their limitations lie on their inability to account for supply-side constraints fully, such as behaviour not related to price mechanisms, as well as incorporating the impact of demand on actual land-use change processes (UNEP-WCMC, 2016). Technically, most of these models are not land-use models as they focus on the market structure for land-intensive commodities and not on an allocation of land specifically (Heistermann *et al*., 2006). IMPACT, GTAPE-L, GTAPEM, AgLU and FASOM are some of the economic models that are widely used.

2.4.3. Integrated Land-use Models

Both economic and geographic land-use models have strengths and weaknesses. For instance, economic equilibrium models can consistently address demand, supply and trade via price mechanisms. However, they are limited in accounting for supply-side constraints, in reflecting the impact of demand on actual land-use change processes and in representing behaviour not related to price mechanisms. On the other hand, geographic models are strong in capturing the spatial determination of land use and in quantifying supply-side constraints based on land resources. They are more flexible in describing the behaviour leading to specific allocation patterns. However, they lack the potential to treat the interplay between supply, demand and trade endogenously (Heistermann *et al*., 2006).

In order to overcome the limitations associated purely with geographic and economic land-use models, Integrated land-use models that combine economic and environmental processes have been developed. EPIC vegetation model, GLOBIOM and GEONAMIC are some of the integrated land-use models (UNEP-WCMC, 2016).

2.5. Application of Remote Sensing and GIS in LULC change Studies

Remote sensing is the process of detecting and monitoring the physical characteristics of an area by measuring it's reflected and emitted radiation at a distance from the targeted area. The world of remote sensing is undergoing change and development at a remarkable pace, more so than any single period since the dawn of spaceborne remote sensing in the 1960s and 1970s. A confluence of factors has made it easier to build, launch, and operate satellites while simultaneously it has become much easier and more efficient for users to access and develop applications with data remotely sensed from space (Christopherson *et al*., 2019).

Remote sensing data have several characteristics, most notably repeated synoptic coverage with consistent observation at a relatively low cost that makes them ideal for modelling land cover change. National centre of geographic information and analysis defines a GIS as; a system of hardware, software and procedures to facilitate the management, manipulation, analysis, modelling, representation and display of georeferenced data to solve a complex problem regarding planning and management of resources (NCGIA, 1990). The GIS technology is employed to assist decision-makers by indicating various alternatives in development and conservation planning and by modelling the potential outcomes of a series of scenarios. It should be noted that any task begins and ends with the real world. Data are collected about the real world. After the data are analyzed, information is compiled for decision-makers. Based on this information, actions are taken and plans implemented in the real world.

Digital change detection is the process that helps in determining the changes associated with land use/ land cover change properties regarding geo-registered, multi-temporal remote sensing data. The collaboration of remotely sensed data and field observations can accomplish land cover classification and change detection, faster and cheaper than either alone (Diallo *et al.*, 2009). There is ample collection of data produced from remote sensing and vary from the very high- spatial resolution images (such as CartoSat, IKONOS and Quickbird), to regional datasets produced at regular intervals (e.g., LISS III, TM/ETM, SPOT), to lower spatial resolution (>250 m) images now produced daily across the entire Earth (e.g., MODIS). The temporal dynamics of the synoptic view of the earth's surface by satellite assisted data capture has given us an important tool to study the variations in land use and land cover over some time (Sohl & Sleeter, 2012). The changes in the land use and land cover manifested as a function of the changes either natural or manmade, have a bearing on the reflectance patterns of incident radiation due to the changes in the vegetative cover, soil moisture or the various modifications of the earth's surface (Giri, 2012). GIS is also a very important tool since the changes in land use and land cover are more or less unidirectional, without much oscillation, it is safe to extrapolate the changes in spatial extents and also calculate the rate of change (Mridha *et al.*, 2012).

2.6. Soil Erosion

Despite almost a century of research and extension efforts, soil erosion by water, wind and tillage continues to be the greatest threat to soil health and soil ecosystem services in many regions of the world. Despite a deep understanding of the physical processes of erosion and the controls on those processes being firmly established, some elements remain controversial. It is often these controversial questions that hamper efforts to implement sound erosion control measures in many areas of the world (FAO, 2019). Soil erosion can be defined as the net long-term balance of all processes that detach soil and move it from its original location (Lupia-Palmieri, 2004).

Soil erosion is a naturally occurring geomorphic process, but human use of the soil typically results in rates of soil detachment and transport that are many times the naturally occurring rates. There are three main types of soil erosion; water, wind, and tillage. Each involves distinct processes that detach and transport soil; hence each also requires different approaches to decrease associated rates of erosion (FAO, 2019). This paper focusses on water erosion because it is the one that affects the greatest area.

The detachment of soil from the soil mass occurs in two ways in water erosion: from the effects of raindrop splash on the soil surface, and forces exerted by water flowing across the surface (runoff). Transport of the detached soil by flowing water first occurs in thin sheets of runoff flowing over the surface (sheet erosion). Often the surface runoff becomes concentrated in small channels (rill erosion) or deeper incisions (gully erosion); in both of these types of channels, the erosive power of the flow is greatly magnified. The rills and gullies resulting from water erosion are some of the most visible signs of erosion operating in the landscape. In some cases, the soil in the flowing water (sediment) settles out of the water when either the depth or velocity of runoff is reduced–for example, when the flowing water contacts a vegetative barrier. This leads to the deposition of eroded soil. In many other cases, however, the runoff and sediment are carried to a stream system (fluvial transport) and is removed entirely from the landscape (FAO, 2019).

According to Tesema, (2011), cited in Mogesie, (2014), the major factors affecting soil erosion are; climate, soil properties, topography, and land use. These factors are not totally independent, as geology affects topography, which can influence climate and soil types. Rainfall drives erosion according to its intensity (how hard it rains) and amount (how much it rains). Temperature and precipitation together determine the longevity of biological materials like crop residue and applied mulch used to control erosion.

Different soil types have a difference in their erodibility, thus the basic soil properties such as texture and organic matter content provide an indication of erodibility. The size of particles and aggregates within the soil is the single most important soil factor influencing soil erodibility. In terms of soil texture alone, clay-dominated textures will resist detachment because of the high cohesion between clay particles, and medium to coarse sand-dominated soils resist transport due to their large particle size. Hence silt-dominated soil and loamy soils (that is, those with roughly equal proportions of sand, silt, and clay) are most susceptible to detachment and transport (FAO, 2019).

Slope length, steepness, and shape are the topographic characteristics that most affect erosion and deposition. Soil erosion increases in a linear relationship with increases in slope: the velocity of the runoff (and its erosive power) increases as slope increases. Additionally, as runoff accumulates down- and across-slope, the depth of flow increases and hence its erosive power increases. On uniform slopes (that is, those with no across-slope curvature), the volume and depth of runoff increase downslope; hence, erosion increases from a minimum at the top of the slope to a maximum at the bottom of the slope (FAO, 2019).

Lastly, land use is the single most important factor affecting soil erosion and it is strongly enhanced by human activities. Human disturbances, such as tillage activity, and natural disturbances, such as severe weather dramatically increase erosion. Of these, the vegetation and some disturbances, and, to a lesser extent, the soil and topography can be managed to reduce erosion (Mogesie, 2014). Erosion is a natural geological process and it is impossible to stop; instead, the goal is to manage human impacts on the soil so that the rate of erosion is within an acceptable range (FAO, 2019).

2.6.1. The Soil Erosion and Reservoir Sedimentation

Human-induced water erosion leads to higher sediment inputs into stream channels and increased sedimentation into reservoirs along the stream channels (FAO, 2019). In fluvial hydraulics, sedimentation is an important parameter as it provides a probability of being used as a capacity predicting device in all storage zones due to which life of a reservoir can be predicted; as there is a unique relationship between capacity and life of a reservoir. To be more explicit, for a given reservoir, sedimentation is dependent on sediment yield, which is defined as the sediment dis-charge through a river outlet per unit catchment area per unit time (ASCE, 1982). Soil erosion in the catchment is also an important parameter as the sediment yield depends on it. In order to reduce the problem corresponding with the number of sediment particles that ultimately deposit into the reservoir after getting eroded from the catchment, attempts have been made to relate the soil erosion, sediment yield and sedimentation into the reservoir, since these three parameters deal with the life of a reservoir directly or indirectly (Dutta, 2016).

The increases in sediment quantity and sedimentation lead to multiple effects. For instance, sedimentation in lakes and reservoirs reduces life span and affects operation efficiency and costs, and in harbour's and estuaries, it requires dredging and its associated costs. Sedimentation and turbidity also disturb salmonid spawning gravel and alter other sensitive habitats as well as habitats along floodplains and associated land use. Soil erosion also contributes to the pollution of waterways by nutrients and by other agrochemicals such as pesticides. This pollution leads to eutrophication of waterways and the resulting impact on aquatic life as well as direct toxicity effects on organisms (Owens, et al., 2005).

2.7. Application of Remote Sensing in soil erosion estimation and mapping

GIS and remote sensing have been used for both detecting erosion features and obtaining erosion model input data for soil erosion assessment in a watershed (Petter, 1992). The Universal Soil Loss Equation (USLE) and The Revised Universal Soil Loss Equation (RUSLE) are the GIS and remote sensing techniques that are widely applied to empirical models for estimating the soil loss (FAO, 2019; Bera, 2017; Gelagay & Minale, 2016). The USLE was developed at the USDA National Runoff and Soil Loss Data Center at Purdue University in a national effort led by Walter H. Wischmeier and Dwight D. Smith in 1978 (Wischmeier & Smith, 1978).

The fundamental concept in establishing factor values in the USLE was the Unit Plot. This conceptual plot was composed of a land parcel 72.6 feet (22.1 m) in length with a 9% slope, maintained in a continuous, regularly tilled fallow condition. with up-and-down hill tillage, thereby representing a condition very near the worst-case management. Such a plot was used as a base condition to which all other topographic, cropping, management and conservation practices were compared. Data from plots with different slopes, lengths and crops were adjusted to the unit plot and compared across locations to establish reliable factor values. Benchmark soil erodibility and other terms (rainfall, slope length, slope steepness, cover-management, and the support practice factors) used in the USLE/RUSLE have evolved over the years from data derived for varied conditions. Few if any unit plots were ever actually developed, but the concept was used to determine how the conditions of actual plots related to the unit plot.

The USLE soil equation is:

$$\mathbf{A} = \boldsymbol{R} * \boldsymbol{K} * \boldsymbol{L} * \boldsymbol{S} * \boldsymbol{C} * \boldsymbol{P} \qquad (1)$$

Adapted from (Renard *et al*., 2011).

where **A:** is the computed soil loss per unit area, expressed in the units selected for K and for the period selected for R (in common practice these are usually selected such that they compute A, soil loss in US tons per acre per year);

R: the rainfall and runoff factor, is the number of rainfall erosion index units, plus a factor for runoff from snowmelt or applied water where such runoff is significant;

K: the soil erodibility factor, is the soil loss rate per rainfall erosion index unit for the specified soil under Unit Plot conditions;

L and **S**: are the slope length and steepness factors concerning the conditions on a unit plot;

C: the cover and management factor, is the ratio of soil loss from an area with specified cover and management to that from an identical area under the tilled continuous fallow Unit Plot conditions (C thus ranges from a value of zero for completely non-erodible conditions, to a value of 1.0 for the worst-case Unit Plot conditions);

and **P**: the support practice factor, is the ratio of soil loss with a support practice like contouring, strip cropping, or terracing to that with straight-row farming up and downslope (Renard *et al.*, 2011).

Because the USLE was based on empirical erosion data collected from relatively small plots or sub-watersheds on relatively uniform hillslopes, the resulting erosion estimates were limited to similar situations. In essence, these results did not include any impact (either erosion or deposition) of the concentrated flow channels that form in the natural swales at the bottom of the roughly planar hillslopes and certainly did not address classical gullying processes that often occur at steep boundaries such as head cuts and sidewall sloughing (Renard *et al.*, 2011). Recognized limitations and advancements in erosion science pointed to the need for updating the USLE.

In 1985, scientists and engineers from the USDA-ARS and the USDA Soil Conservation Service and affiliated academics with expertise in soil erosion assembled in West Lafayette, Indiana. At that workshop, two important decisions evolved, including the need to (1) develop technology to replace the USLE with a physically-based model (subsequently called the Water

Erosion Prediction Project or WEPP); and (2) to computerize and update the 1978 version of the USLE with an improved model, subsequently called the Revised USLE or RUSLE. The first version of RUSLE1, a software program designed to operate in a DOS-based computer environment, was released in 1997. RUSLE1 was supported by USDA-ARS through Agriculture Handbook No. 703 (AH703) (Renard *et al.*, 1997). The computer system soil erosion model described therein was a major conversion of the factor approach presented in AH537. Perhaps the most significant change was the subfactor approach to the calculation of the cover-management factor C, thereby allowing the use of RUSLE1 for any land use that could be adequately addressed by these subfactors. Figure 1 shows the computer-based approach of RUSLE model.

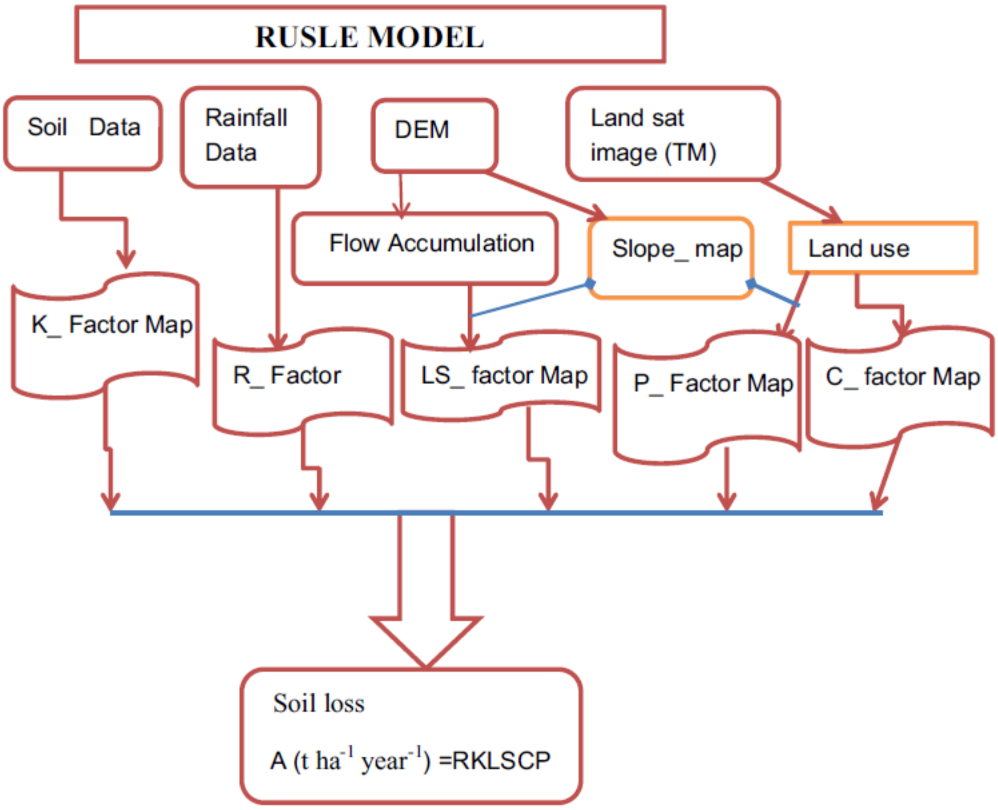

Figure 1 Conceptual Framework of Soil loss Analysis by RUSLE. (Adapted from *(Gelagay & Minale, 2016)*)

The underlying assumption in the RUSLE is that detachment and deposition are controlled by the sediment content of the flow. The erosion material is not source-limited, but the erosion is limited by the carrying capacity of the flow. When the sediment load reaches the carrying capacity of the flow, detachment can no longer occur. Sedimentation must also occur during the preceding portion of the hydrograph as the flow rate decreases. According to Renard *et al.*,

(1997) the controlling factors of soil erosion that are combined in the RUSLE model are; climate, soils, vegetation cover, topography and land management. USLE and RUSLE have been widely used, however in these two models, there is no direct consideration of runoff, although erosion depends on sediment being discharged with the flow and varies with runoff and sediment concentration (Kinnel, 2005). Based on the fact that runoff is a superior indicator of sediment yield than rainfall, a modification was done by replacing rainfall erosivity factor 'R" in USLE by runoff factor and this model was called MUSLE (Williams & Berndt, 1977). The modified version of USLE improves the sediment yield prediction, eliminates the need for delivery rations and allows the equation to be applied to individual storm events (Kinnel, 2005; Williams & Berndt, 1977; Williams, 1975). In general, MUSLE can be expressed as follows:

$$\boldsymbol{Y = 11.8(Qq_p)^{0.56}KLSCP} \qquad (2)$$

Adapted from (Williams,1975)

where **Y**: the sediment yield to the stream network in metric tons,

Q: the runoff volume from a given rainfall event in m^3;

$\boldsymbol{q_p}$: the peak flow rate in $m^3\ s^{-1}$;

K: the soil erodibility factor, is the soil loss rate per rainfall erosion index unit for the specified soil under Unit Plot conditions;

L and **S**: are the slope length and steepness factors concerning the conditions on a unit plot;

C: the cover and management factor, is the ratio of soil loss from an area with specified cover and management to that from an identical area under the tilled continuous fallow Unit Plot conditions (C thus ranges from a value of zero for completely non-erodible conditions, to a value of 1.0 for the worst-case Unit Plot conditions);

and **P**: the support practice factor, is the ratio of soil loss with a support practice like contouring, strip cropping, or terracing to that with straight-row farming up and downslope.

The Q, q_p, and LS parameters can be derived from Digital Elevation Model (DEM), land cover, soil, and rainfall data.

2.8. Impact of LULC change on Water Quality

Camara *et al*., (2019) define Land use as; human use of terrestrial space for economic, residential, recreational, conservation, and government purposes. On the other hand, Water quality is defined as a measure of water-use for different purposes (drinking, industrial, agricultural, recreational, and habitat) using various parameters such as physical, chemical, and biological (Giri & Qiu, 2016). Different water quality parameters are measured and used to assess water quality for different uses. Malawi Bureau of Standards (MBS) is in charge of setting permissible levels or water quality standards for different uses in Malawi. The impact of land-use changes on water quality involves the association of land use and water quality indicators. Many studies have shown that there are significant correlations between land use and water quality indicators (Camara *et al*., 2019; Pullanikkatil *et al.*, 2015; Huang *et al*,2013). These studies of the relationship between land use and water quality through various means and approaches have permitted to estimate and understand water quality in water bodies distressing from diffuse pollution. In general, the higher percentages of land use associated with human activities and economic development in watersheds are often interrelated with high concentrations of water pollutants, while undeveloped areas such as natural forest areas are linked with good water quality. However, knowledge in such relationships at a catchment scale across seasons is still lacking due to the large area and monitoring difficulties. Preserving water quality is an arduous task, mainly because of the presence of point and non-point sources (NPS) of pollution. NPS pollution involves a natural process that can never be totally eliminated. Human activity can, however, have a significant influence on the acceleration or deceleration of pollution rate at the source; therefore, in dealing with non-point source pollution, the challenge is to identify activities that result in significant degradation of water quality and design control programs to minimize problems (Camara *et al*., 2019).

2.9. Techniques to analyze the effects of land use/land cover on water quality

Various techniques have been applied in assessing and understanding the relationship between land use/land cover and water quality in different watersheds worldwide. These techniques include correlation indices (Namugize, *et al*., 2018; Dai, *et al*., 2017), remote sensing and geographic information systems (Patil, et al., 2019), the econometric model (Huang, *et al*., 2013), principal component analysis (Hua, 2017) and Bayesian hierarchical linear regression model (Wan, *et al*., 2014). Most of the researchers use modelling techniques to establish the relationship between land use/land cover and water quality. This is in line with the findings of some researchers such as Abdulkareem, *et al*., (2018) that highlighted the growth of modelling approaches by watershed researchers to address a variety of water-related issues on the watershed level. Camara, *et al*., (2019) further illustrated that in establishing the relationship between land use and water quality, modelling techniques may have some advantages over other techniques due to their suitability in relating the phenomena. As such, statistical modelling may be preferable to physical-based modelling because of the need for a large number of input data associated with continuous observation data for the model building, calibration, and validation process. Statistical packages such as Statistical Package for Social Sciences (SPSS) and Stata can be used to compute the modelling techniques.

Spearman and Pearson correlation indices are one of the preferable statistical modelling approaches. However, their applicability depends on the type of data available. For example; Namugize, *et al.*, (2018) and Dai, *et al.*, (2017) used different types of correlation indices in their studies. The former used Pearson's rank correlation coefficient while the later used Spearman’s rank correlation coefficient. The main difference between the two correlation indices is that unlike Pearson, Spearman does not require the assumption that the relationship between the variables is linear, nor does it require the variables to be measured on interval scales; it can be used for variables measured at the ordinal level. Hence Spearman is mainly used when the distribution of data makes Pearson’s correlation coefficient undesirable or misleading (Hauke & Kossowski, 2011). Dai, *et al*., (2017) used spearman’s rank correlation coefficient because they had ordered data that was distributed at an equal interval of 100 m and it had no normal distribution, on the other hand, Namugize, *et al*., (2018) used Pearson correlation analysis to establish whether a linear relationship between LULC variables, considered as independent variables, and water quality variables, as dependent variables, exists.

3. MATERIALS AND METHODS

3.1. Description of the study area

The upper Lilongwe River catchment is located in the south-west of Malawi's capital city Lilongwe. The catchment stretches from the Dzalanyama forest reserve that forms the boundary between Malawi and Mozambique to Bwaila south in Lilongwe city and lies between Latitudes -14.300016^0 and -14.006209^0 S and Longitudes 33.481918^0 and 33.757852^0 E (Figure 2). The upper Lilongwe river catchment covers approximately 1,870 km^2 of land and the Lilongwe river is one of the tributaries of Lake Malawi.

Lilongwe Water Board (LWB) a statutory corporation established in 1947 and re-established under the Water Works Act, 1995 (Cap 72) is the main stakeholder for managing the catchment since the board abstracts its raw water from Lilongwe River which originates from Dzalanyama Ranges. The utility is responsible for the provision of water supply services to Lilongwe City and other surrounding areas designated as its supply area. Currently, LWB supplies potable water to 75 per cent of the 1.1 million inhabitants of the city through a pipe network of approximately 1,800km long. Its customer base stands at 79,000 and includes domestic, industrial, institutional, commercial, and communal water points (kiosks).

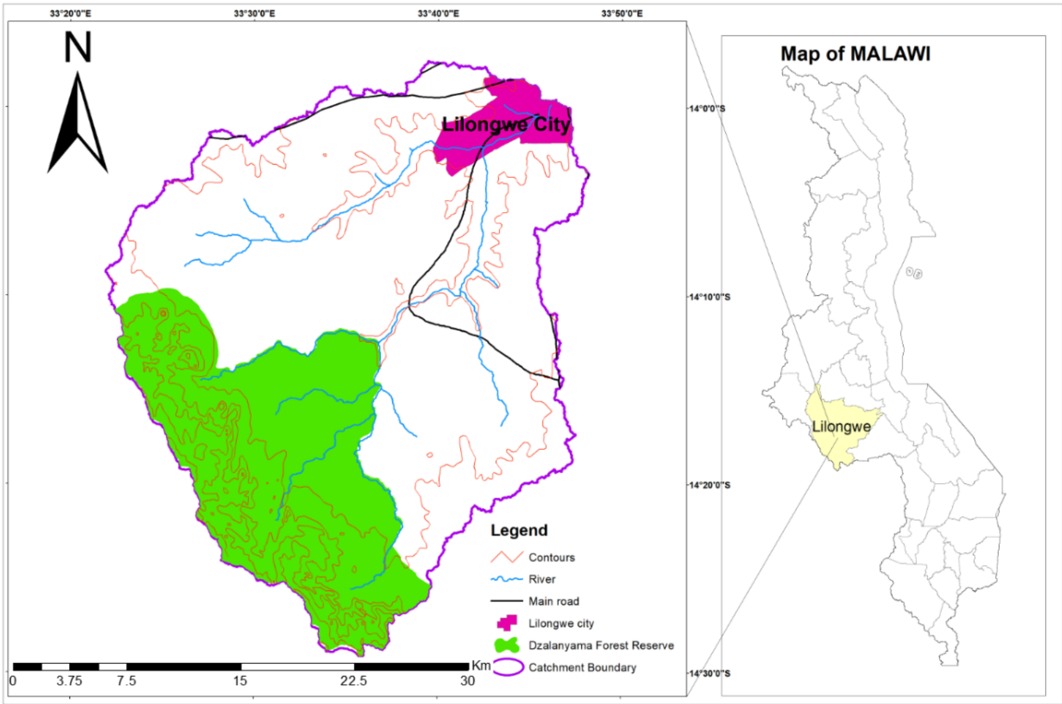

Figure 2 Map of Upper Lilongwe River Catchment

There are two dams constructed along the river; Kamuzu Dam I and Kamuzu Dam II. The two dams; Kamuzu Dam 1 (KD1) and Kamuzu Dam 2 (KD2) were constructed in 1966 and 1989 respectively. The Kamuzu Dam 1 is located on the Lilongwe River approximately 25 km south-west of Lilongwe city. The dam comprises a central spillway with a length of 97.6 m which is flanked by a 205m long embankment on the left abutment and a 90 m long embankment on the right abutment. The outlet structure is located within a non-overflow concrete dam located at the left-hand side of the spillway. The maximum height of the dam is 21 m (World-bank, 2017)

Kamuzu Dam 2 is located on the Lilongwe River approximately 5 km downstream of Kamuzu Dam 1. The original Kamuzu Dam 2 comprised; A 28m high zoned earth-fill embankment with a clay core supported by compacted earth fill shoulders, a reinforced concrete spillway 105m wide at the crest converging to a width of 43m at the downstream end of the concrete chute, a reinforced concrete intake tower, octagonal shape, 30.5m high with three (3) horizontal intakes and a 900mm diameter standpipe in the tower and a reinforced concrete access tunnel connecting the intake tower to the outlet works; the tunnel is horseshoe-shaped, 2.6m in height and 2.8m in width, and contains the 900mm diameter outlet conduit while providing access to the intake tower (NEMUS, 2015).

Water is abstracted at an intake point on the river about 20 km downstream of KD2 and treated in Treatment Works 1 (TW1) and Treatment Works 2 (TW2), with a combined production capacity of 125,000 m^3/day. However, on average, the plants are operating at 70 per cent capacity, due to a combination of low yields from the Kamuzu dam system in the dry season; high levels of siltation in the river during the rainy season; and hydraulic bottlenecks in the existing distribution network producing an average of about 90,000 m^3/day. Current peak water demand is estimated at 130,000 m^3/day, and this is projected to increase to 170,000 m3/day by 2025 and 220,000 m^3/day by 2035. Thus, the water supply system is under strain and the city is already facing water shortages which are expected to become severe over the coming years unless major investments in new water production are undertaken (The World Bank, 2017).

The Lilongwe river is one of the three main river systems draining south Lilongwe Plain. The river is composed of five main tributaries; Likuni, Katete, Lisungwe, Nanjiri, and Nathenje. The headwaters of these rivers form a complex network of deeply dissected valleys which frequently follow joint directions, shear zones, and foliation within Dzalanyama granite (NEMUS, 2015).

3.1.1. Topography, Geology, and Soil

Lilongwe is a flat district, the level of the plain shows gentle southward rise over a distance of 56.3 km from an elevation of 1,143 m at Lilongwe to 1,295 at Mozambican border (NEMUS, 2015). Lilongwe is characterized by deep soil dominated by the south Lilongwe plain and Dzalanyama range that are largely underlain by granulates, gneisses, and schists of the Precambrian basement complex. On the plain, this basement complex is for the most part obscured by thick superficial deposits which include residual soils, alluvium, and colluvium. Thick superficial deposits comprising various types of residual soils; river alluvium and dambo soils cover much of the south Lilongwe plain. According to FAO soil classification, the watershed is characterized by the following soil; arenosol, cambisol, gleysols, Luvisols, ferrasols, leptosols, and lixisol, of which Luvisol is the dominant one. These soil types are slightly vulnerable to soil erosion due to good drainage (Omuto & Vargas, 2019).

3.1.2. Hydrology

The rainy season for the area extends from November to April with annual mean precipitation of 964 mm. Seventy-five per cent of the total annual rainfall occurs in 3 months (December-February) and about 92 % in 6 months (November-April). February is the rainiest month with more than 25 per cent of the annual rainfall. The catchment has five meteorological stations namely; Dzalanyama, Malingunde (KD2), Bunda, Chitedze, Sinyala, and Likuni-Chigwirizano.

The catchment has three streamflow gauging stations, one located in the Katete river and the other two located in the Lilongwe river. The most reliable gauging station 4D4 (Lilongwe at old town bridge) has discharge records since 1953 and it has a catchment area of 1,870 km^2. This gauging station is located just below of LWB's abstraction point (NEMUS, 2015).

3.2. Data Sources and Procedure of Data collection

Both primary and secondary data were used in this research which was acquired through different means and sources. Primary data ranged from water quality data to ground reference data. The secondary data included water quality data, climate data, hydrology data, land use land cover data, and soil data. The following subsequent section will explain how each data was acquired.

3.2.1. Satellite Images

Landsat 5 (Thematic mapper, Landsat 7(Enhanced Thematic Mapper) and Landsat 8 (Operational Landsat Imager) of 1989, 1999, 2014, and 2019 were downloaded from the USGS's Earth Explorer (https://earthexplorer.usgs.gov/). The level 1 product images that were already pre-processed were chosen for LULC analysis in this research. All the images were from the same dry season with less than 30 per cent cloud cover and had a 30 m resolution which is large enough to visualize LULC changes (Jiménez *et al*., 2018). The images were acquired using different paths and rows. These Images were selected because they have a high spectral and spatial resolution Table 1 presents the details of all the images including the date, path/row, and type of sensor.

Table 1 Characteristics of the Landsat Images used in the study

#	Type of Landsat	Date of Acquisition	Path	Resolution (m)
1	8 OLI	2019/09/29	168/070	30
2	8 OLI	2019/10/22	169/070	30
3	8 OLI	2014/10/24	169/070	30
4	8 OLI	2014/10/01	168/070	30
5	7 ETM	1999/10/23	169/070	30
6	7 ETm	1999/29/08	168/070	30
7	5 TM	1989/08/25	168/070	30
8	5 TM	1989/09/17	169/070	30

The already existing LULC maps for Malawi were collected from the Malawi government's department of surveys in Lilongwe, Malawi. The maps were of the following years 1990, 2000, and 2010 as they are produced at 10 years interval. The maps were used to guide the researcher when formulating LULC classes for the area. Ground reference data from selected parts of the catchment were collected for accuracy assessment using Garmin handheld GPS.

3.2.2. Topographic and Soil Data

The Shuttle Radar Topography Mission (SRTM) digital elevation model with the spatial resolution of 90 m by 90 m was acquired from http://srtm.csi.cgiar.org/. The SRTM DEM produced by the National Aeronautics and Space Administration of USA (NASA) provides a major advance in the accessibility of high-quality elevation data for large portions of the tropics and other areas of the developing world. The DEM was gap filled and of top quality hence it fits the purpose of this research. The DEM was used to delineate the watershed, slope steepness, and length for MUSLE and all the building of the CN grid in Hec-GeoHMS.

The soil layer for upper Lilongwe river watershed was extracted from the Malawi soil map which was obtained from the Malawi government's department of Land Resources Conservation under the Ministry of Agriculture, Water, and Irrigation. The soil was classified according to FAO classification to obtain the soil erodibility factor. Figures 3&4 shows the slope map and soil map respectively of the catchment.

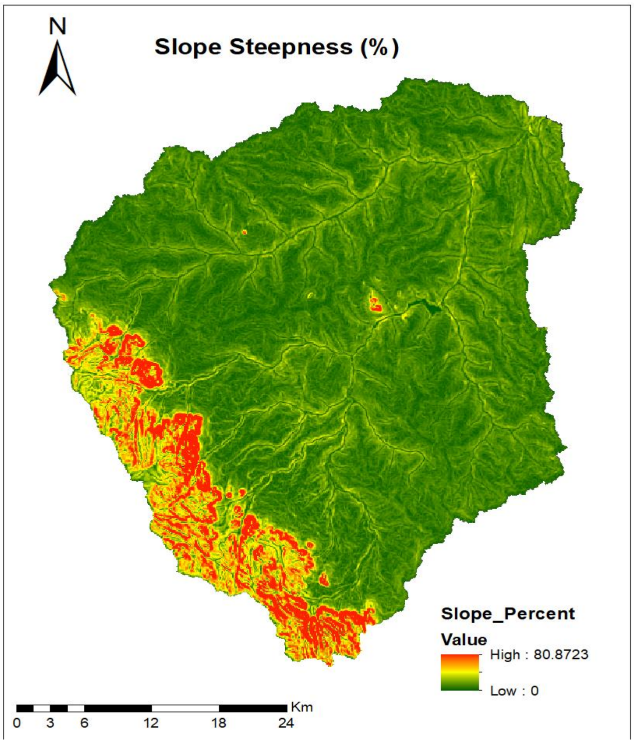

Figure 3 Slope Map of Upper Lilongwe River Watershed

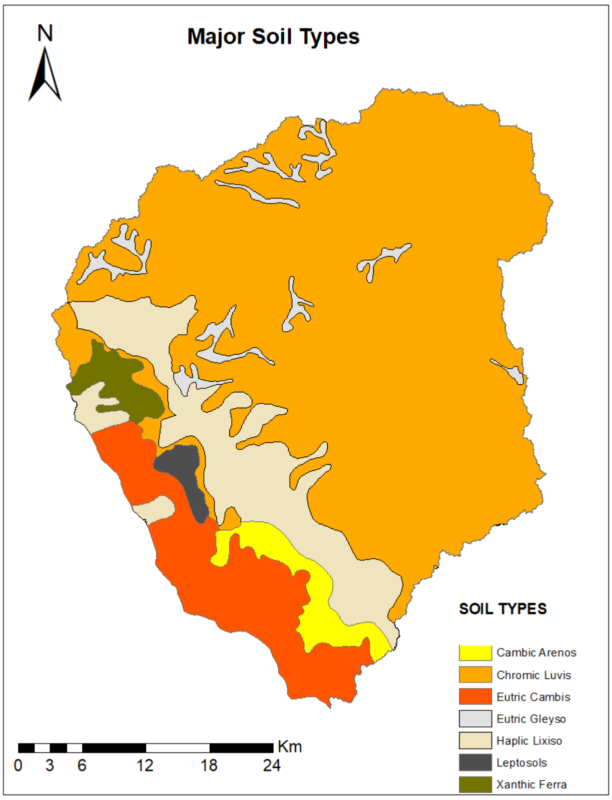

Figure 4 Soil Map of Upper Lilongwe River Watershed

Extracted from; Malawi soil map

Field observations were made on the soil colour to just verify the details in the Malawi soil map. Luvisols are the most dominant and Leptosols are the least soil type in the watershed. The soils are dominated by high fertility sand loam and loamy sand soils hence agriculture is the most dominant land use in the watershed. Table 2 illustrates the characteristics of the soil in the watershed.

Table 2 Soil Classification of Upper Lilongwe River Catchment

FAO_Classification type	sand % topsoil	silt % topsoil	clay % topsoil	OC % topsoil	Coverage Area (ha)
Cambic Arenosol	91.9	3.2	5	0.23	5416.55
Chromic Luvisols	64.3	12.2	23.5	0.63	122581
Eutric Cambisols	36.4	37.2	26.4	1.07	18457.4
Eutric Gleysols	42.8	20.4	36.8	1.3	4916.27
Haplic lixisol	79	5.8	14.8	0.81	23364.3
Leptsols	58.9	16.2	24.9	0.97	1659.14
Xanthic Ferrarsol	72.9	5.9	21.3	0.91	3264.12

3.2.3. Climatic and Hydrological Data

Daily average precipitation and minimum and maximum daily temperature data were provided by the department of climate change and meteorological services of Malawi. Five rain gauge stations are located within and near the watershed hence they are used as meteorological stations for the watershed. The rainfall data were obtained and processed to compute runoff volume in m^3 and temperature data were computed to analyze the impact of temperature on LULC change. The mean annual precipitation and the names of the stations are presented in table 3 below

Table 3 Rainfall Stations Mean Annual Precipitation

Rainfall Station	**Mean Annual Precipitation (mm)**
Dzalanyama	965
Malingunde (Kamuzu dam 2)	827
Sinyala	893
Bunda	827
Chitedze	821

Adapted from: (NEMUS, 2015).

Streamflow data for the Lilongwe river were collected from the Water Resources Department, Surface water division. Three gauging stations data were provided and computed for peak flow required in the MUSLE. The gauging stations were; Lilongwe at Kwenembera (4C3) with the following coordinates Latitude: 13:46:57 S and Longitude: 34:16:10 E with a catchment area of 4,940.0 km^2. The data for this station was provided from 1957. Sation 4D24 (Lilongwe at Masula) is located below both Kamuzu dam 1 and Kamuzu dam 2. The data for this station were provided from 1995. Lastly, station 4D4 (Lilongwe at old town bridge) is located just outside of the catchment outlet with the catchment area of 1,870 km^2. The data for this station was provided from 1953. The flow has been decreasing in the Lilongwe river due to various reasons that include LULC change in the watershed and the construction of the two dams in the river. Nevertheless, the months with the high flow are from January to April. Flow decreases from June to September with October having the least flow rate. The monthly flow data for two different periods 1954/1955 and 2012/2013 is presented in figure five below.

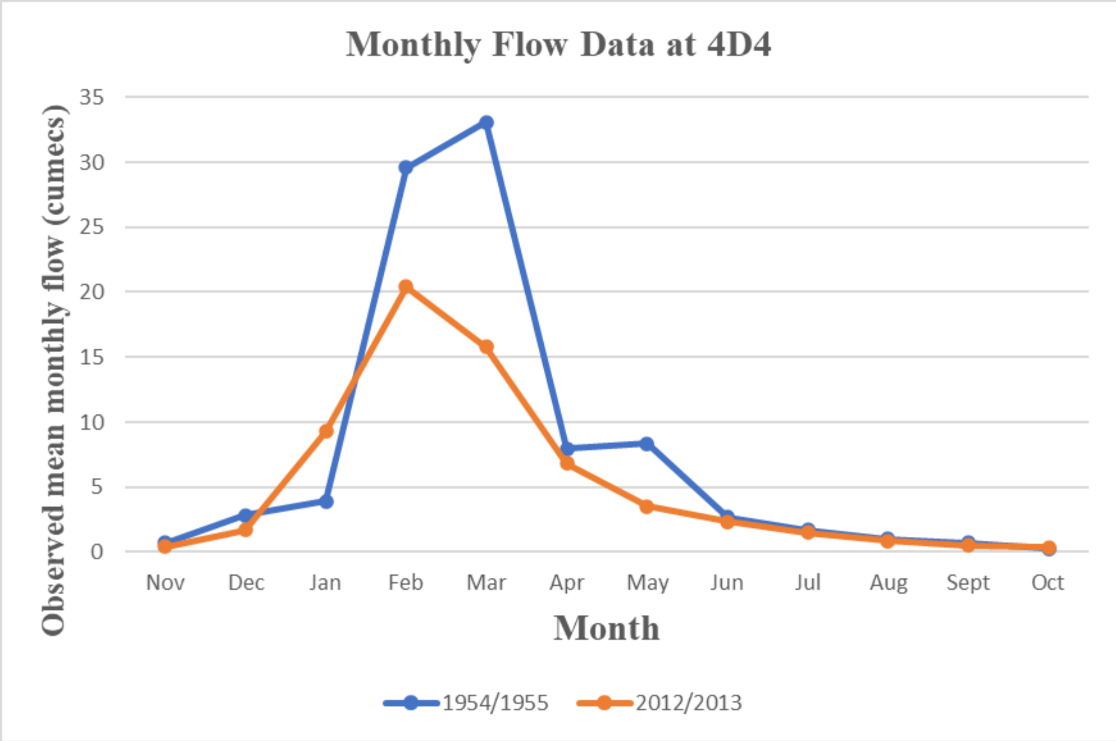

Figure 5 Mean Monthly flow data at Lilongwe Old town bridge (4D4)

3.2.4. Water Quality Data

LWB has water quality monitoring points in Upper Lilongwe river which are sampled on a monthly and sometimes weekly basis depending on the water quality at a specific time. The water samples are sampled following standard methods described by APHA, (2005) and analysed according to international standards in laboratories accredited by Malawi Bureau of Standards (MBS). Nine out of the total of thirteen monitoring points were chosen in this research purposively due to land use activities surrounding each point. The points were also chosen because of consistency in the availability of secondary data. Primary data were only collected for February 2020, while secondary data for the previous period was collected from the division of Water Quality and Environment of LWB.

3.3. Data Processing and Analysis

3.3.1. Land use and Land cover classification for 1989, 1999,2014, 2019

3.3.1.1. Landsat Image Pre-Processing

A total of four dry seasons (to minimize changes in reflectance due to phenological changes in vegetation and sun position) with less than 30 per cent scene and cloud cover Landsat Images of 1989, 1999, 2014 and 2019 were acquired from USGS's online portal (https://earthexplorer.usgs.gov/) using different paths and rows (168/070 and 169/070). The Landsat Images acquired by different sensors such as TM, ETM and OLI are subject to distortion as a result of the sensor, solar, atmospheric, and topographic effects, hence Pre-processing is necessary as it attempts to minimize these effects to the extent desired for a particular application (Young, et al., 2017). However, determining the level of pre-processing is a significant barrier to non-remote sensing scientist who lacks expertise in the constantly changing techniques to pre-process the images (Pettorelli, et al., 2014). Due to this reason, level-1 products that are already systematically pre-processed by USGS to standardized tiers were used because they require few pre-processing steps before Image processing. Since level 1 products images are already terrain corrected which imply that they are already georegistered with geometric accuracy of 50 m globally (Young, et al., 2017), the pre-processing steps involved radiometric correction, atmospheric correction and mosaicking the images using Environment for Visualizing Images (ENVI) version 5.2 software. The Digital Numbers provided in Level-1 products are calibrated radiance values that have been scaled to varying bit depths, as such they cannot be used to compare spectral values across time due to sensor degradation and differences between sensors (Young, et al., 2017). Therefore, Radiance radiometric calibration was performed to convert digital numbers back to radiance by using rescaling factors that are automatically stored in the metadata file. A mosaic of the required images was prepared after radiometric calibration of the images separately. The image was enhanced and subset using region of interest (the area of study's shapefile). Atmospheric correction was performed to correct the errors that arise due to atmospheric errors that arise due to the scattering and absorption of the energy during interaction of the electromagnetic radiation with atmospheric particles such as water vapour, aerosols and gases. The finished pre-processed images were projected to UTM 36 S.

3.3.1.2. Land use Classification

After pre-processing, identification of different land use and land cover classes was performed through a classification procedure that transforms digital numbers contained in satellite images into understandable geographical features (Munthali & Murayama,2011). Change detection involves the application of multi-temporal datasets to quantitatively analyze the changes in land cover/land use classes. If the change detection of the earth's surface is done timely and accurately then the relationship and interaction between natural phenomena and humans can be better analyzed and understood as a result of which better management and use of resources can be done. The change detection can be done by traditional methods and by using remote sensing technologies. The traditional methods are expensive, time-consuming and not so accurate, whereas all these problems do not infer with remote sensing technology (Mishra *et al*., 2017). Although various classification techniques have been proposed, supervised and non-supervised classification methods are considered as favourable for change detection analysis (Hua, 2017).

Unsupervised classification is a pixel-based classification whereby algorithms no prior knowledge about the study area (i.e., training data) is required. An unsupervised change detection algorithm usually produces a binary change map that shows changed versus unchanged areas. The main disadvantage of this type of algorithms is the lack of detailed from-to change information (Ban & Yousif, 2016). On the other hand, supervised classification is whereby spectral signatures are used to classify the image and prior knowledge of the study area is required. It consists of classifying each image in the multitemporal dataset independently using the same classification scheme. The detailed from-to change information can then be extracted by comparing the classified images on a pixel-by-pixel basis. The main drawback with the supervised classification method is the need for high-quality training data to classify each image in the multitemporal dataset. This turns out to be rather difficult to achieve, especially for older images (Ban & Yousif, 2016).

By using prior knowledge of the area and secondary data (LULC maps obtained from the department of the survey), each pixel was classified to the most likely class based on Maximum Likelihood algorithm where each pixel is assigned to the spectral class that has the greatest probability density function for the multispectral values of the pixel (Mzuza *et al*., 2019). Maximum Likelihood Classifier (MLC) is based on probability theory and assumes that while training the data statistics for each class in each band are Gaussian (normal) distributed

(Shivakumar & Rajashekararadhya, 2018). Maximum likelihood algorithm is the most commonly used supervised classification algorithm (Mzuza *et al*., 2019). The catchment was classified into five Land use and Land cover classes as described in Table 4 below;

Table 4 LULC Description

LULC CLASS	DESCRIPTION
Forest	Protected forests, plantations, deciduous forest, mixed forest lands and forest on customary land.
Cultivated Land	This category applies to cultivatable land and cultivated land, and also to agroforestry areas which are not defined as forest land by the national definition
Built-up	This category covers all developed lands (including transport infrastructure, residential, commercial and services, industrial, socio-economic infrastructure).
Waterbody	This category includes areas which are covered by water (including rivers, permanent open water, lakes, ponds, and reservoirs).
Grass/Shrubs/Bare land	This category includes pastures and grazing lands, bare lands, rocks and unmanaged areas which are not covered by any of the above categories.

3.3.1.3. Accuracy Assessment

The image classification produces some percentage of misclassification due to some errors such as noise and unknown pixels. Hence, accuracy assessment is an important step in Land use land cover change analysis (Munthali *et al.*, 2019). There are several types of map accuracies, however, there is a general consensus that using an error matrix with a class-specific user and producer accuracies as well as overall accuracies is most appropriate for remotely sensed map products (Haack *et al.*, 2014). Also, the Kappa coefficient that expresses the proportionate reduction in error generated by the classification procedure by accounting for all the elements of the confusion matrix excluding all agreements that occur by chance thereby providing a more rigorous statistical assessment of the classification is important (MUNTHALI, 2013; Congalton & Green, 2009). A total of 30,690 pixels were randomly selected from all the five classes as reference data using Germini handheld GPS. Accessibility was considered during the ground truthing data collection exercise hence the classes did not have an equal number of pixels. Wetlands and rocks on top of Dzalanyama hill were the most difficult to access due to poor roads during the rainy season. Land use types at the sampling sites were evaluated according to field surveys, where photographs were taken using a camera and coordinates of the spot were taken using GPS. This reference data was only used to assess the accuracy of the 2019 Image, while archived Google earth images were used to extract reference data for 2014 Image whereby a total of 8,917 pixels were sampled randomly. Due to unavailability of ground validation data in the form of aerial photographs for the images of 1999 and 1989, accuracy assessment was not performed on those images. Confusion matrix and Kappa coefficient were used to assess the accuracy of the LULC maps.

3.3.1.4. The Annual Rate of Change

The net change is defined as the difference between gain and loss and it is always regarded as an absolute value (Teferi *et al.*, 2013). The annual rate of change for the three periods (1989-1999, 1999-2014 and 2014-2019 was computed by the formula derived from the Compound Interest Law due to its better estimation and biological meaning (Puyravaud, 2003). This equation (3.1) is prefered by some researchers (Munthali *et al.*,2019; Teferi *et al.*, 2013) as it provides a benchmark for comparing LULC changes that are not sensitive to the differing periods between the study periods.

$$r = \left(\frac{1}{t_2 - t_1}\right) \times \ln\frac{A_2}{A_1} \qquad (3.1)$$

where: r is the annual rate of change for each class per year, and A_1 and A_2 are the area coverage (ha) of a land cover class at the time (years) t_1 and t_2, respectively.

3.3.2. MUSLE PARAMETER ESTIMATION

The Modified Universal Soil Loss equation was employed in GIS environment for the estimation of sediment yield in upper Lilongwe river catchment. MUSLE is the revised version of USLE and RUSLE that have been widely used. However, in both USLE and RUSLE, there is no direct consideration of runoff, despite erosion being majorly influenced by sediment being discharged with the flow and it varies with runoff and sediment concentration (Kinnel, 2005). The MUSLE is different from the USLE and RUSLE in the way that it uses a runoff factor instead of the rainfall erosivity factor used by the USLE and RUSLE (BHATTARAI & DUTTA, 2008). Some researchers have reported that the use of runoff factor in MUSLE simplifies storm-wise prediction of sediment yield and eliminates the need for delivery ratios that are required for USLE (Williams, 1975; Noor & Khalaj, 2018). The use of antecedent moisture conditions and rainfall energy in MUSLE is improved than in USLE (Williams, 1975; (Williams & Berndt, 1977; Kinnel, 2005). Lack of adequate data regarding rainfall, channel geometry and hydraulics of entire stream systems and the necessity to have accurate estimates of sediment yields from catchments are some of the reasons MUSLE model is preferably applied in developing countries (Sadeghi *et al*., 2007). The MUSLE equation was proved to apply to the points where the overland flow enters the streams and then all those points are summed up to give the total amount of sediment delivered to the stream network within a watershed (Williams, 1975; (Zhang *et al*., 2009). The MUSLE was applied to upper Lilongwe river watershed in the following general form:

$$\boldsymbol{Y = 11.8(Qq_p)^{0.56}KLSCP} \qquad (3.2.1.)$$

where Y is sediment yield in tons, Q is the volume of runoff in m^3, qp is the peak flow rate in m^3s^{-1}, and K, L, S, C, and P are respectively the soil erodibility (t.h. t^{-1} $m^{-1}cm^{-1}$), slope length (dimensionless), slope steepness (dimensionless), crop management, and soil erosion control practice (dimensionless) (Williams & Berndt, 1977).

3.3.2.1. The volume of runoff (Q) and peak flow rate (m^3s^{-1})

There are many methods used to estimate rainfall-runoff modelling. Soil Conservation Services (SCS, now Natural Resources Conservation Service, NRCS) Curve Number (SCS-CN) method is one of the widely used for estimating rainfall-runoff due to its simplicity, predictability and stability (Satheeshkumar *et al.*, 2017; Zema *et al.*, 2016; Zhang *et al.*, 2009; Ponce & Hawkins,1996). This method was established in 1954 by the USDA SCS, defined in the Soil Conservation Service (SCS) by the National Engineering Handbook (NEH-4) Section of Hydrology (Ponce and Hawkins 1996). The SCS-CN's two fundamental hypotheses are based on water balance calculation (Jun, *et al.*, 2015). The first hypothesis states that the ratio of the real quantity of direct runoff to the maximum possible runoff is equal to the ratio of the amount of real infiltration to the quantity of the potential maximum retention. The second hypothesis states that the amount of early abstraction is some fraction of the probable maximum retention. According to NRCS, (2004) the two hypotheses can be summarized by equation 3.2.1.1. below;

$$\frac{Q_d}{R} = \frac{F}{S} \qquad (3.2.1.1.)$$

Where Q_d is runoff depth in mm, R is the event rainfall in mm, F is the actual retention after runoff begins in mm, and S is the potential retention parameter which is related to soil and land cover conditions of the catchment. When initial abstraction (I_a) is considered, the amount of rainfall available for runoff is $(R - I_a)$. The Actual retention is the difference between rainfall and runoff depth $(F = R - Q_d)$. An empirical relationship between I_a and S was developed expressed as $I_a = 0.2S$, after substituting these three equations to equation 3.2.1.1, runoff can be calculated from rainfall and potential maximum retention with the equations:

$$Q_d = 25.4\frac{\left(\frac{R}{25.4} - 0.2S^2\right)}{\frac{R}{25.4} + 0.8S} \qquad \text{If } (R \geq 0.2S)$$

$$Q_d = 0 \qquad \text{If } (R \leq 0.2S) \qquad (3.2.1.2.)$$

S is calculated from the curve number (CN): S=$\frac{1000}{CN} - 10$ in inches (Zhang *et al*., 2009)

The peak discharge just like runoff can also be computed using different methodologies based on the availability of the data. For instance, Sadeghi, *et al.*, (2014) in their review article observed that the peak flow and the volume of runoff were obtained through direct measurement of runoff on a storm-event basis (58.70% of studies), using existing data (6.52%) (Khajehie *et al*. 2002, Rezaiifard *et al.* 2002, Porabdullah 2005), applying GIS (6.52%) (Arekhi 2007), lumped runoff values (8.70%) (Jackson *et al*. 1987, McConkey *et al.* 1997, Erskine *et* *al*. 2002, Mahmoudzadeh *et al*. 2002), the Soil Conservation Service (SCS) method (10.87%) (Williams 1977, Blaszczynski 2003, Mishra *et al*. 2006, Chakrabarty *et al*. 2007, Zhang *et al*. 2009) and reverse routing (2.17%) (as cited in Sadeghi, *et al* 2014). In this research, the SCS method was prefered because it can easily be integrated into a GIS environment. The SCS/NRCS 1986 uses graphical peak discharge to compute peak discharge q_p (m^3s^{-1}) which is expressed using equation 3.2.1.3.;

$$qp = q_u A Q_d F_p \qquad (3.2.1.3)$$

Where q_u is the unit peak discharge in m^3 s^{-1} km^{-2} mm^{-1}, A is the drainage area in km^2, Q_d

is the runoff depth in mm, and F_p is the pond and swamp adjustment factor which is the percentage of pond and swamp area over the watershed area. The time of concentration, T, is required for the calculation of q_u and is developed by calculating a travel time for sheet flow and travel time for shallow concentrated flow. Sheet flow is the flow over plane surfaces and usually occurs in the headwater of streams. The time of travel for sheet flow $[T_t sheet]$ of less than 91.4 m is calculated using Manning's kinematic solution:

$$T_t sheet = \frac{0.091(nL)^{0.8}}{J^{0.5}S^{0.4}}$$

where the travel time is in hours, n is the Manning's roughness coefficient, L is the flow

path length in meters, s is the slope in percentage and J is the 2-yr, 24-hr rainfall (typical 24-hour duration precipitation with a 2-year return period) in mm. After a maximum of 91.4 m, sheet flow usually becomes shallow concentrated flow and the time of travel for shallow concentrated flow $(T_t shallow)$ is calculated using the following equation for the remainder of the flow path until it flows into a defined channel:

$$T_t shallow = \frac{3.281 \times L}{3600 \times 16.1345 \times s^{0.5}}$$

where L is the flow path length in m. This equation is based on Manning's equation and two assumptions for Manning's roughness coefficient (0.05) and hydraulic radius (0.4). Now the two times of travel calculations can be added together to come up with the time of concentration (T) where each drainage way discharges into a stream (Zhang *et al*., 2009).

By using SCS methods for computing runoff and peak discharge, GIS can be used to simplify the whole process and get accurate results. In this research Hydrologic Engineering Center – Hydrologic Modelling System (HEC-HMS 4.4) was used to simulate rainfall-runoff and streamflow in Upper Lilongwe River Catchment. HEC-HMS is a hydrological model, developed since 1998 by the 'US Army Corps of Engineers' research and development. The program stimulates precipitation-runoff, and routing processes both natural and controlled (Feldman, 2000). Additionally, the model has been designed to forecast streamflow of dendritic basin systems in a wide range of geographic areas such as large river basins and small urban or natural watersheds (Abushandi & Merkel, 2013).

The HEC-HMS contains four main components. 1) An analytical model to calculate overland flow runoff as well as channel routing, 2) an advanced graphical user interface illustrating hydrologic system components with interactive features, 3) a system for storing and managing data, specifically large, time-variable data sets, and 4) a means for displaying and reporting model outputs (Bajwa & Tim, 2002; Halwatura & Najim, 2013). HEC-HMS was chosen because of its ability to allow spatial data to be prepared in Arc GIS and directly be imported into HEC-HMS.

Before using HEC-HMS, the 90 m resolution was pre-processed in Arc GIS 10.4 using HEC-GeoHMS. The pre-processing included terrain preprocessing; building walls, filling sinks, flow direction, flow accumulation, etc. SCS curve number grid was created using the DEM, Soil map, and Land use map. CN grid and CN lookup tables were created at the end of the pre-processing. Then processing started which consisted of Basin processing, Basin characteristics extraction, estimating, and assigning several watersheds and stream parameters for use in HMS. These parameters included SCS curve number, time of concentration, channel routing coefficients, and the basin was divided into four inter-connected sub-basins.

Out of 11 infiltration methods of the HEC-HMS model, SCS-CN was chosen. The SCS-CN methods implement the curve number methodology for incremental losses. The methodology was originally intended to calculate total infiltration during a storm. The program computes incremental precipitation during a storm by recalculating the infiltration volume at the end of each time interval (Halwatura & Najim, 2013). The method requires the percentage of land use patterns of the catchment and the sub-catchments, total length of the river, and the elevation of the watershed. By following USDA-SCS, (1972) guidelines an average CN value for each sub-basin was computed as a function of cumulative precipitation, soil type, land use, and antecedent moisture content weighted by its area. Model simulation and optimization was carried out in HEC-HMS 4.4 using 2018/2019 observed rainfall and streamflow data to get the final Q and q_p that were used as an input parameter in the MUSLE equation.

3.3.2.2. The Soil Erodibility Factor (K)

Soil erodibility is defined as the inherent aspect of soil properties reflecting the susceptibility and vulnerability of the soil to erode, as influenced by the biophysical and chemical characteristics of the soil (Renard *et al.*, 1997; Fenta *et al*., 2016; Yesuph & Dagnew, 2019). The physicochemical and mineralogical properties of the soil determine the resistance of the soil particles for the detaching and transporting power of the rainfall (Wischmeier & Smith, 1978). The K factor quantifies the cohesive character of the soil type and its resistance to dislodging and transport due to raindrop impact and land flow shear forces (Gelagay & Minale, 2016).

Originally K factor was computed for experimental plots using nomograph. The nomograph establishes the relationship between K-factor and soil type based on the soil's properties such as particle size distribution, organic matter content, soil structure, and permeability (Wischmeier *et al.*, 1971). The monograph comprises five soil profile parameters (per cent modified silt; per cent modified sand; per cent organic matter; classes for structure and permeability). According to Goldman *et al.*, (1986) coarser textured soils, such as sandy soil, have low K values ranging from 0.05 to 0.2. Although these soils have easily detachable particles, the low surface runoff caused by excessive infiltration is responsible for the low values of K observed for this type of soil. For medium texture soils, such as the silt loam soils, K values typically range from 0.25 to 0.4. It can be assumed that these K values are due to moderate runoff and easier detachment of medium-textured soils. Wischmeier *et al*., (1971) further add that silt content is also an important factor of soil erodibility. Since they are easily detached, silts tend to crust and produce high rates of runoff, soils with high silt content are the most erodible of all soils. Accordingly, their soil erodibility factors are greater than 0.4. Organic matter has a measurable effect on soil erosion. It reduces erodibility, decreases susceptibility to soil detachment, and increases infiltration rates. High infiltration rates reduce runoff and erosion (Ndolo Goy, 2015).

Lately, different approaches have been developed by different researchers to determine soil erodibility factor. The type of data available in a specific area governs the choice of approach to employ (Yesuph & Dagnew, 2019). The K-factor for this study was computed using Williams (1995) as illustrated by equation 3.2.2. below:

$$K_{Factor} = f_{csand} \times f_{cl-si} \times f_{orgc} \times f_{hisand} \qquad (3.2.2.)$$

Where K_{factor} is the soil erodibility factor, f_{csand} is the factor that gives low soil erodibility factors for soils with high coarse-sand contents and high values for soils with little sand contents, f_{cl-si} is the factor that gives low soil erodibility factors for soils with high clay to silt ratios, f_{orgc} is the factor that reduces soil erodibility for soils with high carbon content, and f_{hisand} is the factor that reduces soil erodibility for soils with extremely high sand content. All the four factors are computed using subsequent equations;

$$f_{csand} = (0.2 + 0.3 \times exp[-0.256 \times m_s\{1 - m_{silt}/100\}]) \qquad (3.2.2.1)$$

$$f_{cl-si} = ((m_{silt}/[m_c + m_{silt}])^{0.3}) \qquad (3.2.2.2.)$$

$$f_{orgc} = (1 - 0.25 \times orgC + exp^{3.72-2.95\times orgC}) \qquad (3.2.2.3)$$

$$f_{hisand} = \left(1 - \frac{0.7 \times [1 - m_s/100]}{(1 - m_s)} \times exp^{-5.51+22.9\times[1-m_s/100]}\right) \qquad (3.2.2.4)$$

Where m_s is the percentage of sand, m_{silt} is the percentage of silt, m_c is the percentage of clay and $orgC$ is the percentage of organic carbon/matter.

All the fractions of sand, clay, silt, and organic carbon were represented to the topsoil cover of the catchment because topsoil is the one that is directly impacted by the raindrops. Table 5 provides the K values for the soil types in the catchment area.

Table 5 Upper Lilongwe River Watershed Soil properties

FAO_Classification type	sand % topsoil	silt % topsoil	clay % topsoil	OC % topsoil
Cambic Arenosol	91.9	3.2	5	0.23
Chromic Luvisols	64.3	12.2	23.5	0.63
Eutric Cambisols	36.4	37.2	26.4	1.07
Eutric Gleysols	42.8	20.4	36.8	1.3
Haplic lixisol	79	5.8	14.8	0.81
Leptsols	58.9	16.2	24.9	0.97
Xanthic Ferrarsol	72.9	5.9	21.3	0.91

Adapted from: Malawi Soil Map, FAO classification

3.3.2.3. Slope Length and Slope Steepness Factor (LS)

The slope length factor (L) and the steepness factor (S) account for the effects of topography on soil erosion modelling. Wischmeier and Smith (1978) and Renard *et al*., (1997) defined slope length as “the horizontal distance from the origin of overland flow to the point where either the slope gradient decreases to a point at which deposition begins or runoff becomes concentrated in a defined channel. The LS factor represents a ratio of soil loss under given conditions to that at a site with the ‘‘standard’’ slope steepness of 9 % and slope length of 22.13 m. LS is normally computed together because the steeper the slope of the land the higher will be the speed and erosive power of runoff (Wischmeier and Smith 1978; Renard *et al.* 1997).

Several methodologies have been developed to compute the LS factor from the digital elevation model in a GIS environment. However, some researchers have argued that some of these methodologies do not consider the three-dimensional complex nature of the terrain as they only consider that soil erosion only depends on slope length in the essence that the longer the slope the higher the soil loss (Robert & Hilborn, 2000). Other researchers as cited in Gelagay (2016) recommend that the correct approach should replace slope length by the upslope contributing area because soil loss does not depend on slope length for three-dimensional complex terrain where there is flow convergence and divergence, instead, it is influenced by the upslope contributing area (Desmet & Govers,1996a; Moore & Burch,1986a, 1986b; Mitas &Mitasova,1996; Simms, Woodroffe, & Jones,2003). Therefore this research employed advanced LS computation approach as suggested by (Moore & Bruch, 1985; Moore & Burch 1986; Moore & Wilson, 1992; Gelagay & Minale, 2016) which is illustrated in equation 3.2.3 below;

$$LS = (\frac{Bx}{22.13})^{0.6} \times (\frac{\sin \emptyset}{0.0896})^{1.3} \qquad (3.2.3)$$

Whereby LS is the slope steepness-length factor, Bx is the specific catchment area, i.e. the upslope contributing area per unit width of contour drains to a specific point which is given by $[Flow\ accumulation \times DEM\ cell\ size]$, and $\emptyset$ is the slope angle.

A 90 m resolution SRTM DEM was pre-treated by filling the sinks of the digital terrain model to remove slight imperfections in the data (Chadli, 2016). The slope in degrees was computed using the spatial analyst tool in Arc-GIS 10.4. The flow direction and accumulation were computed using Arc-Hydro tools in Arc-GIS and map algebra was used to compute LS by using the following equation 3.2.3.1;

$$Pow[(flow\ accumulation] * 90/22.13{,}0.6) \times Pow[\sin(slope_{in} degree) * 0.01745/0.0896{,}1.3] \qquad (3.2.3.1)$$

Figure 6 shows the summarized steps taken in Arc GIS to compute the LS factor

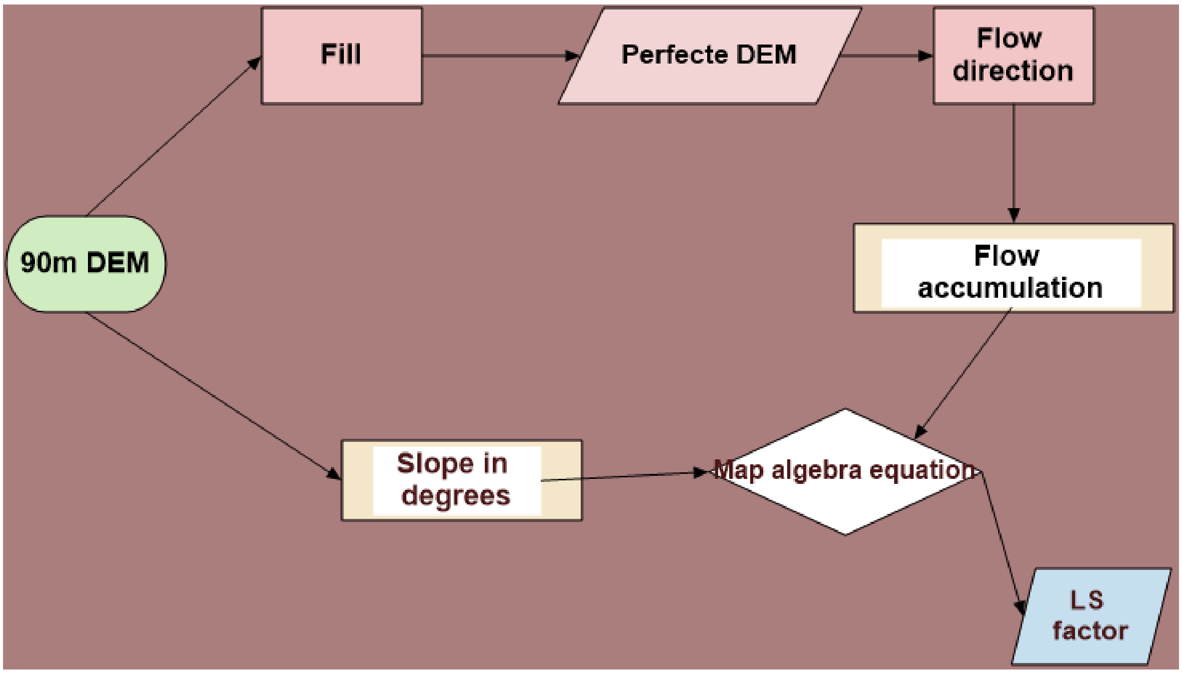

Figure 6 Steps followed in Arc GIS to compute LS

3.3.2.4. Land cover and Management Factor (C)

The Land Cover and Management Factor (C) represents the effect of vegetation, soil cover, below-ground biomass, cropping, soil-disturbing activities, and management practices on soil erosion (Ndolo Goy, 2015). It is used to determine the relative effectiveness of soil and crop management systems in terms of preventing soil loss (Chadli, 2016). The C factor is the same as a soil loss ratio (SLR) which is defined as the ratio of soil losses under actual conditions to losses experienced under the clean-tilled continuous fallow reference conditions. An SLR is the result of multiplying subfactor values that depend on previous cropping and management, vegetative canopy, surface cover and roughness, and, in some cases, soil moisture (Ndolo Goy, 2015). C- factor is a single factor due to quick changes in land use in different seasons, for instance, agricultural land this year planted with a certain crop might not be the same the next growing season as farmers do intercrop sometimes or even fallow the land. This factor is also considered mostly when developing a land management conservation plan (Gelagay & Minale, 2016).

The land management conservation plan is directly influenced by the density of the protective cover of crops or vegetation on the land since the density of vegetative cover affects directly soil erosion. Therefore, the cover management factor (C) value will be 1 in the case of continuous bare fallow with no vegetation coverage (in standard plot condition) and lower in case of more vegetation or crop cover producing a lower amount of soil erosion. This land would require immediate land conservation actions. In the case of dense and mature forest with trees canopy and undergrowth vegetation covering between 75 to 100% of the land area, C value is close to 0.001. In this last case, land conservation actions are not required (Ndolo Goy, 2015).

Primarily, maximum likelihood supervised classification was performed on Landsat 8 image to produce the 2019 land use land cover map of the study area. The LULC map was classified into five major classes; Water, Built-up, Forest, Cultivated land, and Grass/Shrubs/Bare land. After converting the LULC map from raster to vector, the C Factor was assigned to each land-use class based on Wischmeier & Smith, (1978) tabulated C-values and the average annual C values have been used before for Malawian conditions by Mughogho, (1998). Table 6 shows the land use type and its corresponding C- value that was used in this study.

Table 6 Adopted C-values for different LULC classes in the Upper Lilongwe River Catchment

Land use Land cover Class	**C-factor**
Waterbody	-
Forest	0.01
Grass/Shrubs/Bare Land	0.04
Cultivated land	0.08
Built-up	0.13

Adapted from: Wischmeier & Smith, (19780; Mughogho, (1998).

3.3.2.5. Support Practice/Erosion Control Factor (P)

Support practice factor is the ratio of soil loss from any conservation support practice to that with up- and downslope tillage. P is used to evaluate the effects of contour tillage, strip cropping, terracing, subsurface drainage and dryland farm surface roughening (Stone & Hilborn, 2012). The surface that is tilled with up- and downslope row orientation or relatively smooth, tend to develop a drainage pattern that allows eroded sediment to be readily transported downslope. On the other hand, tillage on the contour allows the excessive rainfall to be stored in the furrows between the tillage ridges enabling significant amounts of depression storage and sedimentation (Mughogho, 1998).

The effectiveness of contour to hold excessive rainfall depends on the ability of the tillage marks to store runoff and is imparted by the following factors; size or roughness of the tillage system, the amount of runoff, and the peak intensity of the rainfall. As the concentrated flow moves downslope, the number of runoff increases thus reducing the effectiveness of a given contour tillage system. The P values are obtained from tables of the ratio of soil loss with and without the practice. P values vary with the slope steepness (Wischmeier & Smith,1978). From the field observation in the study area, contour tillage is practised in the cultivated land. Therefore just like in the case of C-factor, average annual P values were assigned to each LULC class. The slope was taken into consideration only in the cultivated land and the rest of the LULC classes were assigned a P-value of 1 irrespective of the slope. Table 7 Shows the Land management practice values that were used in this study based on Wischmeier & Smith's (1978) tabulated values for the USA.

Table 7 Land Management Factor Values for Upper Lilongwe River Catchment

Land use Land cover Class	**Slope Category (%)**	**P factor**
Cultivated Land	0-5	0.10
	5-10	0.12
	10-20	0.14
	20-30	0.19
All the other classes	All	1

Adapted from: Wischmeier & Smith's (1978)

3.3.3. Water Sampling

Lilongwe Water Board is the statutory corporation responsible for the provision of potable water in Lilongwe city and surrounding areas. Since LWB abstract water from the Upper Lilongwe River Catchment, it monitors sections of upper Lilongwe river and its tributaries. Nine already existing monitoring/sampling points were purposively chosen from all the LWB's monitoring points. The water samples were collected during the rainy season in February 2020. A total of 9 grab samples (one from each of the sampling points) were analysed for the following parameters pH, EC, Nitrate, Phosphate, TDS, TSS, Turbidity and Faecal coliform using (APHA, 2005). The river was in high stream flows since February is the rainiest month. Grab water samples of 1000ml were collected in plastic bottles for Physico-chemical analysis and 100ml bottles were used to collect samples for biological analysis. All the quality control measures were taken during sampling and transportation. The sample bottles were washed with distilled water before being washed with the sampled water thoroughly, then transported by using a cooler box to the laboratory. Some of the parameters (pH, EC, TSS and Turbidity) were measured on-site while the rest were transported immediately and analysed at the Department of Water's central laboratory in Lilongwe. Secondary data for the previous years that encompassed dry and rainy season from 2003 was collected from Lilongwe water board; Water Quality and Environmental Division. The names of the sampling points and their location are presented in Table 8 and graphically presented in figure 7.

Table 8 Physical attributes of water quality sampling points in the Upper Lilongwe River Catchment

Sampling Point	**Location**	**Elevation (m)**	**UTM Easting**	**UTM Northing**
Katete	Katete river at Dzalanyama gate	1085	564293.74	8429722.54
KD1	An outlet of Kamuzu dam 1 (KD 1 bridge)	1084	569230.2	8432931.13
KD 2	An outlet of Kamuzu dam 2	1081	573996.24	8434153.5
Lisungwi	Lisungwi river at Nsinja bridge	1081	576939.69	8435315.8
LL-Lisungwi Confluence	Lilongwe river-Lisungwi river confluence point	1066	575954.87	8437445.59
LL-Malili bridge	Lilongwe river at Malili bridge	1057	576852.7	8442757.77
Likuni	Likuni river at Likuni bridge	1055	576397.72	8448249.31
LL-Likuni Confluence	Likuni river-Lilongwe river confluence at Chinsapo	1054	577026.02	8448518.29
Treatment Plant	Water abstraction point at the Treatment plant	1053	581675.3	8451428.88

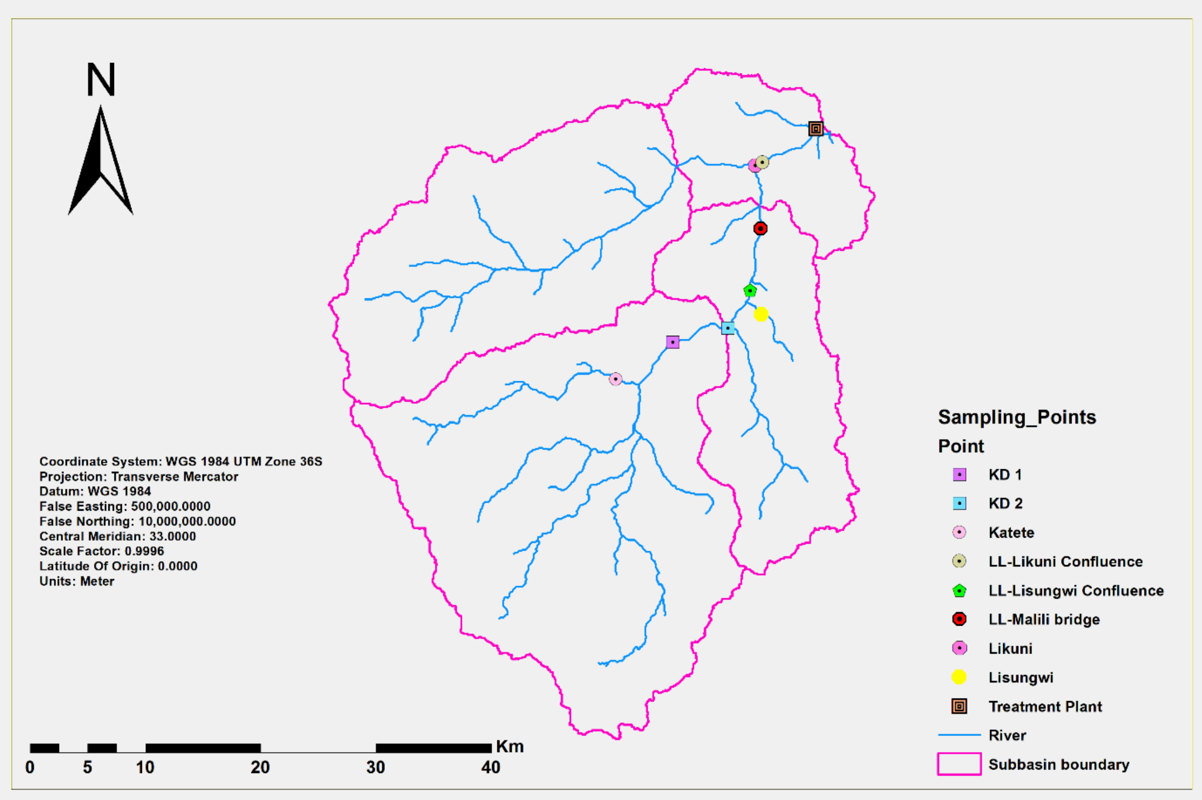

Figure 7 Sampling Points and Sub-basin of the Catchment

3.3.3.1. Water Quality Data Analysis

Data were analysed using Statistical Package for Social Sciences (SPSS) version 25. The paired t-test was used to compare the means as well as the seasonal differences in water quality of the water in the Lilongwe river. The river was divided into three sections based on the dominant land use in each section. Forest and Grassland were the dominant land use in section A which comprised of the following sampling points; Katete, Kamuzu dam 1 and Kamuzu dam 2. Section B was dominated by Cultivated land which comprised the following sampling points; Lisungwi, LL-Lisungwi and LL-Malili bridge. Lastly, section C which had the following sampling points; Likuni, LL-Likuni Confluence and Treatment plant was dominated by Built-up area. This was done to assess the spatial and temporal variability of water quality parameters in the catchment. The mean values of the parameters for different locations and seasons were used for the temporal and spatial water quality analysis of the catchment.

Various techniques have been applied in assessing and understanding the relationship between land use/land cover and water quality in different watersheds worldwide. These techniques include correlation indices (Namugize *et al*., 2018; Dai *et al*., 2017) and the econometric models (Huang *et al*., 2013). The use of modelling techniques in establishing the relationship between land use and water quality have some advantages over other techniques due to their suitability in relating the phenomena. Thus, statistical modelling may be preferable to physical-based modelling because of the need for a large number of input data associated with continuous observation data for the model building, calibration, and validation process in the later (Camara *et al*., 2019).

In this study, Pearson's correlation coefficient was employed to establish whether a linear relationship between LULC variables, considered as independent variables, and water quality variables, as dependent variables, exist. Due to a lot of missing data for some of the parameters, the relationship between LULC variables was only established for the following water quality variables; nitrate, phosphate, turbidity, TDS, EC and pH. SPSS version 25 was used to compute the Pearson correlation coefficient r, to give more precision to the relationship between the dependent and independent variables, depending on whether there is a positive, negative or no correlation between these two variables. Based on the Pearson correlation coefficients, the relationship between two variables can be considered as strong, medium, weak and none, depending on whether the absolute values of r were, from 1 to 0.68, 0.67–0.36, 0.35–0.10 and 0.09–0.00, respectively (Namugize *et al*., 2018). Level of significance was assessed at a 95 % confidence interval.

3.3.4. Ethical Consideration

Primary and secondary data were collected after written consent from different responsible government institutions, LWB, and local village leaders where ground training data were collected. No single picture was taken before seeking consent from the people in the picture or the owners of the private property.

4. RESULTS AND DISCUSSION

4.1. Land use Land Cover Change

From table 9 below, it shows that the overall accuracy for the 2014 classification map was 95.03 per cent. The producer's accuracy ranged from 80.24 to 99.95 per cent, with the Built-up having the lowest producer's accuracy and Forest having the highest. In terms of users' accuracy, the accuracy ranged from 91.20 to 98.70 per cent with Cultivated land having the lowest and Grass/Shrubs/Bare land having the highest.

Table 9 Confusion (Error) Matrix Table for 2014 LULC Map

	Reference Data						
Class	**Waterbody**	**Cultivated Land**	**Forest**	**Grass**	**Built-Up**	**Row Total**	**User's Accuracy**
Water body	1550	2	1	0	117	1670	**92.81**
Cultivated Land	14	2291	0	15	192	2512	**91.2**
Forest	46	0	1948	3	0	1997	**97.55**
Grass/Shrubs/Bare Land	16	0	0	1422	2	1440	**98.75**
Built Up	35	0	0	0	1263	1298	**97.3**
Column Total	1661	2293	1949	1440	1574	8917	
Producer's Accuracy	**93.32**	**99.91**	**99.95**	**98.75**	**80.24**		

The 2014 image produced both very good producer and user accuracy hence the overall accuracy was 95.03 per cent with the kappa coefficient of 0.9373. The error matrix table for 2019 LULC map produced a slightly lower accuracy compared to the one of 2014. Table 10 Shows the Confusion matrix table for the 2019 LULC

Table 10 Confusion Matrix Table for the 2019 LULC Map

	Reference Data						
Class	**Waterbody**	**Cultivated Land**	**Forest**	**Grass/Shrubs/Bare Land**	**Built-Up**	**Row Total**	**User's Accuracy**
Water body	1926	63	69	34	201	2293	**83.99**
Cultivated Land	5	6544	2	1	106	6658	**98.29**
Forest	139	13	12709	475	0	13336	**95.3**
Grass/Shrubs/Bare Land	10	44	152	3405	13	3624	**93.96**
Built Up	42	704	2	0	4031	4779	**84.35**
Column Total	2122	7368	12934	3915	4351	30690	
Producer's Accuracy	**90.76**	**88.82**	**98.26**	**86.97**	**92.6**		

The 2019 LULC confusion matrix produced, producer's accuracy ranging from 88.82 to 98.26 per cent with Cultivated land having the lowest and Forest the highest. The map produced User's accuracy ranging from 83.99 to 98.29 per cent with Waterbody having the lowest and Cultivated land the highest. However, the overall accuracy was good with an overall accuracy of 93.24 per cent and the Kappa coefficient of 0.9064.

Both the 2014 and 2019 LULC map met the minimum accuracy requirement for post-classification change detection analysis as stipulated by Anderson *et al*., (1976) that the minimum level for interpretation accuracy in the identification of land use and land cover categories from remote sensing data should be at least 85 per cent. The lower Producer's accuracy in the 2014 LULC map can be attributed to the reflectance of different roofing systems used in Malawi such as Iron sheet and thatching grass that might have been committed to Grass/Shrubs/Bare land class. Both the overall and kappa coefficients obtained in this research are higher than the ones obtained by other researchers in Malawi. For instance, Munthali, (2019) in their study in Dedza (which share part of Dzalanyama forest reserve) obtained an overall accuracy of 91.86 % with a kappa coefficient of 0.866. The slightly lower accuracy was attributed to the similarity of reflectances between different LULC classes. In another study, which was carried only on the upper part of this study's area (Upper Lilongwe River Catchment), Munthali & Murayama, (2011) had overall classification accuracies ranging from 80 to 84 per cent for different years with the oldest year (1990) having the lowest accuracy. The error was attributed to disparities in observation time of the satellite imagery and the reference data which had 4-5 years gap. The high accuracies values obtained in this research can be attributed to uniformity between the observation time of the imagery and the reference data which had only 3 months difference for the case of 2019 Image and a single month difference for the case of 2014 Image. The reliance on ancillary data during image classification might have also contributed to the high overall accuracy.

4.1.1. Land use land cover dynamics

The dominant land use land cover following the classification for the 1989-1999 period was Forest and cultivated land that comprised over 60 per cent of land use in the catchment area. Built-up was the least common land-use type in the catchment in1989 but the situation changed in 1999 whereby Waterbody became the least common land-use type in the catchment. The spatial extents of each land-use type for the year 1989 and 1999 are shown in Table 11 which are further graphically portrayed in figure 8.

Table 11 Spatial distribution of Land Use Classes-1989 and 1999

Land cover Type	1989		1999	
	Area (ha)	%	Area (ha)	%
Forest	66727	36.87	54640	30.19
Waterbody	14702	8.12	12769	7.05
Grass/Shrubs/Bare land	29460	16.28	32025	17.70
Built-up	14164	7.83	17763	9.82
Cultivated Land	55924	30.90	63780	35.24
Total	**180977**	**100**	**180977**	**100**

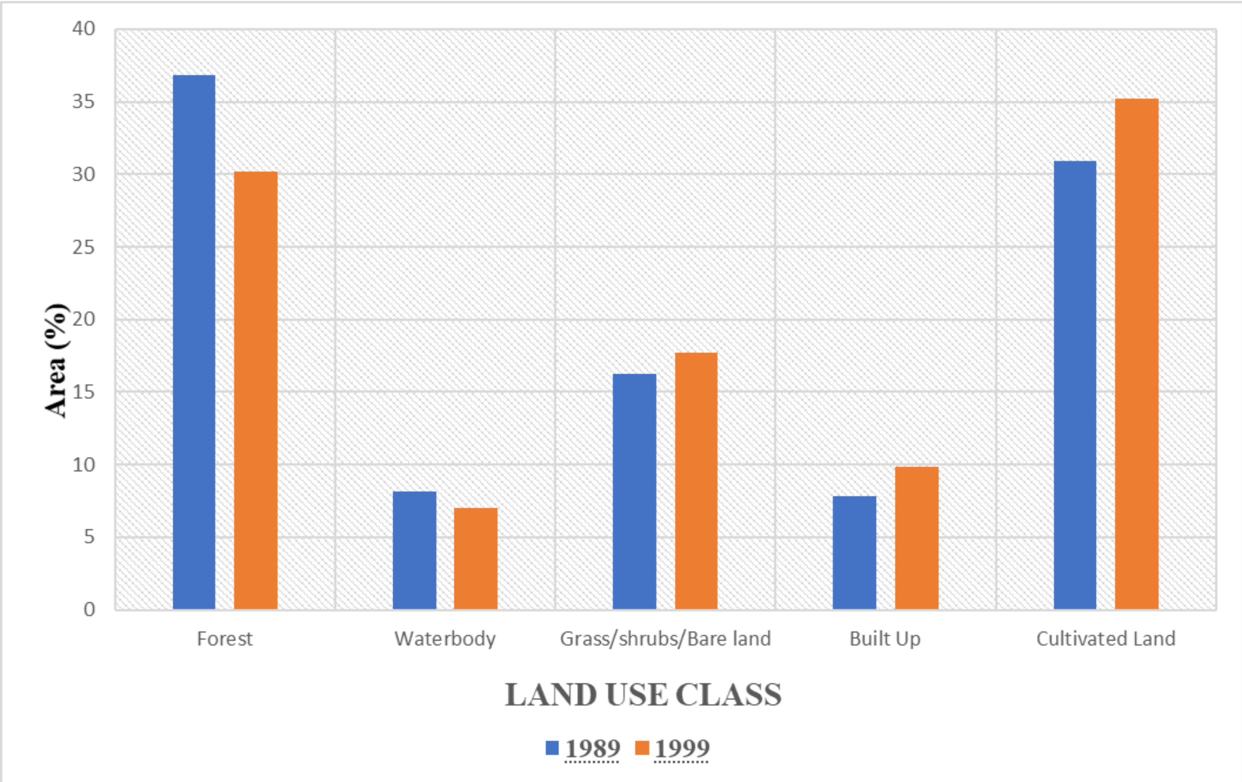

Figure 8 Spatial Distribution of Land use Classes-1989 & 1999

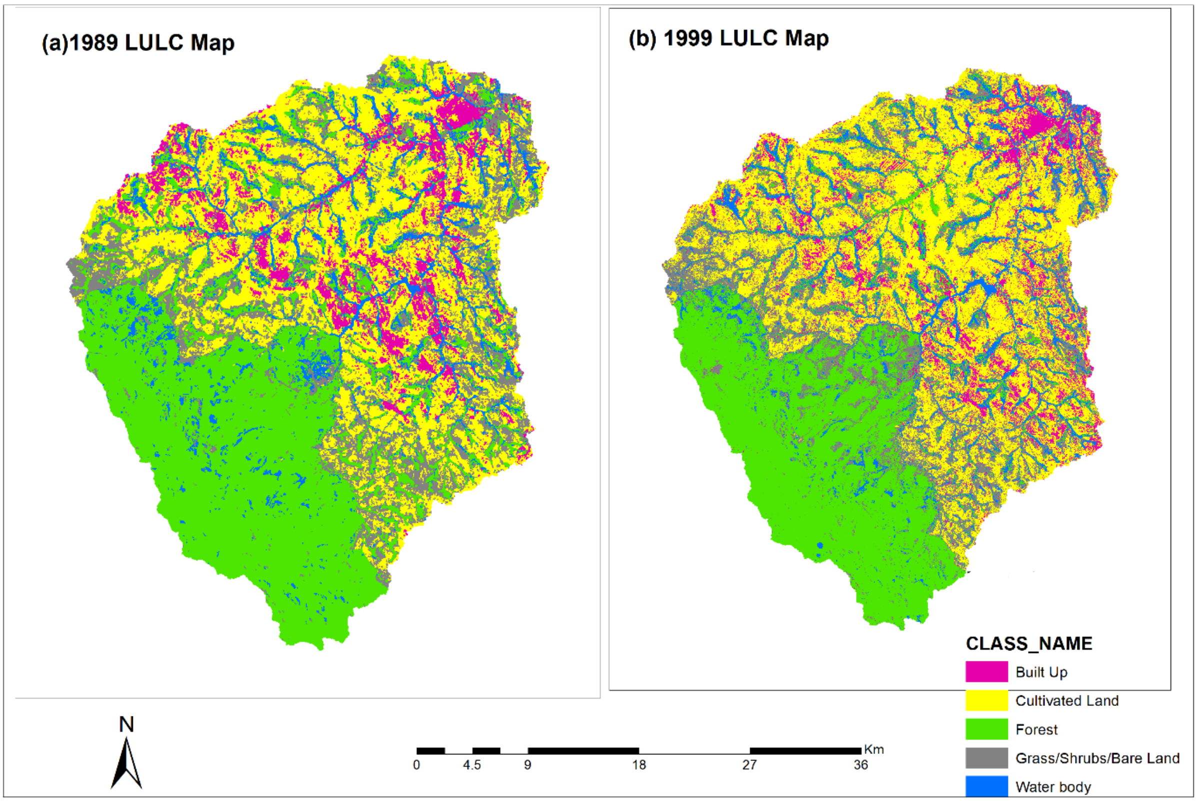

Figure 9 1989 and 1999 LULC Maps

From the figures 8 and 9 above indicates large areas of forested land which is mainly located on the upper catchment inside the protected area of Dzalanyama forest reserve occupying 66,727 ha and 54,640 ha in 1989 and 1999 respectively. There was also some percentage of forest in Lilongwe city in 1989 which is observed to be different in 1999. The abundance of forested land starts decreasing. In both periods (1989 and 1999), Cultivated land extended from the boundaries of Dzalanyama forest to Lilongwe city. However, in 1989 some of the cultivated lands which had some minor percentage of plantations (forest) started being deforested which saw the increase in Grass/Shrubs/Bare. The deforestation along the river banks is another reason Grass/Shrubs/Bare land increased in the watershed. Minor extents of lands were occupied by Built-up and waterbody in both 1989 and 1999. The main difference is that Built-up was the least extent land cover (14,164 ha) in 1989 and the situation changed in 1999 where Waterbody became the least extent land use (12,769 ha) in the catchment.

The magnitude of the coverage in the catchment for the period 1999-2014 took a different trend from the one observed between 1989 and 1999 in Grass/Shrubs/Bare land class only, while the rest of the classes remained with the same trend observed in the previous period (1989-199). Cultivated land kept on increasing that saw the extent of land being cultivated reaching 76,701 ha in 2014. Deforestation in the catchment kept increasing that saw a further staggering 13,252 ha of forest cover between 1999 and 2014. The smallest category was still occupied by Waterbody (11,828 ha) as presented in Table 12 and graphically illustrated in figure 10.

Table 12 Spatial distribution of Land Use Classes-1999 and 2014

Land cover Type	1999		2014	
	Area (ha)	%	Area (ha)	%
Forest	54640	30.19	41388	22.88
Waterbody	12769	7.05	11828	6.545
Grass/Shrubs/Bare land	32025	17.70	26506	14.65
Built-up	17763	9.82	24554	13.56
Cultivated Land	63781	35.24	76701	42.38
Total	**180978**	**100**	**180977**	**100**

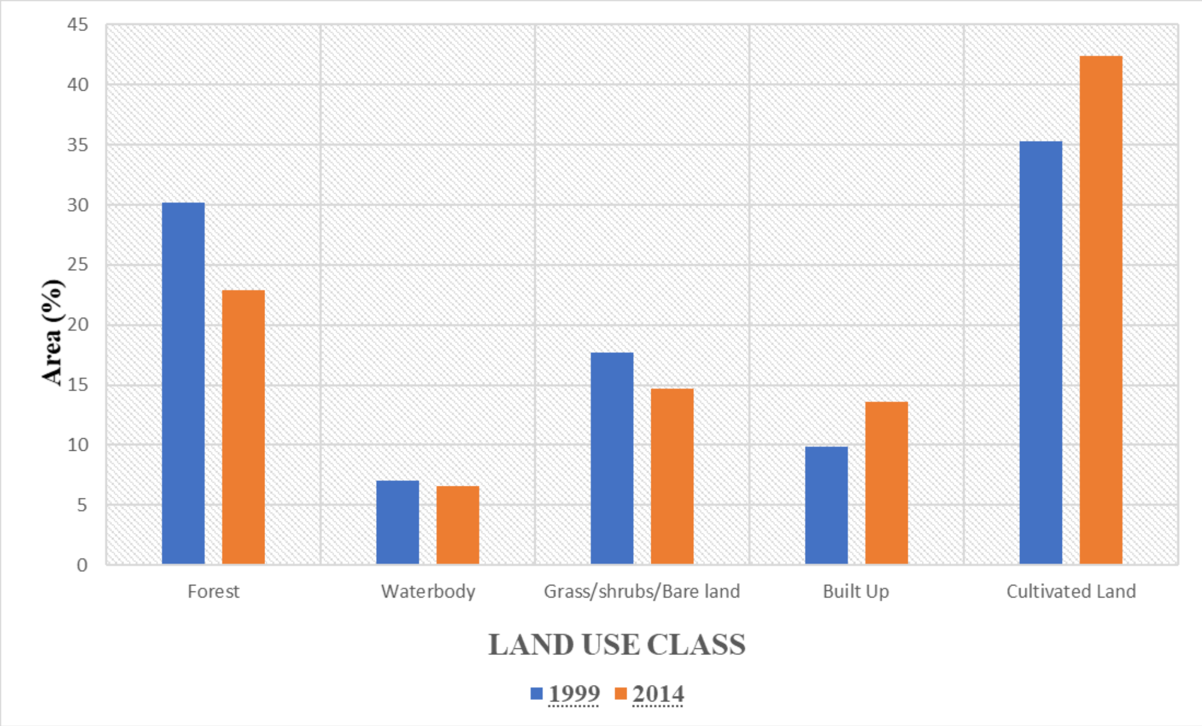

Figure 10 Spatial Distribution of LULC Classes-1999 and 2014

Despite Cultivated land remaining the most dominant land use in the study area up to 2019, the cultivated land class took a different trend from the one observed in the previous two periods (1989-1999 and 1999-2014). The period between 2014 and 2019 saw cultivated land starting to decrease, at the same period it saw Built-up area overtaking Grass/Shrubs/Bare land as the third prominent land-use class in the catchment after Cultivated land and forest. Waterbody remained the least prominent Land use land cover class in the watershed in the year 2019. Table 13 shows the spatial distribution of land use in upper Lilongwe River Watershed of the year 2014 and 2019 which is further illustrated graphically by figure 11.

Table 13 Spatial distribution of LULC Classes-2014 and 2019

Land cover Type	**2014**		**2019**	
	Area (ha)	**%**	**Area (ha)**	**%**
Forest	41388	22.88	35594	19.67
Waterbody	11828	6.545	10980	6.07
Grass/Shrubs/Bare land	26506	14.65	26074	14.4
Built-up	24554	13.56	32696	18.07
Cultivated Land	76701	42.38	75633	41.79
Total	**180977**	**100**	**180977**	**100**

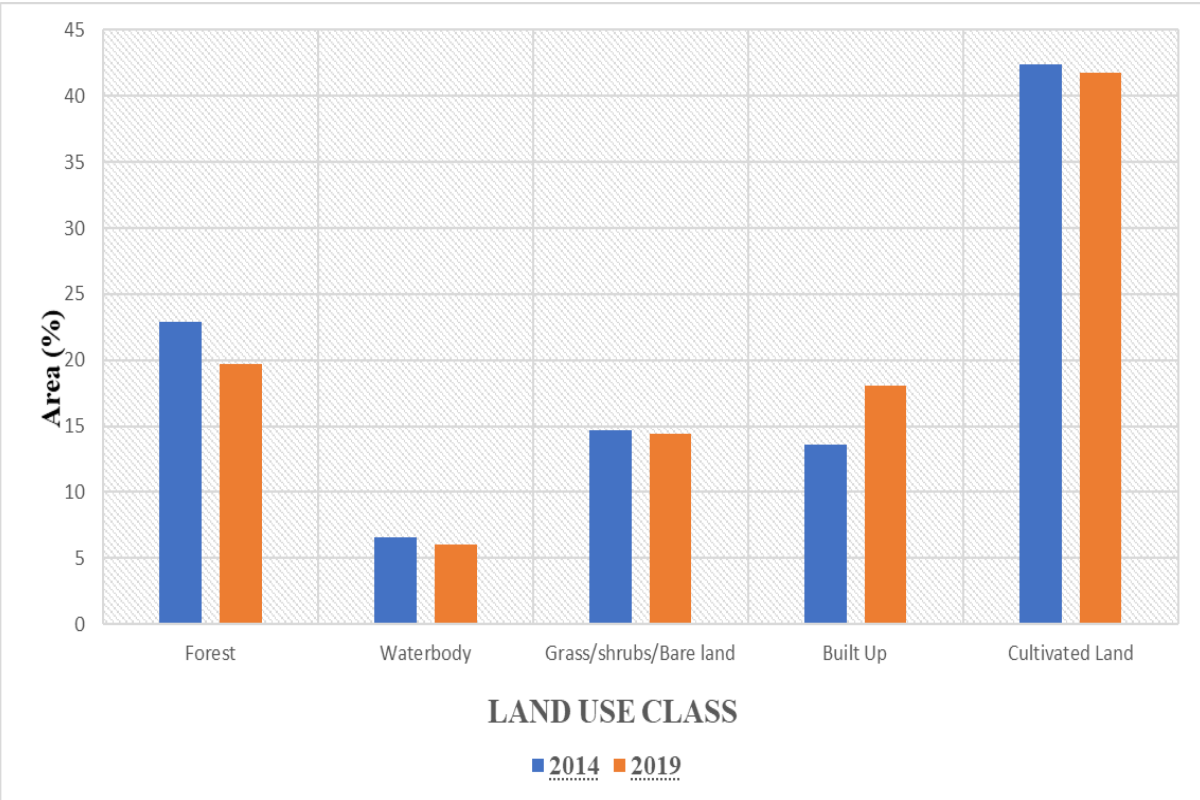

Figure 11 Spatial distribution of LULC Classes-2014 and 2019

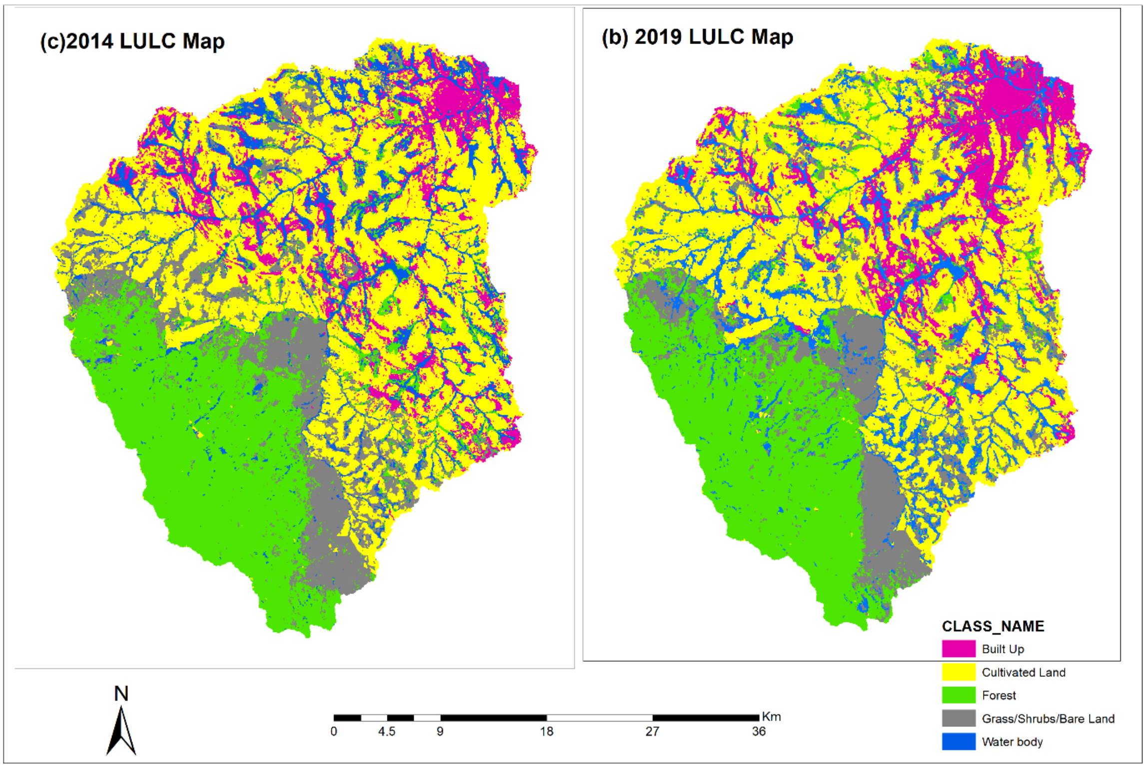

Figure 12 2014 and 2019 LULC Maps

Figures 11 and 12 above show that there is serious deforestation in the upper part of the catchment mainly in the protected area of Dzalanyama forest. The forested land is being converted mainly to Grass/Shrubs/Bare land in Dzalanyama forest. The lower part of the watershed has seen a tremendous increase in the built-up area. The magnitude of grass/shrubs/bare land remains almost constant in the whole watershed despite the increase in the upper part because there is a huge reduction in the middle and lower part of the watershed due to urban expansion and continuous conversion of grass/shrubs/bare land into cultivated land.

4.1.2. The Annual Rate of LULC Changes

The study period comprised of 30 years (2019-1989) was divided into three periods (1989-1999, 1999-2014 and 2014-2019). The annual rate of land use and land cover change throughout the study period of 30 years showed fluctuation trend as shown in Tables 14-16 below.

Table 14 1989:1999 Annual Rate of Change for different Classes

Land Use type	**1989**		**1999**		**Change%[b]**	**Annual Change rate %[c]**
	Ha	**%[a]**	**Ha**	**%[a]**		
Forest	66727	36.87	54640	30.19	-6.68	-2.0
Waterbody	14702	8.12	12769	7.05	-1.07	-1.41
Grass/Shrubs/Bare land	29460	16.28	32025	17.70	1.42	0.83
Built-up	14164	7.83	17763	9.82	1.99	2.26
Cultivated land	55924	30.90	63781	35.24	4.34	1.31
Total Area	**180977**	**100**	**180977**	**100**		

[a] Percentage of each class out of the total area; [b] percentage change in the class; [c] percentage annual rate of change

Table 15 1999:2014 Annual Rate of Change for Different classes

Land Use type	**1999**		**2014**		**Change%[b]**	**Annual Change rate %[c]**
	Ha	**%[a]**	**Ha**	**%[a]**		
Forest	54640	30.19	41388	22.87	-7.32	-1.86
Waterbody	12769	7.07	11828	6.54	-0.53	-0.51
Grass/Shrubs/Bare land	32025	17.70	26506	14.65	-3.05	-1.27
Built-up	17763	9.82	24554	13.57	3.75	2.16
Cultivated land	63781	35.24	76701	42.38	7.14	1.24
Total Area	**180977**	**100**	**180977**	**100**		

[a] Percentage of each class out of the total area; [b] percentage change in the class; [c] percentage annual rate of change

Table 16 2014: 2019 Annual Rate of Change for Different LULC Classes

Land Use type	2014		2019		Change%[b]	Annual Change rate %[c]
	Ha	%[a]	Ha	%[a]		
Forest	41388	22.87	35594	19.67	-3.2	-3.02
Waterbody	11828	6.54	10980	6.07	-0.47	-1.49
Grass/Shrubs/Bare land	26506	14.65	26074	14.41	-0.24	-0.33
Built-up	24554	13.75	32696	18.07	4.32	5.73
Cultivated land	76701	42.38	75633	41.79	-0.59	-0.28
Total Area	**180977**	**100**	**180977**	**100**		

[a] Percentage of each class out of the total area; [b] percentage change in the class; [c] percentage annual rate of change

The annual rate of decline in Forest slowed down from -2.0% ha^{-1} between the period 1989-1999 to -1.86% ha^{-1} between the period 1999-2014. However, deforestation increased again to -3.02% ha^{-1} between the period 2014-2019 indicating that the environmental management practices (reforestation programmes) being taken by different stakeholders such as LWB, Ministry of Forestry and communities are not at the same pace with the deforestation rate in the catchment, mainly Dzalanyama forest reserve. Waterbody in the study area showed a decrease at an increasing rate from the rate of -1.41% ha^{-1} between the period 1989-1999 to -1.49% ha^{-1} between the period 2014-2019. The increased water demand in Lilongwe city among different water users, climate change, urbanization and population growth could be some of the factors that are contributing to the declining water quantity in the catchment.

Grass/Shrubs/Bare land changed from increasing at an annual rate of 0.83% ha^{-1} between the period 1989-1999 to decreasing at a rate of -0.33% ha^{-1} between the period 2014-2019. The higher deforestation rate between 1989-1999 saw a lot of land being converted to Grass/Shrubs and Bare land that saw an increase of grass/shrubs and bare land in the catchment. However, the situation has changed now due to population growth, people have now resorted to using Grass/Shrubs/Bare land for some other uses such as settlement and cultivation. Lilongwe city being the capital city of Malawi have seen a high rate of population growth and urbanization. This has significantly contributed to the increase in the annual rate of change for Built-up from 2.26% ha^{-1} between the period 1989-1999 to 5.73% ha^{-1} between the period 2014-2019. Higher annual rates of change for Built-up were reported for the Lilongwe's neighbouring district of Dedza by Munthali, (2019) that reported an annual change rate of 9.80% ha^{-1} for the year 2015. The higher rate in Dedza can be attributed to the study's scope of the whole district that covers a total area of 3,624 km^2, while the current study only covered a small part of Lilongwe district with a total area of 1,870 km^2 out of 6,159 km^2 for the whole Lilongwe district. The cultivated land slowed down from the annual change rate of 1.24% ha^{-1} in 1989-1999 to -0.28% ha^{-1} indicating pressure the cultivated land is receiving from other land uses such as settlement due to population growth.

4.1.3. Land use and Land Cover Change (Transition) Matrix

The Land use and Land cover transition (Tables 17 and 18.) shows the distribution of main transitions in the five LULC used in the study for the two study periods (1989-1999; and 1999-2014) and the last period (2014-2019) is presented graphically (figure 13).

Table 17 LULC Transition Matrix between 1989 and 1999

LULC	Built-Up	Forest	Grass	Cultivated	Water	Total 1989
Built-up	**4,945.00**	64.00	699.00	8,216.00	240.00	**14,164.00**
Forest	545.00	**49,059.00**	10,133.00	948.00	6,043.00	**66,728.00**
Grass	3,602.00	996.00	**11,721.00**	11,990.00	1,151.00	**29,460.00**
Cultivated	6,371.00	363.00	6,408.00	**41,943.00**	840.00	**55,925.00**
Water	2,300.00	4,158.00	3,064.00	685.00	**4,495.00**	**14,702.00**
Total 1999	**17,763.00**	**54,640.00**	**32,025.00**	**63,782.00**	**12,769.00**	

N.B: The bold numbers indicate unchanged LULC proportions from 1989 to 1999

Table 18 LULC transition Matrix between 1999 and 2014

LULC	Built-Up	Forest	Grass	Cultivated	Water	Total 1999
Built-up	**10,910.00**	180.00	1,333.00	5,340.00	0.00	**17,763.00**
Forest	581.00	**37,387.00**	11,122.00	3,694.00	1,856.00	**54,640.00**
Grass	5,195.00	1,401.00	**9,296.00**	12,201.00	3,932.00	**32,025.00**
Cultivated	8,833.00	311.00	3,055.00	**52,043.00**	858.00	**63,781.00**
Water	1,987.00	109.00	2,700.00	2,824.00	**4,601.00**	**12,769.00**
Total 2014	**26,506.00**	**41,388.00**	**26,506.00**	**76,701.00**	**11,828.00**	

N.B: The bold numbers indicate unchanged LULC proportions from 1999 to 2014

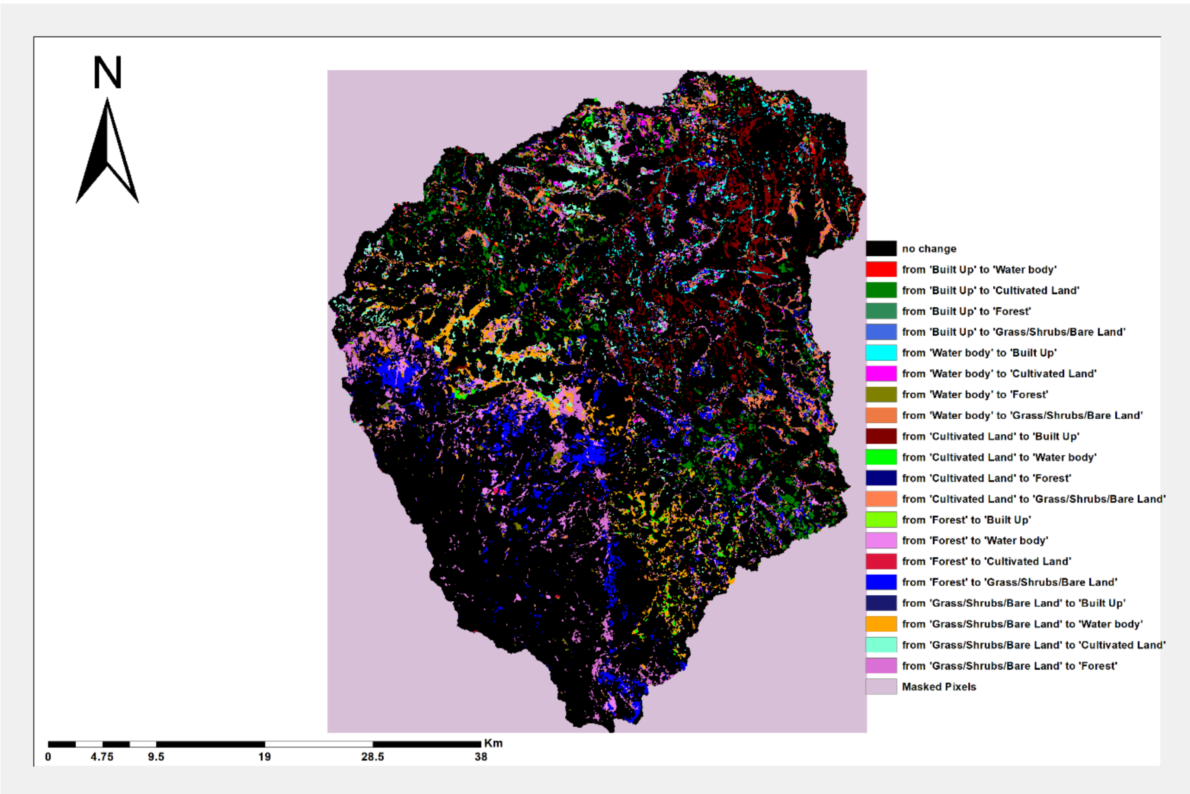

Figure 13 Observed LULC Change for the period between 2014 and 2019

The results from tables 17 and 18 and figure 13 reveal that significant LULC transitions have occurred in the study area over the past 30 years. The current major land use in the Upper Lilongwe river catchment is Cultivated land, while the situation was different 30 years ago where Forest was the most prominent land use in the catchment. Forest cover has seen the biggest change in the catchment with a loss of its 31,133.00 hectares of land over the study period representing an annual loss of 2.1% ha^{-1} between 1989 and 2019. The rate of the forest has been fluctuating with the highest rate (3.2% ha^{-1}) occurring between 2014 and 2019. Malawi's forest loss is estimated at 2.6% per annum (Mwanakatwe, 2015). Lilongwe city is currently estimated to have an annual growth rate of 3.8% (NSO, 2019). This rapid population growth is putting a strain on natural resources such as forest and water which has seen the increase in urbanization and cultivated land. This has been evidenced by the percentage of forest being converted into other land uses such as grass/shrubs/bare land, built-up and cultivated land in this study.

Poverty and high dependency on wood for energy is another factor contributing to forest loss in the catchment. Over 85 per cent of the population in Lilongwe district rely on firewood, charcoal, shrubs and grass as a source of energy for lighting and cooking (NSO, 2019). The study found that most of the forest land in the catchment is being lost to Grass/Shrubs and Bare land due to most of the change happening inside a protected area of Dzalanyama forest reserve where people cut down trees for different purposes such as biomass and timber production. The rate of encroachment for cultivation and settlement is relatively lower. The findings of this study suggest a negative correlation between population growth and dwindling of forest cover in the catchment. However, comparing with other areas in Malawi, the study area has relatively lower annual forest loss. For example, middle shire river catchment has an annual forest loss of 4.3 per cent (Mzuza *et al*., 2019). The relatively lower deforestation rates in the study area can be attributed to different environmental management measure being taken by different stakeholders to conserve the forest in the area which includes yearly reafforestation programs by Lilongwe Water Board, Local bylaws introduced by traditional leaders in the area and periodic guarding of the forest by Malawi Defense Force (MDF) soldiers since they use Dzalanyama forest for military training.

Lilongwe being the capital city of Malawi at the same time having very good fertile soils (Fiwa *et al*., 2014), the catchment area has seen agricultural land increasing tremendously from 55,925 ha in 1989 to 76,701 ha in 2014 representing annual change rate of 1.26% ha^{-1} which has yielded an addition of 20,776.00 ha of land to Cultivated in 25 years. However, recently the land under cultivation in the catchment has been declining at a rate of 0.28% ha^{-1} from 2014 to 2019. This land is mainly being converted into built-up. Despite the decline in agricultural land, there is also an increase in newly cultivated land in some parts of the catchment. The intensification of cultivation along the river banks during the dry season was observed during the field data collection exercises can be attributed to the increase in the cultivated land in the catchment. The transition matrix tables show that waterbody is being converted into agricultural land, although it is happening at a slower rate compared with the conversion of the other land use. This observed trend of waterbody being converted into cultivated land is in line with the findings of Pullanikkatil *et al.*, (2016) and Munthali *et al*., (2019) that concluded that the land-use changes in Likangala catchment in Zomba and Dedza district respectively was due to cultivation of river banks, deforestation and overexploitation of natural resources in their respective study areas. Also from the transition matrix tables above, it was observed that there is a continuous conversion of grass/shrubs/bare land into cultivated land. During the early period (1989-199) because the population was not big, people had enough land to cultivate but the rapid population growth has forced people to go back to the deserted land in the catchment that was occupied by grass/shrubs/bare as new sources of land for cultivation. Malawi's economy over-dependence on agriculture is not helping to halt conversion of other land uses such as grassland, water body and forest into cultivated land

At the entire study period, Built-up has increased by a total of 18,532 hectares of land. An increase in built-up is due to several factors that include, population growth and urbanization. Lilongwe city is the fastest growing city in Malawi and Southern Africa region, growing at a rate of 4.3 per cent per year (World-bank, 2017). The urban growth and consequent demand for better services are putting a strain on the natural resources in the city. The higher rates of deforestation in the catchment is due to an increase in infrastructure development in the city that requires firewood that is used to burn bricks, and timber that is used for construction. Globally, large expanses of forest are being converted int bare land for domestic purposes, mainly due to harvesting of timber (Lambin, et al., 2001). Sand-mining in Lilongwe river and the conversion of wetlands into built-up areas without an environmental impact assessment has seen the deterioration of water resources in the city as evidenced by the continued declining of water body from 1989 to 2019. The decline of grass/shrubs/bare land in the catchment from 1999 to 2019 has been due to increased conversion of these land to settlement, industrial and academic purposes in the city. This land has been exhausted hence people are now using cultivated land for these purposes which just put on more pressure on the limited land resources in the catchment for different conflicting users. Furthermore, the increase in urban construction leads to urban heat island (UHI). The UHI influences energy flow in urban ecological systems as well as alters their structure and functions, exerting series of ecological and environmental effects such as hydrologic situations, soil properties, and extreme high temperatures and flooding. Kaonga *et al*., (2015) noted that rainfall has been declining in Lilongwe District since 1989 while temperature and solar radiation have been fluctuating positively suggesting a decrease in forest land and grasslands and an increase in built-up areas leading to urban heat island (UHI). The observed trend aligns with the analysis made by MUNTHALI, (2013) that predicted bare land and cultivated land in Dzalanyama forest to be declining due to increased demand for land required for settlement.

4.2. Estimated Soil Loss from the Watershed using MUSLE

To estimate annual soil loss in the Upper Lilongwe River Catchment, the Modified Soil Loss Equation was employed. MUSLE parameters were derived from different sources that included rainfall, streamflow, DEM, Soil map and Land use the land cover map. All these data sources had different projection and format hence they were all converted to raster and projected to UTM 36 S before multiplying all the parameters using raster calculator in Arc GIS 10.4 to get the soil erosion map of the watershed. All the parameters were computed in the GIS environment. MUSLE was chosen because it has an improved accuracy of soil loss estimation over USLE and RUSLE (Sadeghi *et al*., 2007) and it applies to the points where the overland flow enters the streams and then all those points are summed up to give the total sediment delivered to the stream network within a catchment (Zhang *et al*., 2009), therefore Upper Lilongwe River Catchment fit the requirements for the model.

i. Runoff and Stream peak flow

The model used the daily precipitation and streamflow data that occurred between November 2018 to October 2019 to estimate runoff (Q) and peak discharge(q_p) using HEC-HMS 4.4. The period (2018-2019) was chosen because it is the most recent year which had full annual observed/recorded both rainfall and streamflow data (2019/2020) could not be used. After all, the dry season has not started yet. HEC-HMS was chosen to estimate the runoff to take advantage of the high speed and accuracy of the computer-based program instead of using an excel spreadsheet (Kalita, 2008). The model performance was evaluated by the Nash–Sutcliffe efficiency index which is the widely used and potentially reliable statistic for assessing the goodness of fit of hydrologic models (McCuen *et al.*, 2006). One advantage of the Nash–Sutcliffe index is that it can be applied to a variety of model types. The index results of the predictions of a linear model if unbiased, then the efficiency index lies in the interval from 0 to +1. For the biased models, the efficiency index may be algebraically negative. However, for the nonlinear models, which most hydrologic models are, negative efficiencies can result even when the model is unbiased (Nash & Sutcliffe, 1970). For the validation and calibration process, SCS-CN loss method was used. The SCS-CN implements the curve number methodology for incremental losses (Halwatura & Najim, 2013). Figure 14 shows the curve number grid that was created as an input data for the runoff and peak flow estimation. The CN grid was created by overlaying the DEM, soil map, Land use map and CN lookup table as proposed by Merwade, (2019).

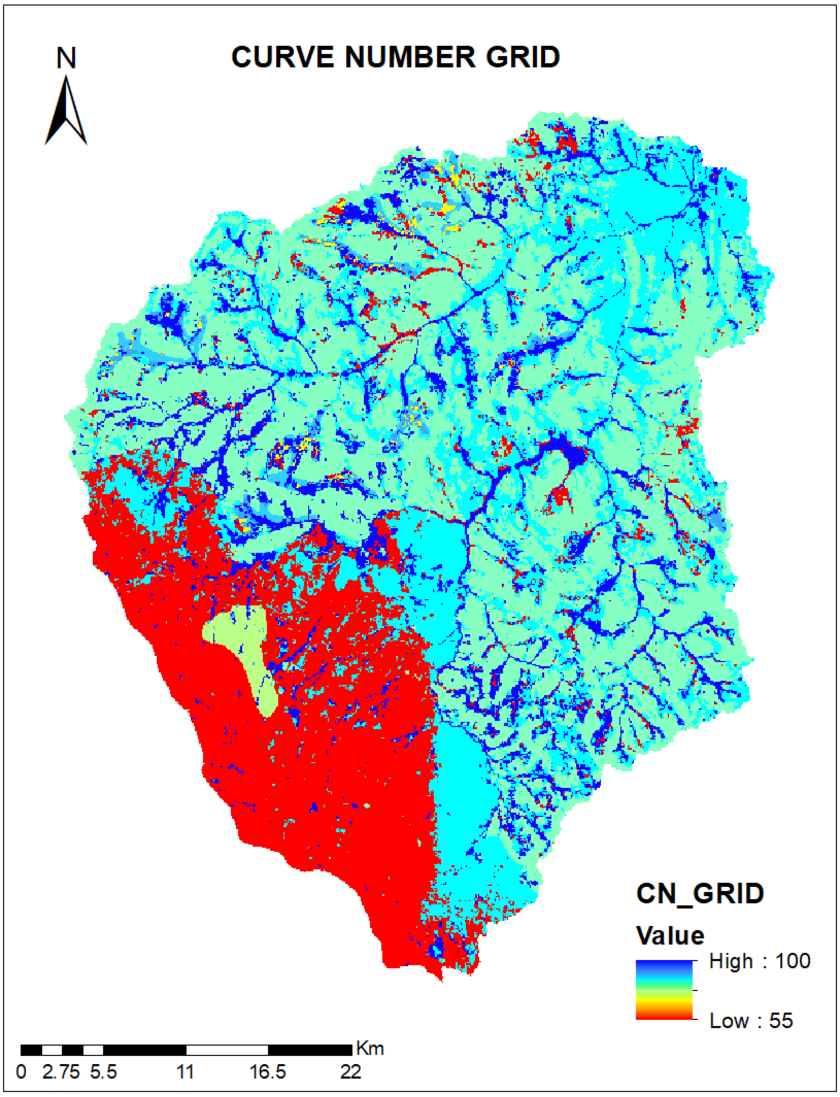

Figure 14 The Curve Number Grid

The CN grid ranged from 55 to 100 with densely forested areas having the lowest values and open water bodies having the highest values. Land use and soil hydrological group have an impact on the curve number. Ninety-six per cent of the soil in the watershed belongs to soil hydrological group B with moderate infiltration rate due to their moderately fine to coarse texture. Only 2.7 and 0.9 per cent of the soils in the watershed belong to soil hydrological group C and D respectively. The watershed is characterized by highly fertile soil (Omuto & Vargas, 2019) which is one of the reasons that agriculture is the most dominant land use, followed by forest, Grass/Shrubs/Bare land, Built-up and lastly Waterbody.

Figure 15 shows the simulated and the observed flows. HEC-HMS computed peak flow from the simulated runoff.

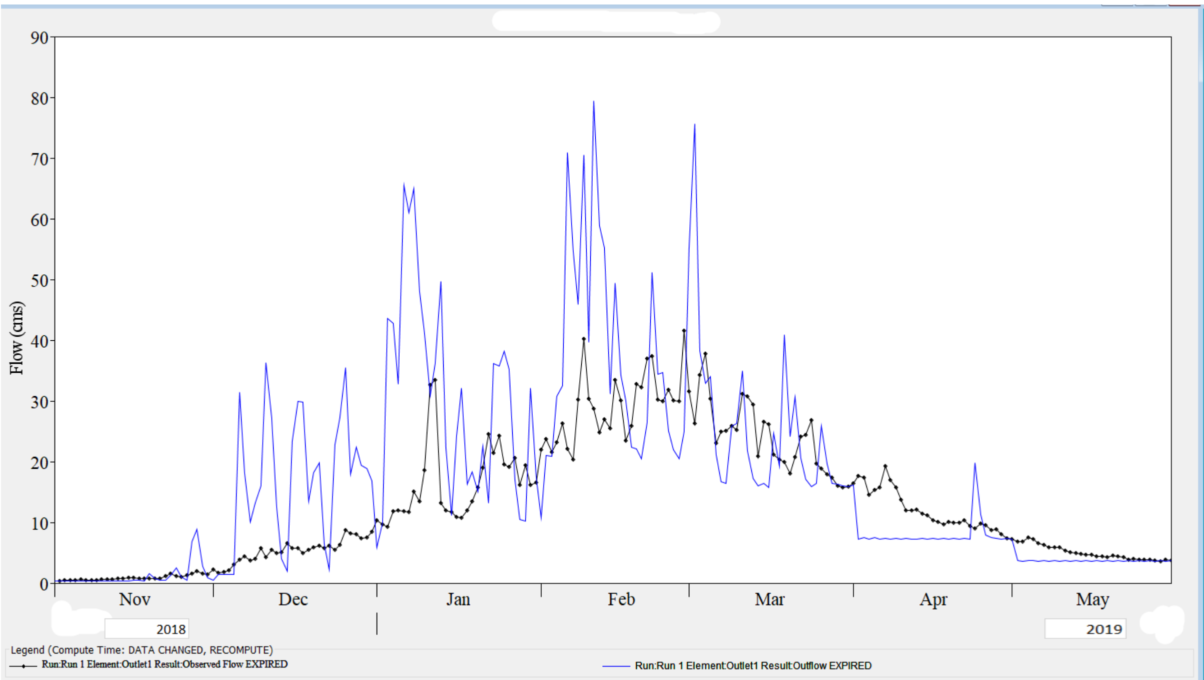

Figure 15 Upper Lilongwe River Simulated and Observed Flow at the Outlet (Lilongwe Old Town).

The results from HEC-HMS showed that both observed and simulated flow portrayed the same trend in a way that flow starts peaking from December and reaches the highest peak in February then starts reducing. This trend is also portrayed by the rainfall in the catchment in the essence that rain starts in November and the rainiest month is February (NEMUS, 2015). The dry season has the lowest flow and Lilongwe water board is supposed to be using Kamuzu dam 1 and 2 as the sources of raw water for the people in Lilongwe city while during the rainy season the Lilongwe river is supposed to provide enough water for the people in the city. However, the real situation on the ground is different in a way that low stream flows during the dry season imply that water is in short supply for domestic water which forces LWB to apply domestic water rationing. Meanwhile, during the wet season, a lot of soil particles and evasive vegetation are detached from land and stream banks causing sedimentation and blockages at Lilongwe river's abstraction point for LWB causing critical water shortages in the city (Wiyo *et al*., 2015).

From the results obtained from HEC-HMS, the computed runoff and peak flow values were 182,340,000.00 m^3 and 40.5 m^3/s respectively. In terms of NSE and RMSE standard deviation, Upper Lilongwe River Catchment produced the values of 0.698 and 0.5 respectively which can be considered good (Zema *et al.*, 2016), hence were taken as valid enough to be input data for the MUSLE model.

ii. Soil Erodibility Factor

According to the Malawi soil map produced by the Department of Land Resources Conservation, the soils in the watershed consist of four different colours but seven different types. Dark brown soil (Chromic luvisols) are the most prominent with 68.23 per cent, followed by brown soil (Haplic lixisol and Cambic arenosol) with 16 per cent and finally yellowish-brown soil (Xanthic ferrarsols and Eutric cambisol soil). The K factor was undersigned to each of the soil type based on Williams' (1995) equation. The K_value of 0.07 was undersigned to Cambic arenosol, 0.10 to Haplic Lixisol, 0.12 to Xanthic Ferrarsol, 0.14 to Chromic Luvisols, Eutric Gleysol and Leptosols, and 0.16 to Eutric Cambisol. Cambic arenosol has the lowest K_ value implying that they have high resistance to raindrop detaching power, unlike Eutric Cambisol with the highest 0.16 which implies it is the highly vulnerable soil in the watershed to be easily washed away by rainfall. The soil in the watershed is dominated by soils with K_ values ranging from 0.10 to 0.14 which are less susceptible to the erosive force of the rainfall. Figure 16 shows the graphic representation of the soil erodibility factor in the study area which was converted into a raster format.

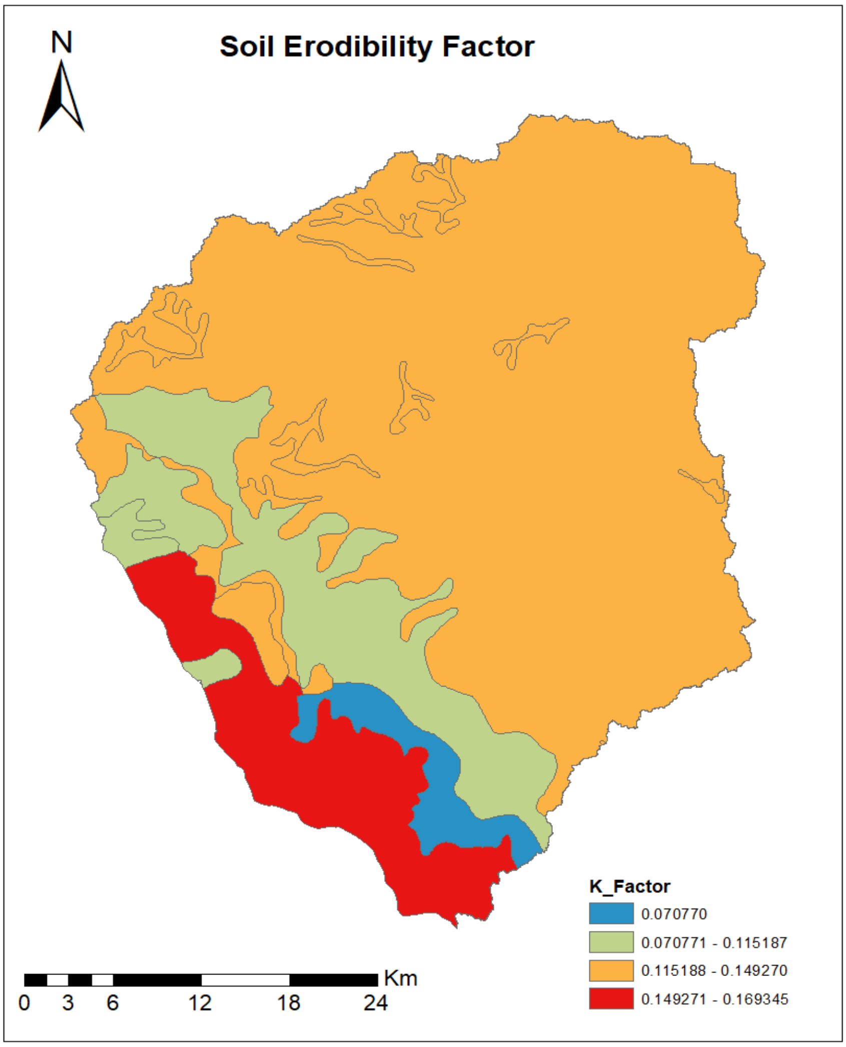

Figure 16 Upper Lilongwe River Catchment Soil Erodibility Map

The findings of this study are in line with the findings of Fiwa *et al*., (2014) that categorized the soil in the watershed to be well structured, deep and well-drained soils. However, it should be noted that by using a different soil map for the same area with a different K_classifcation approach would give a different range of K_values, probably higher values that would show that the soil is highly susceptible to soil erosion. For instance, by using Wiyo *et al*,' (1999) soil classification of the area that it is dominated by red (ferric luvisols) clayey texture and Hurni's, (1985) soil erodibility factor approach, the dominant soil in the watershed would have a K_value of 0.25 which would mean it is highly susceptible to soil erosion. However, Hurni's (1985) approach was intended for Ethiopian conditions and its applicability to southern African conditions have not been evaluated yet from the literature hence could not be applied in this research.

iii. The Slope Length and Gradient Factor

The slope length and gradient can not be informative soil loss parameters independently (Gelagay & Minale, 2016). Therefore LS was computed by using Moore & Wilson,' (1992) equation which substitutes slope length with the upslope contributing area to take into account the flow convergence and divergence in a three dimensional complex of terrain condition. As illustrated in figure 17 (upper left) below the slope length is higher in the lower part of the catchment area due to the high flow accumulation after the Lilongwe river and Likuni river Confluence in Likuni, and low on the upper part of the catchment, especially the upper part of Likuni river due to few tributaries. On the other hand, the gradient is high on the upper part (Dzalanyama hill/forest) and almost flat on the largest part of the catchment area because Lilongwe is a plain district. The LS factor extends from 0 on the lowest part of the watershed (including the water abstraction point) to 156 on the steepest part (Dzalanyama hills). This implies that LS is only a significant factor to soil erosion in the catchment in the upper part of the catchment which has a smaller area compared to the area where it is insignificant.

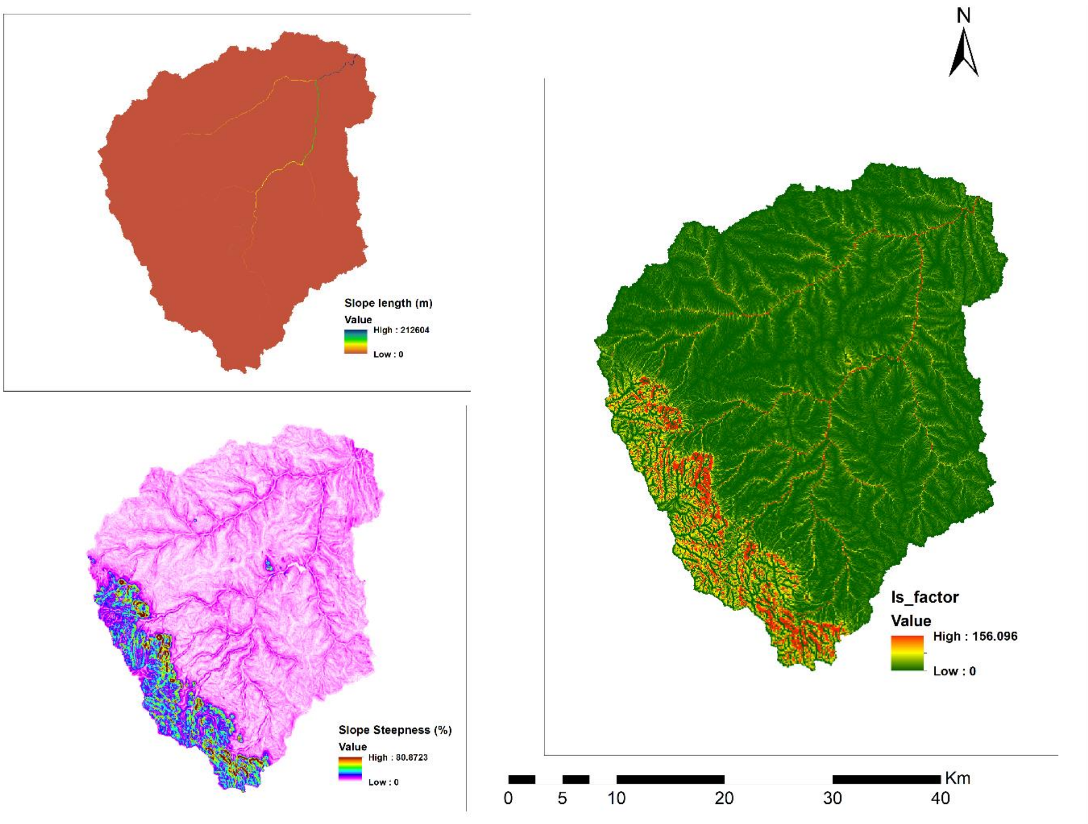

Figure 17 Slope length (Upper left) Slope gradient (Lower left) and LS Factor (right) Map

iv. The Land cover and Management Factor

The Landsat 8 image with less than 30 per cent cloud cover was radiometrically and atmospherically corrected before image classification. Maximum likelihood supervised classification was employed to produce the land use land cover map for the study area. The ground truth data for each class collected using handheld GPS was used for accuracy assessment of the LULC map. The map had a high accuracy of 93.24 per cent and a kappa coefficient of 0.9064. The Land use and cover of the study area were categorized into five classes; Waterbody, cultivated land, Forest, Grass/Shrubs/Bare land, and Built-up area. Cultivated land is the most prominent land use in the study area, followed by Forest, Grass/shrubs/Bare land, Built-up and lastly Waterbody. In many cases, the C values for large agricultural areas are estimated by traditionally assigning uniform empirical values from literature to land use/land cover data (Ali & Hagos, 2016).

Since the C-factors are not available for most of the Malawian crops from the literature, the average annual Wischmeier & Smith,' (1978) values were used to indicate the effect of cropping and management practices on soil erosion rates on agricultural land. The upper part of the catchment is dominated by forest and grass since it falls in the protected area of Dzalanyama forest reserve. The middle part of the watershed is dominated by cultivated land with maize being the most dominant crop as observed during field data collection exercise. The cultivated land extends up to the lower side of the watershed where Built-up is dominant. An interesting observation was also made in the Lilongwe river banks, the upper part it is covered with shrubs and grass but toward the lower part of the watershed, people are encroaching on the river banks by cultivating on the land. Demarcations on the river banks were observed that were put by LWB that no one should settle or cultivate on the land beyond that point, but people are still encroaching and sand mining was observed in the middle part of Lilongwe river. The upper part of the watershed had the C value of 0.01 and 0.04 for forested land and grass/shrubs/bare land respectively. Despite that Grass/Shrubs and Bare land were combined to be one class, Grass and Shrubs were more dominant than bare land hence the lower C-value. Cultivated land had a C- a value of 0.085 and Built-up had a value of 0.13. This implies that the contribution of crop and management factor for soil erosion model in the study area is higher in the case of Built-up and Cultivated land on the lower side than in the case of forest and grassland in the upper side of the catchment.

v. Support Practice/Erosion Control Factor

Field observation revealed that some conservation practices are happening in the catchment. Maize being the dominant crop is grown on contour tillage and even sweet potatoes are grown with bigger contours than Maize. Vetiver (*Chrysopogon zizanioides*) grass was also observed in some of the agricultural lands but it was very prominent around Kamuzu dam 1 and Kamuzu dam 2. An informal interview with the local traditional leader revealed that the vetiver grass was planted as a demarcation between Lilongwe water board land which no one is supposed to encroach and the local people's land. If anyone is found encroaching LWB's land they pay a heavy penalty that includes being arrested. Both Kamuzu 1 and 2 reservoirs are surrounded by plantations. Just like in the case of C-factor, there is no information from the literature about the P-values for Malawi hence the average Wischmeier & Smith,' (1958) tabulated values were used. The land containing, Built-up, Forest, and Grass/Shrubs and Bare land were assigned a value of 1 regardless of the slope and Waterbody had a value of 0. While in the Cultivated land, the slope was taken into account and classified into 3 classes. However, Lilongwe being a flat plain area, the impact of the slope was not significant on cropland. The implication is that Forest, Shrubs/Grass/Bare land and Built-up areas have a significant contribution in terms of erosion practice and management factor than cultivated land. Figure 18 shows the land use/cover, C-factor and P-factor map of the study area.

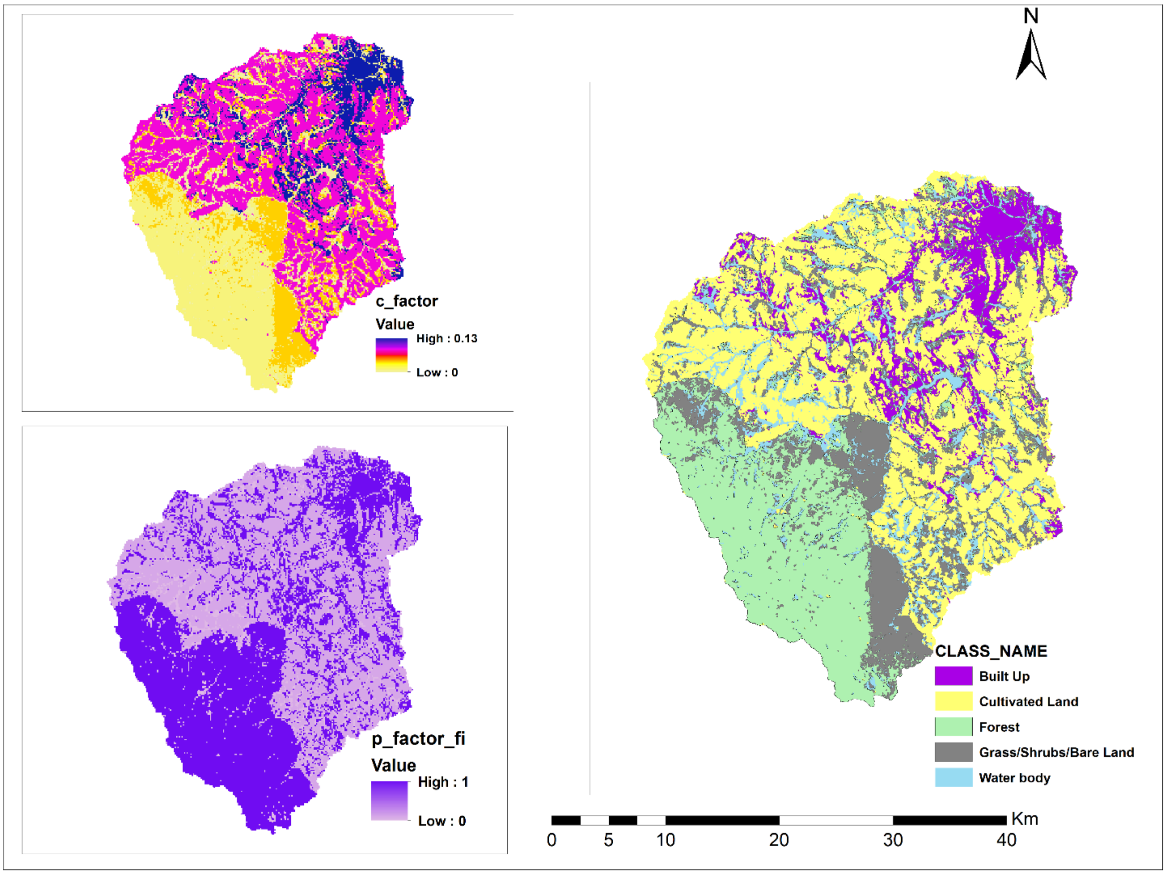

Figure 18 LULC, C-Factor and P-Factor Map

4.2.1. The Annual Soil Loss Rate

The final map that shows potential annual soil loss for the year of 2019 for the Upper Lilongwe River Catchment was produced by overlaying the above five parameters $11.8(Qq_p)^{0.56}$, K,LS,C, and P using raster calculator in Arc GIS 10.4 after co-registering each parameter to a common pixel (90 m) and datum (WGS 1984, UTM 36 S). The soil rates were represented in terms of extent, degree, and severity which were developed by FAO, (2011) because the same criteria were used by Vargas & Omuto, (2016) in their assessment for soil loss in the whole Malawi which was published in conjunction with Malawi's Ministry of Agriculture, Irrigation and Water Development.

The 2019 annual soil for Upper Lilongwe River watershed ranged from less than 1 to 9.93 ton/ha/yr. The soil loss in the catchment falls within severity class of none to light, whereby 83 per cent falls in the class of none and 17 per cent in the class of light. Table 19 present the numeric soil loss range, severity class and area coverage of the Upper Lilongwe River Catchment.

Table 19 Numeric soil loss, area coverage and Severity class

Numeric Soil loss rate t ha^{-1} yr^{-1}	**Severity Class**	**Area (ha)**	**Proportion (%) of the area occupied by the degree of soil loss**
0-1	None	148,248.55	83.0692261
1-10	Light	30,215.31	16.9307739
10-20	Moderate	0	0
20-50	Severe	0	0
>50	Very severe	0	0

From the finding of this study, only 1.95 per cent in the light severity class is closer to moderate class as it ranged from 5.96-9.93 while the rest was below this range and about 54 per cent was only within the range of 1-2.14. In terms of agricultural productivity, the soil erosion rate in the catchment is not worrisome as 100 per cent of the soil loss falls within Malawi's soil loss tolerance level and this implies that crop productivity in the catchment can still be sustained economically. However, this being a catchment which is the source of drinking water for Lilongwe city and surrounding areas, this rate of soil erosion has the potential to cause serious problems if left unchecked. For instance, the increased flooding events in the lower sub-basin can increase and it also poses a great sustainability risk of sedimentation and siltation in the reservoirs (Kamuzu dam 1 and 2), Lilongwe river, and significantly deteriorate the water quality which can increase the treatment cost. The impact of this soil erosion on water quality in the catchment will be explained in the next **subsection (4.3).** Figures 19 and 20 illustrate the 2019 soil loss erosion map and severity map of the Upper Lilongwe River Catchment.

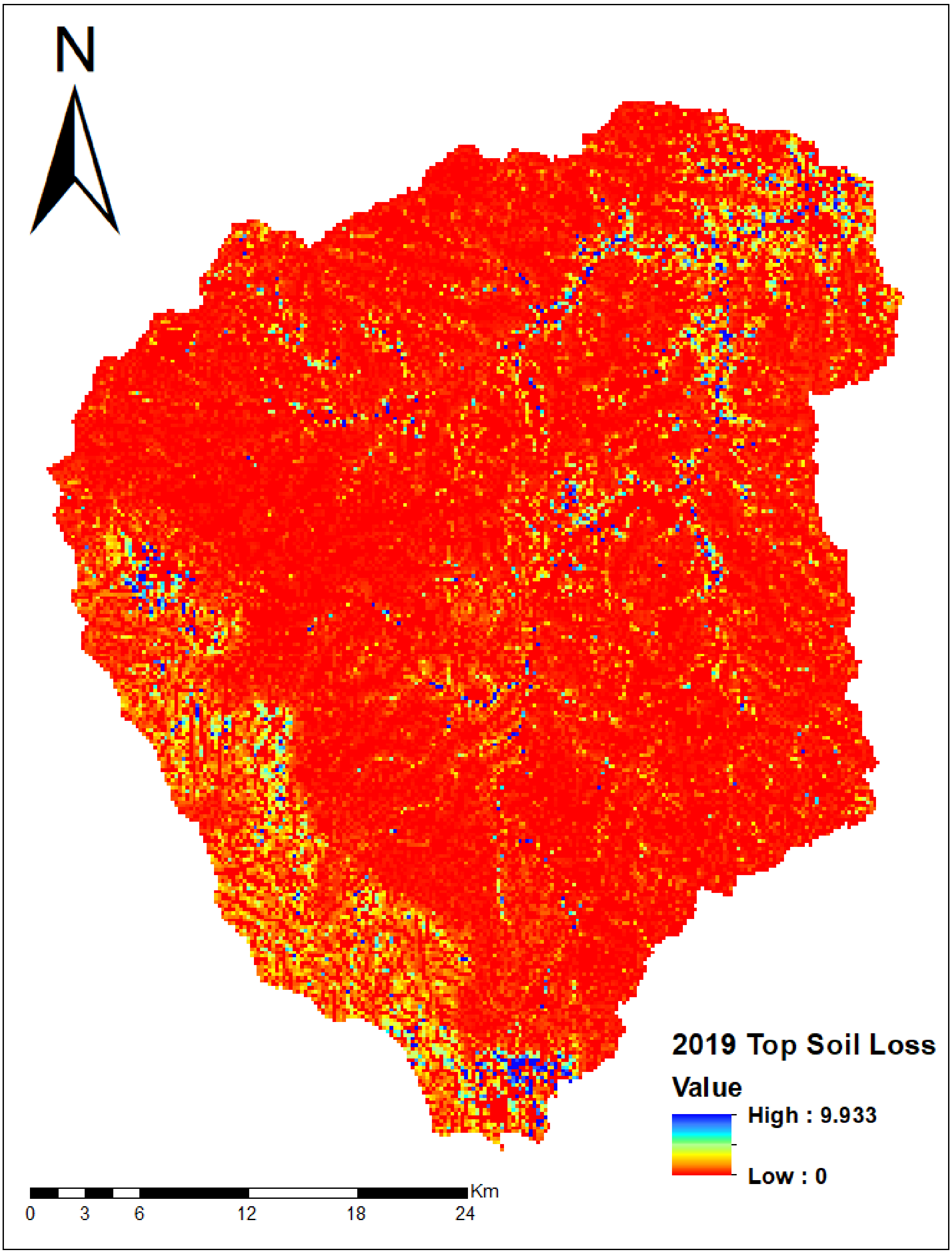

Figure 19 2019 SOIL EROSION MAP

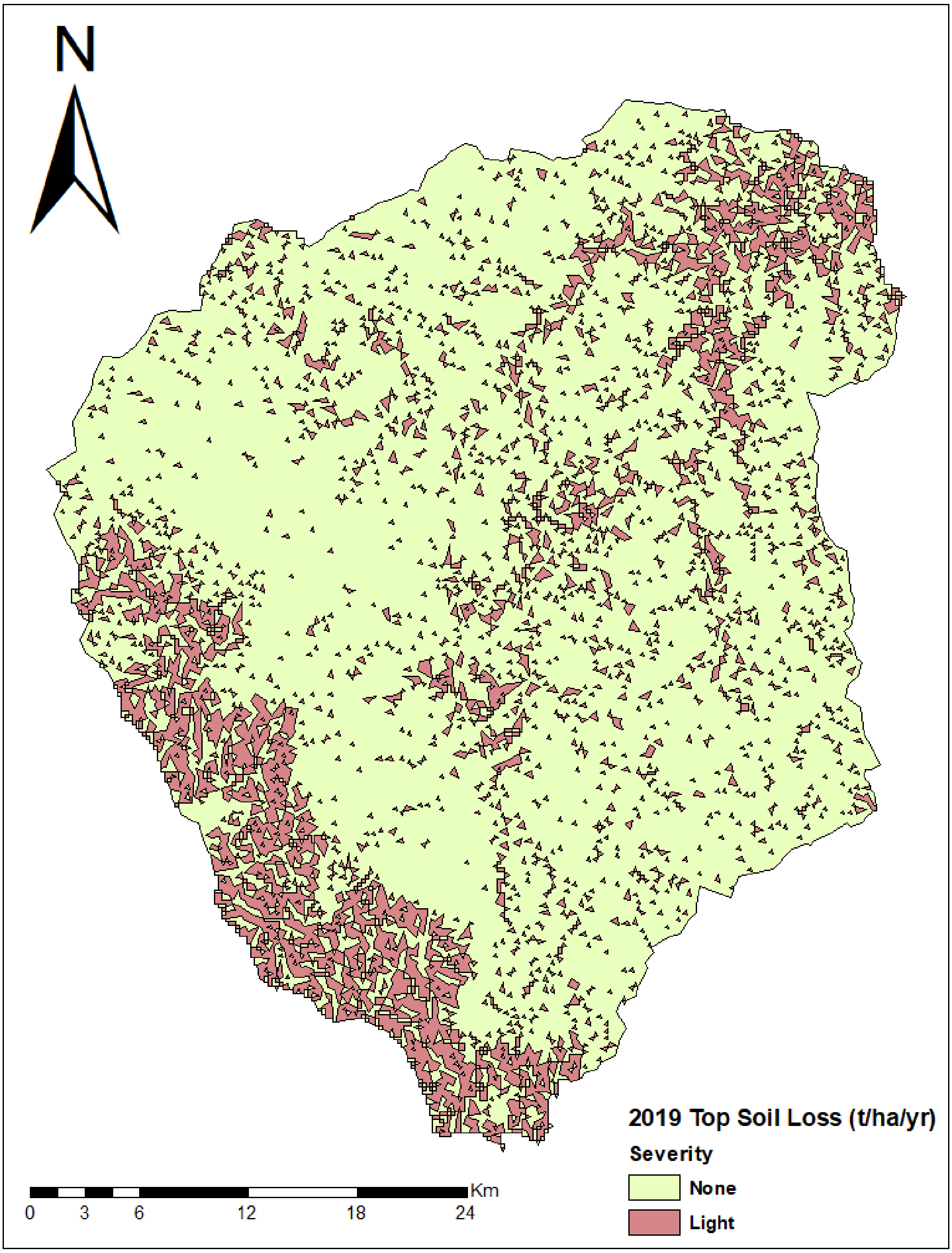

Figure 20 2019 Soil Loss Severity Class Map

From figures 19 and 20 above, the results show that the Dzalanyama ranch and Lilongwe city had the highest rate of annual soil loss while most of the agricultural land had the lowest soil erosion rate. The findings of this study are in line with the findings of Vargas & Omuto, (2016) that produced the 2014 soil erosion map for the whole Malawi. Lilongwe District was categorized into the range of 0.24-8.17 ton/ha/yr. Vargas and Omuto,'(2016) study used Soil Loss Estimation Model for Southern Africa (SLEMSA) that was developed by Elwell, (1978) for Zimbabwean conditions to predict long term average annual soil loss by sheet and rill erosion. SLEMSA, just like MUSLE can be easily integrated into the GIS environment. However, SLEMSA is not practical for the prediction of soil loss on an event basis hence it was not used in the current study.

The slope and steepness factor, coupled with the high rate of deforestation (Munthali & Murayama, 2011; Katumbi *et al*., 2015) on the upper part of the catchment is the contributing factor to the higher soil loss rate on the upper part of the catchment. Deforestation leaves the soil weaker and the soil particles are easily detached and the gravity fuels the rate of soil erosion. This is supported by the findings of Vargas & Omuto, (2016) that found that in Malawi, highest rates of soil erosion was reported from the areas with high steep slopes, fragile soils and significant decline in forest cover.

The soil erodibility factor coupled with the steepness factor and conservation and practice factor contributed significantly to the lower rates of soil erosion in the catchment. The catchment is characterized by very deep (> 150 cm) to deep (100-150 cm) soil (Omuto & Vargas, 2019) that are highly resistant to soil erosion because of high infiltration rate. The soil erodibility factor in the catchment ranged from 0.07 to 0.16 which is considered being lower. Lilongwe district being a flat plain, the slope and steepness factor in the catchments tends to reduce the speed of runoff hence increasing the infiltration rate. Contour and tied ridging are some of the conservation practices happening in the catchment. Both contour and tied ridging are being promoted to reduce sediment and nutrient losses due to runoff. Tied ridging on its own it has a capacity of up to 80% to reduce surface runoff in Malawi's subsistence farmer's farms (Wiyo *et al*., 2000). These are some of the reasons the cultivated land had low values of soil erosion. However, it was also reported that some of the cultivated lands had a light rate of soil erosion. This was mainly near the river banks, where sugarcane and vegetables are mainly planted in the dambos without any ridges. Flash floods happening near the river banks also contributes to the soil loss near the river banks.

Contrary to the findings of Vargas & Omuto, (2016), this study also found that the Built-up area was contributing significantly to soil loss in the catchment. The impervious surface in Lilongwe city contributes to the high rate of surface rate and flood risk in the lower part of the catchment. In the other study, carried in some part of Malawi, a similar trend was observed whereby the lower part of the catchment which had built up as the dominant land use had higher levels of sediment yield and flood events (Munthali *et al*., 2011). Impervious surface in urbanized areas has a positive correlation with surface runoff (Hu *et al*, 2020).

4.3. Spatial and Temporal Variation of Water Quality Parameters

A comparison of the three sections of the catchment showed that section A which is located upstream of the catchment had good water quality compared to section B (located in the middle) and section C (located downstream). Turbidity in the river during dry season ranged from 5.3 NTU to 9.61 NTU with section A having the less turbid water and section B having more turbid water. The trend was the same during the rainy season with section A having less turbid water (17.93 NTU) and section B having more turbid water (228.56 NTU). The good water quality in terms of turbidity in the upstream (Section A) can be attributed to the prominence of Forest and Grass in the section, and the two reservoirs (Kamuzu dam 1 and 2) located in the upstream. The more turbid water in the middle section (B) can be attributed to the agricultural land in this section. Rainfed agriculture is practised during the rainy season at a very high scale while during dry season irrigated agriculture along the river banks is practised at a small scale. Suspended and colloidal matter such as silt, clay, fine, organic and inorganic matter causes water to be more turbid. The runoff during the rainy season carries of silt, clay, fine particles, organic and inorganic matter hence higher turbidity in rainy season than dry season throughout the catchment. Forest and grassland can reduce runoff by increasing soil's resistance to being easily washed off, and the reservoirs retain the suspended and colloidal matter through sedimentation (Wolancho, 2012). The slightly higher turbidity values during the rainy season in section A is due to the increased deforestation and increase of cultivated land in the area which coupled with the topography in this section of the catchment is increasing the rate of soil erosion as revealed in 4.2 above. However, there was no significant difference in terms of turbidity in section A during the rainy and dry season. This implies that both during the rainy and dry season, sedimentation in the reservoirs is helping to reduce turbidity in the catchment. The case was different for section B and C where a significant seasonal difference was observed. The rate of runoff can be a contributing factor to this huge difference between the two seasons in these two sections. The rate of runoff is higher during the rainy season than during the dry season. Table 20 shows the turbidity, electrical conductivity (EC), total dissolved solids (TDS) and suspended solids (SS) levels in the catchment during different seasons.

Electrical conductivity ranged from 73.96 μS/cm to 240.22 μS/cm during the rainy season, while during the dry season it ranged from 75.61 μS/cm to 294.72 μS/cm. Both of the seasons had a similar trend with section A having the lowest values and section C having the highest values. The higher values during the dry season are due to the accumulation of ions such as nitrates, phosphates, bicarbonate, Chloride and sulphate from agricultural and built-up areas. The accumulation effect of the ions saw section C yielding highest rate of EC in both the dry and rainy season. However, the lower values in the rainy season are due to dilution of the ions arising from increased water volume in the river. There was no any significant difference between the two seasons in EC levels in any of the sections. Similar observations to the current study were made by Pullanikkatil, (2015) who studied the impact of land-use change on Likangala river water quality in Zomba, Malawi. The authors observed slightly higher EC values during the dry season than the rainy season.

Total dissolved solids ranged from 52.98 mg/l to 206.19 mg/l and 37.24 mg/l to 64.38 mg/l during the dry and rainy season respectively. The lower values during the rainy season can be attributed to dilution effect from increased runoff and rainwater (Pullanikkatil *et al*., 2015). Sand mining, cultivation and building along the river banks are the reasons behind high values of TDS in section C. Section B and C showed a significant difference between the two seasons implying that the rainwater is helping to dilute the dissolved solids in the water. The suspended solids took a different trend from the one observed with TDS. SS was higher during the rainy season ranging between 14.20 mg/l to 198.36 mg/l and lower during dry season ranging between 7.74 mg/l to 20.21 mg/l. However, in terms of significance difference, SS showed a similar trend with TDS whereby section B and C showed a significant difference between the two seasons, indicating that rainfall has a huge impact on suspended solids in the water. The dry season is normally full of less runoff and slow stream flows compared with the rainy season, this increases the time of concentration of the suspended solids to settle down through sedimentation in the river.

According to the environmental management act (ema,1996), discharge of liquid and solid waste into water bodies and use of non-biodegradable pesticides is prohibited in Malawian waterbodies riparian sites. Additionally, the catchment control order prohibits farmers to encroach the river banks, and sand mining is not allowed along the river banks. In contrary to all these laws, what was observed during the field data exercise is that none of the above laws and bylaws is being followed which is resulting in high suspended solids (mostly plastics), and dissolved solids that end up degrading the surface water quality. This has resulted in turbidity and suspended solids in section B and C during the dry season to be beyond the acceptable limit of drinking water standard set by MBS, (2005) as shown in table 20. There is a huge economic cost to treat back this water to acceptable standards and the worse part is it was observed in the Dzalanyama forest that people that graze, burn charcoal and collect firewood in the catchment drink the raw water from the river without any treatment. This can cause some health complications. Additionally, the accelerated reservoir siltation reduces the useful life of the reservoir (Wolancho, 2012) and sediment in river banks increases the probability and severity of floods (Hellerstein *et al*., 2019).

Table 20 Turbidity, EC, TDS and SS Levels in different sections of Lilongwe river in the dry and rainy seasons

Section of the River	Dry Season (Mean± SE)				Rainy Season (Mean±SE)			
	Turbidity (NTU)	EC (µS/cm)	TDS (mg/l)	SS (mg/l)	Turbidity (NTU)	EC (µS/cm)	TDS (mg/l)	SS (mg/l)
A	5.43±0.99	75.61±5.96	52.98±4.21	7.74±1.04	17.98±6.04	73.96±7.61	37.24±3.10	14.20±4.75
B	9.69±3.24	184.06±42.74	128.86±29.91	12.60±3.70	228.56±51.11	157.79±30.29	49.51±5.52	127.78±36.42
C	9.41±1.46	294.72±73.54	206.19±51.51	20.21±6.70	218.17±88.50	240.22±41.11	64.38±6.21	198.36±48.60
MBS standard	25	NA	450-1000	50	25	NA	450-1000	50

Table 21 Nitrate, Phosphorus, pH and Total Faecal coliform levels in different sections of Lilongwe river during the dry and rainy seasons

Section of the River	**Dry Season (Mean± SE)**				**Rainy Season (Mean±SE)**			
	Nitrate NO_3^- (mg/l)	**Phosphate PO_4^{-3} (mg/l)**	**pH**	**Total Faecal Coliform (CFU/100ml)**	**Nitrate NO_3^- (mg/l)**	**Phosphate PO_4^{-3} (mg/l)**	**pH**	**Total Faecal Coliform (CFU/100ml)**
A	1.59±0.15	0.29±0.03	7.89±0.15	29.33±9.18	4.20±1.27	0.38±0.04	7.08±0.13	1240.00±452.32
B	1.66±0.12	0.30±0.06	7.99±0.07	1080.0±289.06	6.20±1.50	0.52±0.94	7.54±0.19	8087.78±2588.80
C	1.20±0.21	0.40±0.89	8.09±0.11	2001.11±336.45	7.49±1.51	1.20±0.27	7.64±0.23	14793.33±4174.78
MBS standard	10 mg/l	10mg/l	5-9.5	0-50	10mg/l	10mg/l	5-9.5	0-50

From table 21 above it shows that there was high nitrate concentration during rainy season ranging from 4.20 mg/l to 7.49 mg/l with the lowest concentration in the upper section (A) and highest in the downstream (section C). The trend was different during the dry season with middle section (B) having the highest concentration of 1.66 mg/l and section C having the lowest concentration of 1.20 mg/l. From the data obtained from LWB, it showed that there are high levels of algae in the upstream than downstream of the river. Kamuzu dam 1 and Kamuzu dam 2 are highly concentrated with the following types of algae; *ulothrix, navicula, trachelomonas, anabaena, mallomonas, ankistrodesmus*. Even if some of the algae are beneficial to self-purification of the water, the high presence of algae in the upstream during the dry season is an indication of high levels of nitrogen and phosphorus that causes algae bloom. Algae are known to be good indicators of pollution of many types for different reasons that include; easier to detect and sample, wide spatial and temporal variability, quick response to the changes in the environment due to pollution and easily to be correlated with some specific type of organic pollutants (Sen *et al*., 2013). There are many sources of nitrate in the upper section that include organic manure from Dzalanyama forest (grazing land), and inorganic fertilisers from surrounding cultivated land. The high concentration of nitrate during the rainy season in section C can be attributed to the built-up point sources such as organic waste from Chigwiri, Likuni and Chinsapo markets and cropland non-point sources where urea and NPK fertiliser are commonly applied in the catchment. Seasonal differences were significant in all the sections with the rainy season having higher values than the dry season. There was a significant difference between up and lower section during rain season ($p<0.05$) but no difference was observed between up and middle section or middle and lower section.

The concentration of phosphate was lower in the upper section (A) 0.29mg/l and highest in the lower section (C) 0.40 mg/l. The similar trend was observed for the rainy season with the highest concentration of phosphate 1.20 mg/l in the lower section (C) and the lowest concentration of 0.38 mg/l in the upper section (A). Just like in the case of nitrate, the higher values in middle and lower sections can be attributed to the inorganic fertilisers from cultivated land. The urea and NPK that is applied for Maize' healthy growth and bumper yield contains high levels of phosphorus. Domestic and industrial wastewater can be another factor contributing to the high levels of phosphate in the lower section (C). The seasonal difference was not significant only in the upper section A, with the remaining two sections having significant differences. During the rainy season, there was a significant difference ($p<0.05$) between the upper section and the lower section, with the other sections having no any significant difference between each other. The lower values of phosphate than nitrate in the water is due to phosphate's moderate solubility in water and relatively lower mobility in soil than nitrate (Hellerstein *et al.*, 2019).

The wastewater from Natural resources college (NRC), Ccicod, Likuni schools and Likuni hospital might be the point source of pollutants causing high levels of nitrogen and phosphate during both dry and rainy season in the lower section as highest values of the two parameters most of the time are recorded from Likuni river's sampling point at Likuni bridge. The high levels of nutrients in water have a lot of impacts starting from reducing the water quality and ending up increasing the treatment cost for the water to reach different standards required for different uses. The enrichment of nutrients in water bodies stimulates algae blooms that cause taste and odour in water, clogged pipelines, aquatic life kills and reduced recreation opportunities (Sen, 2013). LWB's has been struggling with clogging at its intake point due to high suspended solids and plants in the river. This problem can be mitigated by reducing the nutrient effluent from both point and non-point sources in the catchment.

pH values ranged from 7.89 to 8.09 in the dry season with all the sections having slightly alkaline water. The situation was different in the rainy season where slightly lower values of pH were observed ranging from 7.08 in the upper section to 7.54 in the lower section (C). The relatively lower values in the rainy season in all the sections could be due to incoming fertilizers such as calcium ammonium nitrate and urea from the cultivated land due to surface-runoff. The similar trend was observed by Phiri *et al.*, (2005) that reported lower pH values in the rainy season compared to the dry season in Lilongwe river. Their study was conducted a few distance downstream of the current study area which is dominated by commercial and industrial areas hence in both seasons their reported pH was lower than the current study's findings. Their lower pH was attributed to the effluents from industries that contained lactic acid which was making the water acidic. Despite the seasonal variability of pH in all the sections, the observed pH is within the acceptable level by MBS (5-9.5) for drinking or recreational water.

Table 22 Two paired Sample statistics for different parameters

Parameter	Mean paired diff	Std. Deviation	Std. Error Mean	t-value	P. Value
$Turbidity_{dryA}$ Vs $Turbidity_{rainyA}$	12.54815	18.73530	6.24510	-2.009	0.079
$Turbidity_{dryB}$ Vs $Turbidity_{rainyB}$	218.86667	156.90834	52.30278	-4.185	**0.003**
$Turbidity_{dryC}$ Vs $Turbidity_{rainyC}$	222.43704	257.64951	85.88317	-2.590	**0.032**
EC_{dryA} Vs EC_{rainyA}	1.64815	10.19660	3.39887	0.485	0.641
EC_{dryB} Vs EC_{rainyB}	26.26296	67.21155	22.40385	1.172	0.275
EC_{dryC} Vs EC_{rainyC}	54.50000	179.10524	59.70175	0.913	0.388
TDS_{dryA} Vs TDS_{rainyA}	15.73889	20.81426	6.93809	2.268	0.053
TDS_{dryB} Vs TDS_{rainyB}	79.34444	76.83317	25.61106	3.098	**0.015**
TDS_{dryC} Vs TDS_{rainyC}	141.81111	149.11106	49.70369	2.853	**0.021**
SS_{dryA} Vs SS_{rainyA}	6.46296	13.93567	4.64522	-1.391	0.202
SS_{dryB} Vs SS_{rainyB}	115.18148	109.23679	36.41226	-3.163	**0.013**
SS_{dryC} Vs SS_{rainyC}	178.14815	154.28028	51.42676	-3.464	**0.009**
$Nitrate_{dryA}$ Vs $Nitrate_{rainyA}$	3.41111	3.67446	1.22482	-2.785	**0.024**
$Nitrate_{dryB}$ Vs $Nitrate_{rainyB}$	4.53704	4.44243	1.48081	-3.064	**0.015**
$Nitrate_{dryC}$ Vs $Nitrate_{rainyC}$	5.50159	4.57354	1.52451	-3.609	**0.007**
$Phosphate_{dryA}$ Vs $Phosphate_{rainyA}$	0.08519	0.13114	0.04371	-1.949	0.087
$Phosphate_{dryB}$ Vs $Phosphate_{rainyB}$	0.21833	0.33317	0.11106	-1.966	0.085
$Phosphate_{dryC}$ Vs $Phosphate_{rainyC}$	0.79637	0.93440	0.31147	-2.557	**0.034**

pH_{dryA} Vs pH_{rainyA}	0.80667	0.67320	0.22440	3.595	**0.007**
pH_{dryB} Vs pH_{rainyB}	0.44778	0.46962	0.15654	2.860	**0.021**
pH_{dryC} Vs pH_{rainyC}	0.45333	0.76099	0.25366	1.787	0.112
$Faecal_{dryA}$ Vs $Faecal_{rainyA}$	1210.67	1360.85	453.615	-2.669	**0.028**
$Faecal_{dryB}$ Vs $Faecal_{rainyB}$	7007.78	7814.56	2604.85	-2.690	**0.027**
$Faecal_{dryC}$ Vs $Faecal_{rainyC}$	12792.22	12366.29	4122.10	-3.103	**0.015**

dryA, dryB,dryC represents the respective water quality in such section during the dry season, the same applies for the rainy season with rainyA, RainyB and RainyC

The Faecal coliform levels were above MBS standard (table 21) in all the section except section A during the dry season, while during the rainy season, none of the section met the MBS standard (0-50 CFU/100 ml). The higher values of faecal coliform in the upstream can be attributed to the wastewater coming from cattle and goats kraals in Dzalanyama forest and communities surrounding Kamuzu dam 1 and Kamuzu dam 2. Nevertheless, human beings can not be spared as the source of faecal coliform in the waters of Lilongwe river since highest levels were recorded in the downstream in both seasons, 2001 CFU per 100 ml and 14793 CFU per 100 ml in the dry and wet season respectively. A world bank city-wide survey in 2017 showed that only five per cent of the population in Lilongwe city is served by a sewer system, while the majority relies on onsite sanitation systems (69 per cent pit latrines and 25 per cent septic tanks) and 1 per cent rely on open defecation (World-bank, 2017). The situation is bad in Lilongwe rural whereby approximately 89 per cent of the population rely on pit latrines. The dilapidated toilet facilities coupled with poor waste management in the city could be the cause of the high level of faecal coliform in the lower section C. There was a significant seasonal difference in all sections as shown in table 22. The increase in faecal coliforms over the wet season is an indicator of diffuse pollution from runoff from the catchment and points to shortcomings in land management (Pullanikkatil *et al*., 2015).

4.4. Relationship between LULC and Water quality variables

The Pearson correlation coefficients showed that the degree of association between LULC classes and water quality varied from one parameter to the other. The same LULC class might have a positive relationship with other water quality parameters while having a negative relationship with the other parameters. The following subsequent subchapter will explain the relationship between LULC classes and selected water quality variables.

i. Effect of Cultivated land on Water Quality

A significant strong positive correlation was found between Cultivated land with nitrate (r=0.983), phosphorus (r=0.927), and medium correlation with turbidity (r=0.365), TDS (r=0.425) and pH (0.533) and weakly correlated with EC (r=0.153). As revealed in this study, the increase in cultivated land and built-up areas comes at a cost of forested and grassland. The conversion of the land with vegetation into the built-up area and cultivated land aggravates the soil erosion and consequently increase the amount of dissolved and suspended solids into the runoff that ends up in water bodies. In this study, high rates of soil erosion were found to be in the deforested, cultivated land along the river banks and built-up areas. The soil erosion coupled with an intensification of agriculture by application of chemical fertilisers increases the concentration of nitrate and phosphate in the water as observed in this study, where high levels of nitrate and phosphate were recorded in the cultivated and built-up land. Additionally, water in section B and C that is dominated by cultivated land was more turbid than in section A. Several studies ((Dai *et al.*, 2017; Huang *et al.*,2013; Namugize *et al.*, 2018) have suggested that farmlands are the dominant non-point source of pollution of river water, and pesticides and fertilizers are the main components of agricultural non-point sources pollutants. As much as farmlands can absorb and retain inorganic pollutants, these inorganic chemicals applied to farm-lands can be carried by surface runoff to rivers, and the transfer of these pollutants is affected by rainfall and river water flow (Hua, 2017), this explains the higher levels of nitrate, phosphate and silt particles in Lilongwe river water during the rainy season than during the dry season. It should, however, be noted that even if a positive correlation between cultivated land and the other water quality parameters was observed in the current study, the relationship was not significant across all the parameters as there was no significant correlation between cultivated land with the following Physico-chemical parameters; turbidity, TDS, EC, and pH. Wan, *et al*., (2014) observed that the effects of agricultural land on river water quality also have a close correlation with its slope in such a way that farmlands in areas that are closer to water bodies and have high slopes are the main type of non-point source pollution. The low slope in the study area can be a contributing factor to the relationship between cultivated land and some water quality parameters being less significant.

ii. Effect of Built-up on Water Quality

A strong relationship was established in the study between built-up and nitrate (r=0.989), phosphorus (r=0.987), Turbidity (0.746), no relationship with TDS (0.03) and EC (0.015) and an inverse relationship with pH (- 0.336). The observation of this study is supported by the findings of Namugize, *et al.*, (2018) that attributed the presence of E. coli and high nutrient levels to contamination by sewage spilling and waste dumping from the built-up areas. A similar observation was found by Huang, *et al.*, (2013) whereby the built-up area was positively related to TP, TN, NH_3-N, and CODmn and was negatively related to DO, indicating that the increase of the built-up area tends to degrade the water quality. Furthermore, Dai, *et al.*, (2017) concluded that the high population density and the concentration of economic activities contribute to high pollutant emissions from built-up land, posing a serious challenge to the surface water's self-purification capacity, thereby affecting its water quality. This conclusion was made after finding that the proportion of built-up land area was negatively correlated with the DO concentration, and positively correlated with most of the other indicators including E. coli, BOD, COD, TSS, NH_3N and trace elements. Table 23 shows the results of Pearson correlation analysis between water quality parameters and LULC variables.

Table 23 The correlation coefficients between different land use and water quality variables at the scale of the whole watershed

Physical-chemical parameters	Land use/land cover changes				
	Cultivated	Built-up	Forest	Grass/shrubs	Waterbodies
Nitrate	0.983	0.989	-0.964	-0.757	-0.883
P.value	0.019*	0.011**	0.031*	0.243	0.117
Phosphate	0.927	0.987	-0.967	-0.835	-0.862
P.value	0.012**	0.013**	0.016*	0.165	0.138
Turbidity	0.365	0.746	-0.551	-0.404	-0.572
P.value	0.635	0.254	0.449	0.596	0.428
TDS	0.425	0.03*	-0.315	0.184	-0.382
P.value	0.575	0.969	0.449	0.816	0.618
EC	0.153	0.015*	-0.315	0.533	-0.336
P.value	0.847	0.985	0.685	0.321	0.664
pH	0.533	-0.336	0.051	-0.572	0.604
P.value	0.467	0.664	0.949	0.428	0.396

***** significant at p<0.01, * significant at p<0.05***

iii. Effect of Forest and Grass/Shrubs/Bare land on Water quality

Forest was strongly negatively correlated with nitrate (r= -0.964), phosphorus (r= -0.967), medium relationship with turbidity (r=0.551), TDS (r= -0.315) and EC (r= -0.315) and finally no relationship with pH (r= 0.051). Meanwhile, Grass/Shrubs/Bare land were strongly negatively related with nitrate (r= -0.757), phosphorus (r= -0.835), medium relationship with turbidity (r= -0.404), medium positive relationship with EC (r=0.533), pH (0.428), and weak positive relationship with TDS (r=0.184). Naturally, forest and grassland can improve water quality in a watershed by offering water self-purification services and reducing soil erosion and sedimentation in the watershed (AWWA, 2016) hence the strong negative correlation between those two LULC variables with most of the water quality parameters. A similar relationship was discovered by Dai, (2017) that reported an inverse correlation between the following water parameters NH_3-N, TP, TN, CODcr and BOD_5 and forest and grassland. This was attributed to biological, chemical, physical and hydrological processes within the stream, interactions of the stream wetlands and river' self-purification services highlighting the role that naturally functioning ecological infrastructure can play in water quality. The current study found that the relationship between nitrate, phosphate and grass/shrubs/bare land was not significant despite being a negative relationship. This might have arisen due to the combination of grass, shrubs and bare land into one class. These classes especially Grass and Bare land on their own have a different impact on water quality. For instance, grassland can reduce the nutrient salts brought into a waterbody by reducing surface runoff and absorbing the nutrient through plant intake required for its growth, while bare land is susceptible to soil erosion hence can increase the nutrient salts brought into the surface water bodies, hence the positive relationship between Grass/Shrubs/Bare land with EC and TDS. This is in so doing because in the middle and lower section of the catchment, bare land is dominant than grassland. The significant negative relationship between the forest land, grassland and nutrients indicate that the forest and grassland play a key role in reducing the nutrients. Huang *et al,* (2013) evaluated the impacts of land-use on water quality in Chaohu Lake Basin in China and found a significant negative correlation between, TN, and COD and forest and grassland.

5. CONCLUSION AND RECOMMENDATIONS

The study revealed that there have been serious LULC changes in the watershed over the past 30 years that have seen a total of 31,133 ha of forest land being lost representing forest cover loss of 46.65 per cent. The waterbody and grass/shrubs/bare land classes have reduced by 25.32 and 11.49 per cent respectively. This implies that a total of 3,722 ha and 3,386 ha of waterbody and grass/shrubs/bare land respectively has been converted into other land use classes since 1989. At the same period, there has been a tremendous increase in cultivated and built-up land which are currently consisting of 41.49 and 18.07 per cent respectively of the total land in the upper Lilongwe river catchment. These two classes (cultivated and built-up) have increased by 26.06 % and 56.68% respectively, indicating addition of 19,709 ha in cultivated land and 18,532 ha in Built-up since 1989. The deforestation and loss of grassland in the catchment have resulted in numerous watershed problems that include an increase in the rate of soil erosion and deterioration of water quality.

The annual soil loss from upper Lilongwe river catchment was estimated to be between less than 1 to 9.93 ton/ha/yr. The study revealed that about 83% of the area was classified to not have any soil erosion risk (< 1 ton/ha/yr) and 16 % light risk (1-10 tons/ha/yr). Even if this is not a serious loss in terms of agricultural productivity, it is causing serious problems in Lilongwe water board's provision of potable water to people living in Lilongwe city and surrounding areas.

The factors affecting surface water quality are complex and their sources have been described in many pieces of literature. However, establishing a relationship between land-use/ land cover and water quality is not an easy and straight forward process. This study established that built-up, agricultural activities and deforestation are the main factors causing Lilongwe river water pollution. Additionally, the results showed that different land uses have a different impact on water quality parameters. Furthermore, despite the spatial variability of water quality in the catchment, water quality also varies with seasonal changes with the dry season having better water quality than the rainy season in the catchment.

This study revealed correlations between systems of land use and water quality and therefore recommends the following;

- Integrated watershed management should be implemented by all the relevant stakeholders; LWB, Department of forestry, Lilongwe city assembly, Local village leaders.
- The annual tree programme by LWB should not focus only on the upstream but also in the middle and lower sections of the catchment.
- There is a need to review and amend weak policies that encourage non-compliance to regulations of managing watershed resources such as forest and water bodies.
- The government should institute programs that curb the effect of population growth on land resources, the programs can include; family planning, conservation agriculture/permaculture, discourage river bank cultivation and sand mining in Lilongwe river, and intensify afforestation programs.
- LWB should increase the water monitoring points in Likuni river, the upstream and middle section needs to be monitored to help in identifying the sources of pollution and management.
- Lilongwe city council should increase the sewer lines in the city to reduce the number of people using onsite sanitation facilities.
- There is a need for integrated solid waste management, powers should be invested in local authorities to ensure environmental management.
- The findings of this study do not provide all the answers as a ‘ one fits all’ solution to the current water pollution in Lilongwe river hence further studies should be conducted to evaluate how other factors like climate change are affecting water resources in the catchment.
- This study only assessed seasonal variation of water quality, however the long-term temporal variation of water quality in the catchment needs to be assessed.

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7. List of Appendices

Appendix 1: List of equipment/method used for Water Quality Analysis

Parameter	Equipment
pH	Digital pH meter
Electrical conductivity	Conductivity meter
TDS	TDS meter
SS	Analytical balance
Turbidity	Turbidimeter
Nitrate	UV/Visible spectrophotometer
Phosphates	UV/Visible spectrophotometer
Faecal coliform	Membrane filter technique

Appendix 2: Water sampling and transportation


TOYOTA

Appendix 3: Ground Truthing Data Collection