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Modelling of Land Use/Land Cover Changes and their Implication on Surface Water Quality Using Cellular Automata-Markov and Geographically Weighted Regression

by

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Science Pledge

By my signature below, I certify that my thesis is entirely the result of my work. I have cited all sources I have used in my thesis and I have always indicated their origin.

Abstract

Anthropogenic activities are a major driver of land use and land cover changes. These anthropogenic activities in a watershed can impact the quality of the river's water quality. This study analyzed the historical land use and land cover changes that have occurred in the upstream part of the Lilongwe River watershed, and then using Cellular Automata -Markov chain model simulated the 2050 land use and land cover status. The study also analyzed the historical water quality information of Lilongwe River to ascertain whether the quality of the water has changed with time. Finally, the study utilized the Geographically Weighted Regression to relate the land use and land cover changes to the changes in water quality. The study found that increase in grassland and cropland had a significant relationship with turbidity, total suspended solid and nitrate. For the sustainability of Lilongwe River, further monitoring of various water quality parameters and research is recommended. Integrated and collaborative catchment management activities are also recommended.

Key words:

Cellular Automata-Markov, Land Use and Land Cover, Geographically Weighted Regression, Surface water quality, Lilongwe River

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“*Determine that the thing can and shall be done, and then we shall find the way*.”– Abraham Lincoln

This journey was not easy, but to have made it thus far is a true testament of the Lord Jesus’s favor and grace. I am privileged to have this strong belief that “*it is possible, and I can do it*”.

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ACRONYMS AND ABBREVIATIONS

AICc	Akaike Information Criterion
BOD	Biochemical Oxygen Demand
CA	-Markov Cellular Automata-Markov
COD	Chemical Oxygen Demand
DEM	Digital Elevation Model
DN	Digital Number
EC	Electrical Conductivity
GIS	Geographical Information System
GWR	Geographically Weigthed Regression
Ha	Hectare
IHS5	Integrated Household Survey
IPCC	Intergovernmental Panel on Climate Change
LCM	Land Change Modeller
LULC	Land Use and Land Cover
LWB	Lilongwe Water Board
MASDAP	Malawi Spatial Data Portal
MBS	Malawi Bureau of Standards
MDG	Millenium Development Goals
M-GWR	Multi-Scale Geographic Weighted Regression
NSO	National Statistical Office
NTU	Nephelometric Turbidity Units
OLS	Ordinary Least Squared
OSM	Open Street Map
SDG	Sustainable Development Goals
SRTM	Shuttle Radar Topography Mission
TDS	Total Dissolved Solids
TSS	Total Suspended Solids
TW	Treatment Works

WHO World Health Organisation

WQEM Water Quality and Environmental Management

1. Chapter One: Introduction

1.1 Background

Land Use and Land Cover (LULC) as well as changes to LULC are a major component of the interaction between humans and the environment and therefore play a vital role in the sustainability of human development as well as the sustainability of natural resources (Lambin, et al., 2001, Wilson 2015). LULC changes have a direct bearing on the sustainability of natural resources including water, vegetation, and soil. This has made LULC changes an area of interest for researchers such that the topic is extensively studied to understand the drivers of LULC changes (Lambin, et al., 2001, Bürgi, et al., 2017, Berihun, et al., 2019, Munthali, et al., 2020) to identify and classify LULC patterns and changes (Halmy, et al., 2015, Twisa and Buchroithner 2019, Vivekananda, et al., 2021), to assess the impact of LULC (Nie, et al., 2011, Garg, et al., 2019, Munthali, et al., 2020) as well as to project future LULC (Singh, et al., 2015, Hamad, et al., 2018).

Anthropogenic activities have been identified as a major driver of LULC changes (Bronstert 2004, Zhang, et al., 2012, Hua, 2017). The LULC of any area is generally a reflection of the socio-economic status of a society and its interaction with the environment through the use of natural resources. Human activities such as deforestation, urbanization, waste management, agricultural expansion, and other agricultural activities, are some of the activities identified to drive LULC (Hassan, et al., 2016, Ngwira and Watanabe, 2019, Matlhodi, et al., 2021, Nkwanda, et al., 2021). These and other anthropogenic activities directly lead to changes in LULC, which in turn has an associated impact on the environment. LULC changes have a direct relationship with the environment and its processes, including its influence on the ecosystems, biodiversity, productivity of the land, water, energy cycles, and climate variability (Näschen, et al., 2019, Belete, et al., 2020, Hasan, et al., 2020, Roy, et al., 2022). Information about LULC changes is thus important as it guides the appreciation of the interaction between human and natural phenomena and therefore provides the necessary information for better management and decision-making (Lu, et al., 2019, Munthali, et al., 2020).

LULC changes impact hydrology and water resources due to their effect on the hydrological cycle (Mahmood, et al., 2010, Woldesenbet, et al., 2017). LULC changes in a watershed influence the hydrological processes of water infiltration, groundwater recharge, base flow, and runoff. Anthropogenic activities influencing LULC changes, as well as other natural activities, can be a source of pollutants within a watershed and then the pollutants are mobilized and delivered to a river. LULC status is thus of vital importance as it has an influence on the source of pollution as well as on the mobility of pollutants to rivers (Mainali and Chang 2018, Guo, et al., 2021).

The United Nations World Water Development Report 2021 states that “water quality has deteriorated as a result of pollution in nearly all major rivers in Africa, Asia, and Latin America”. Other studies estimate that nearly half of the world’s water quality has deteriorated and continues to do so due to human activities (Najar and Khan, 2012, Mustapha, et al., 2013, Boretti and Rosa, 2019). Contaminated rivers threaten aquatic life as well as humans (Najar and Khan 2012, Wan, et al., 2014). Contaminants can lead to the rapid growth of aquatic plants thus disturbing aquatic life systems, death to other aquatic life, as well as health implications for humans using the water. It is thus important that all factors that affect the quality of the water and consequently, also influence the availability of clean water are monitored.

1.2 Study Rationale

Studies on the relationship between LULC and water quality are relevant because water resource is a global concern due to its finite nature, and current limited access. Demand for freshwater use continues to increase globally, and will continue to do so driven by industrialization, developing energy sectors, and increased population (UNESCO 2021). Despite this, access to safe and clean water is currently still a challenge. In Africa, only 56% of city-dwellers have access to piped water (GIZ Synthesis Report 2019). In Malawi, only 10% of the population has access to piped water, while only about 88% has access to clean water (NSO Census Report 2018, NSO Fifth IHS5 Report 2012). This situation is in danger of worsening due to the effects of climate change and water resource pollution. It is thus imperative that water resources are comprehensively studied and managed for the sustainability of the resource.

There are several global initiatives aimed at increasing access to safe water as well as maintaining environmental sustainability. One of the major initiatives was the Millennium Development Goals (MDG) which covered the period from 2000 to 2015. The MDGs included Goal number 7, "ensure environmental sustainability" which focused on the management of natural resources and ecosystems in light of identified challenges of climate change, increased water scarcity and conflicts over access to resources. One of the objectives of this goal was to "Halve, by 2015, the proportion of the population without sustainable access to safe drinking water and basic sanitation". The Sustainable Development Goals (SDG) which succeeded the MDG's to cover the period from 2015 to 2030 have Goal number 6 as "clean water and sanitation". This goal was developed among other factors based on identified challenges including "3 in 10 people lack access to safely managed drinking water services" and "water scarcity affects more than 40 percent of the global population and is projected to rise" (https://www.un.org/sustainabledevelopment/water-and-sanitation/). This further emphasizes the global concern for water resource accessibility.

Understanding the relationship between the spatial and temporal character of LULC changes to river water quality is therefore important as it provides the necessary information for effective land use planning and management. It is one step in achieving the desired SDG's objectives to "improve water quality by reducing pollution, eliminating dumping, and minimizing release of hazardous chemicals and materials", "implement integrated water resources management" as well as "protect and restore water-related ecosystems" (https://www.un.org/sustainabledevelopment/water-and-sanitation/).

The ability to project LULC change provides a forewarning and basis for pre-emptive action as well as planning for resilient and sustainable programs. Information technology developments and specifically in the remote sensing and Geographical Information Systems (GIS) field now provide tools for studying the earth's surface for understanding and identifying land cover changes and dynamics and how this relates to the environment. Campbell (2011) posits that a comprehensive assessment of the impact of LULC change requires an understanding of both the past and present LULC as well as potential future LULC. In the specific case of the country of Malawi, several studies have looked at image classification for LULC pattern identification as well as LULC changes, but this research has only found two published papers of a study projecting LULC changes in Malawi (Munthali and Murayama 2015, Munthali, et al., 2020)

The city under study, Lilongwe City, is the fastest-growing urban population center in the country (NSO Census Report 2018). The population is projected to continue to grow and thus it can be expected that there will also be a resultant increase in demand on natural resources. This current study will therefore add to the body of knowledge by applying GIS tools and remote sensing technology to project LULC and investigate impact on surface water quality for the purpose of forming a basis for sustainable economic and environmental management initiatives. The emphasis of this paper is therefore not to determine whether there is a relationship between LULC and water quality since this has been established before by other studies, but rather to examine whether the use of Geographical Weighted Regression (as opposed to use of traditional Ordinary Least Squares Regression and other statistical correlation measures) uncovers other interesting variations in the relationship, and to produce a modeled prediction of LULC change.

1.3 Study Aim & Objectives

This research intends to further the knowledge in the area of LULC by analyzing trend of LULC changes, projecting future LULC and its associated impact on surface water quality. The water quality parameters that are assessed include fecal coliform, turbidity, Sulfate, Phosphate, Nitrates, Potassium, Sodium, Total Dissolved Solids (TDS), Total Suspended Solis (TSS), Electrical Conductivity (EC) and pH scale. The analysis of these water quality parameters is to varying degrees depending on the availability of water quality data. The research is proposed on the hypothesis that water quality within the Lilongwe River is progressively deteriorating with time due to anthropogenic-driven LULC changes, and the quality of the water worsens as the river flows further downstream due to increased and cumulative impact of human activity.

Aim of the study:

"To project LULC changes and associated impact on surface water quality".

Specific Objectives of the study:

- To identify trend of LULC change

- To analyse the relationship between the river's water quality to LULC change
- To model future LULC and the resultant impact on water quality

Research Questions:

a. What is the LULC change trend for the Lilongwe River catchment?
b. What is the Lilongwe River water quality trend in a similar period?
c. What is the relationship of the water quality trend to the LULC trend?
d. Based on historical LULC trend, what will be the future LULC pattern for the area?
e. Based on the projected LULC, what will be the estimated impact on surface water quality.

1.4 Study Area

The country of Malawi is in the southeastern part of Africa and is located between latitudes 9° 22¨S and 17° 03¨S and longitudes 33° 40¨E and 35° 55¨E. The capital city of Malawi is Lilongwe city located in the Lilongwe District in the Central Region of the country (Figure 1).

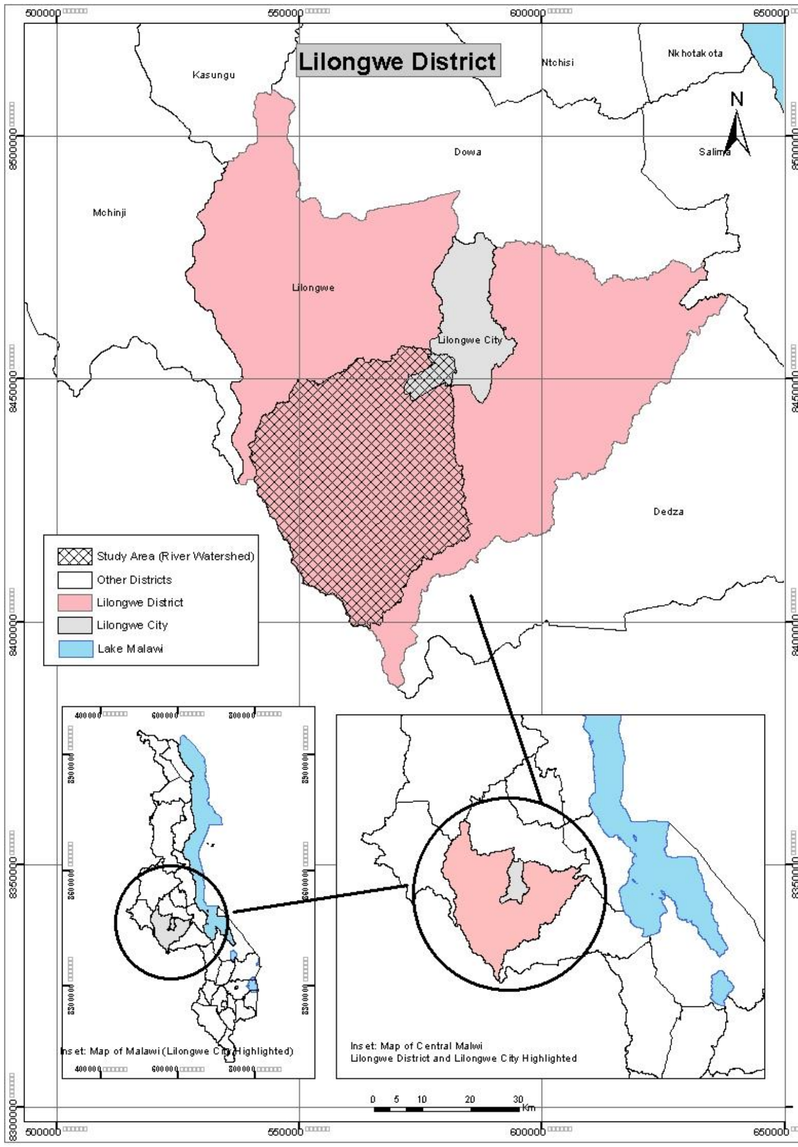

Figure 1- Lilongwe District

Lilongwe River, with a total length of approximately 200km, is one of the major rivers running through Lilongwe District. The river originates in the Dzalanyama mountain range, passes through the rural part of Lilongwe, then through Lilongwe city, and drains into the Linthipe river. The Lilongwe River has five main tributaries, namely Likuni, Katete, Lisungwe, Nanjiri, and Nathenje Rivers.

Apart from its ecological importance, the river is home to a variety of aquatic life, including fish and crocodiles, it also provides support to animal and tree life as it passes through the Lilongwe Nature Sanctuary, the Lilongwe River is crucial for other human uses, including domestic purposes like cooking, washing, bathing, and drinking, according to National Statistical Office (NS0) Census Report of 2018. The Lilongwe River is also important because it is the primary source of water for the city's water supply company, Lilongwe Water Board (LWB). The river has two dams (Kamuzu Dam 1 and Kamuzu Dam 2) constructed to store water for abstraction by LWB. Water is abstracted from the river at about 20 km downstream of Kamuzu Dam 2 and treated on-site (Lilongwe Water Board Annual Report, 2020-2021).

Lilongwe City is the most populated city in Malawi with 5.6% of the total country population. It also has the fastest-growing population in the country reported at 3.8% in the period 2008 – 2018 and it is projected to grow at an annual rate of 2.3% per year until 2050 (NSO Census Report, 2018).

The river's catchment area within the city is being affected by the city's population growth as evidenced by increased human settlements. Online satellite imagery, such as Google Earth and Open Streetmap, show a marked difference in land-use within the city boundary and outside the city boundary. Land outside the boundary is predominantly either agricultural or forest (greenery), whilst the land within the city along the river is mostly built up or in the process of development.

Understanding the relationship between LULC change and the water quality of rivers is an important step in identifying threats to water quality, strategies for managing water resources and building resilient innovations. Previous studies on the Lilongwe River's water quality have already concluded that the water in the Lilongwe River is below the World Health Organization (WHO) standard for clean and safe water (Phiri, et al., 2005, Nyasulu, 2010, Nkwanda, et al., 2021).

2. Chapter Two: Literature Review

This chapter discusses relevant previous studies and publications that provide guidance of thought for carrying out the current study. Topics that are reviewed include remote sensing, LULC classification, LULC change, impact of LULC on surface water quality, Geographic Weighted Regression (GWR), and Cellular Automata–Markov Chain model (CA-Markov) for predicting LULC changes.

2.1 Remote Sensing

Remote sensing has become one of the most useful tools for the provision of repetitive, continuous, and cost-effective data for the assessment of LULC. Advancements in remote sensing technology as well as the availability of free data, such as from the Landsat Program have brought new opportunities for researchers and policymakers for sources of information. Remote sensing and GIS together have extensively been used in various LULC studies with significant results and impact on the body of knowledge (Campbell and Wynne, 2011, Lillesand, et al., 2015, Phiri and Morgenroth, 2017).

Remote sensing can be defined as the "process of acquiring information about an object, area, or phenomenon from a distance" (Hay, et al., 2000). There are various definitions available for the term remote sensing, but crucially the central theme through the definitions remains "gathering information from a distance" (Campbell and Wynne 2011, Lillesand, et al., 2015).

Sensors carried on remote sensing devices capture and record Electro-Magnetic Radiation which is reflected or emitted from the earth's surface and objects. The characteristics of the reflected radiation vary depending on the earth's material or object surface that is being monitored (Hay, et al., 2000, Campbell and Wynne 2011, Lillesand, et al., 2015). The sensors observe and record the "variations in the way earth surface features reflect and emit electromagnetic energy" (Lillesand, et al., 2015). Then this data about the characteristic variation is compared to a known pattern of emission/reflection to identify the features and their characteristics such as LULC.

2.2 Land Use & Land Cover Classification

The terms land use and land cover are often used interchangeably even though they are distinct. Fisher, et al., (2005) notes that while the land cover can be determined by observing the land, land use requires further understanding and interpretation of the "socio-economic activities" taking place on the land. Land cover refers to what is observed "covering the earth's surface" at any given time thus this is a singular status at a time. On the other hand, various land use can exist within the same space and time. Land use refers to human activity that is occurring in space, such that varied activities can occur in the same space at the same time (Comber, 2008). For example, recreational land use can occur at the same time as agricultural land use (for instance a public park can be within a forest). While it is clear that the terms are indeed different, they have over time been used together and interchangeably due to their close linkage.

LULC classification relates to the process of analyzing remote sensing images to allocate known land cover/land use information to image pixels. Campbell and Wynne (2011) defined image classification as the process of "assigning pixels to classes". Lillesand, et al., (2015) posit that the overall aim of the classification process "is to automatically categorize all pixels in an image into land cover classes or themes". The classification process uses the spectral and textural characteristics of an image to identify pixels with close and distinct similarities to each other. Groups of similar pixels are understood to represent a particular land cover category (Phiri and Morgenroth, 2017, Alshari and Gawali, 2021). The variation of image patterns and their tone, shapes, and sizes is the basis for the delineation of different LULC categories (Jensen, 2005, Campbell and Wynne, 2011).

The LULC classification process is an important step in deriving information from remote sensing images since it transforms the image data into categorized information that can be input into further analysis. A classified image will display the spatial distribution of different land cover/land use categories. This information was originally contained in the remote sensing image as random data but is now extracted using the image classification process (Lu and Weng, 2007, Campbell and Wynne, 2011, Lillesand, et al., 2015). The image classification process is therefore an important step to derive LULC information from satellite images and in turn, the LULC maps play a significant role in different planning, management, and monitoring programs.

The most basic form of classification involves visual inspection of an image to identify and delineate land cover categories. This is an old form of classification practiced in the 1950s and 1960s (Phiri and Morgenroth, 2017). Since then, there have been advancements in information technology (remote sensing technology and GIS tools and systems) that have allowed classification methods to advance (Lu and Weng, 2007, Phiri and Morgenroth, 2017). The modern classification methods now operate as computer programs called classifiers (Lu and Weng, 2007, Phiri and Morgenroth, 2017).

One of the major distinctions between modern classification methods is whether the classification method is supervised or unsupervised and whether classification methods are pixel-based or object-based.

Supervised image classification methods involve the use of training data to guide the classifier to allocate land cover values. The user selects image sample pixels and known areas that best represent the land cover classes to be identified by the classifier. This training data are extracted from known areas that have homogenous LULC areas on the ground which can also be identified on the map. This approach requires prior knowledge of the area under study for one to select optimal training sites (Campbell and Wynne, 2011, Lillesand, et al., 2015, Phiri and Morgenroth, 2017). The idea behind supervised classification is that, since existing ground LULC information and the characteristics of the image pixels for the training sites are known, these can be matched and used to guide the classifier to further classify the rest of the pixels on the image.

The unsupervised classification method does not involve the use of training data, instead the classifier automatically aggregates the image pixels into ‘natural’ groups of similar spectral characteristics (Campbell and Wynne, 2011, Lillesand, et al., 2015, Phiri and Morgenroth, 2017). These groups can then be defined and attributed to a LULC class. The unsupervised classification approach does not require prior knowledge of the area and has less interaction with the user (Campbell and Wynne, 2011, Lillesand, et al., 2015, Phiri and Morgenroth, 2017). In supervised classification the user guides the identification of pixels while in unsupervised classification the user does not guide the system in identifying pixels but provides related LULC information after the pixel groups have been identified.

Another distinction between classification methods is between pixel-based and object-based classification methods. Pixel-based classification identifies each pixel as a separate and independent entity. Pixel-based image classification identifies the "spectral information-digital values (DNs)" (Gao and Mas, 2008) that are associated with the image pixel stored in the image. In this sense, the spectral values for each pixel are identified and classified separately unrelated to all other pixels in the image. This approach does not take into account the role of spatial relations nor texture, when classifying the pixel since each pixel is analyzed separately from the other pixels (Gao and Mas, 2008, Alshari and Gawali, 2021).

Object-based classification classifies the image based on the segmentation of the image into objects instead of individual pixels. The segmented objects allow other relationships outside the individual pixel spectral character to be considered during classification. This would include shape characteristics and neighborhood (Gao and Mas, 2008). Two steps are followed in object-based classification, firstly segmentation of the remote sensing image into discrete objects, and secondly the classification of the segmented objects (Campbell and Wynne, 2011). Segmentation identifies the spectrally homogenous patches within the image. These regions are thus the groupings of pixels that represent land parcel LULC to be identified. The spectrally homogenous patches are identified by the classifier based on the prevalent spectral values of their pixels, as well as the determined conditions input of the user and then categorized and classified into LULC classes (Lu and Weng, 2007, Campbell and Wynne, 2011, Lillesand, et al., 2015, Alshari and Gawali, 2021).

Recently other classification methods have been introduced to counter the disadvantages of hard classification methods, such as those described above. These include methods that are termed sub-pixel methods, hybrid classification methods, or fuzzy classification methods. These methods aim at better representing the imprecise and heterogeneous nature of reality of the earth surface. Due to the imprecise nature of the earth's surface, it is possible for multiple land cover types to be contained within one pixel and thus be possibly misclassified. When using fuzzy classification techniques, each pixel is given a proportional membership of all possible classes. In other words, each pixel is given a value in the form of a ratio or percentage that describes the proportion of LULC types within each pixel extent. The proportions can then be converted to actual areas of identified LULC on the ground (Jensen, 2005, Phiri and Morgenroth, 2017).

All these options for classification have different advantages and challenges to achieving optimal classification results. One classification method may not be the best fit for all classification needs and study objectives, thus it is up to the user to decide on the method that best satisfies the study objectives and produces the required results.

Overall, the accuracy of the image classification process is affected by many factors, and usually the process might need to be reiterated a number of times with amendments to settings or inputs to get satisfactory results. The complexity of the landscape being studied, the quality of the remotely sensed data, and instruments used to collect the data, the selected image classification, as well as, the capability of the user, are some of the factors that will affect the classification process (Lu and Weng, 2007, Nguyen, et al., 2020, Alshari and Gawali 2021). Accuracy in this case is referred to as the level or measure of agreement between classified LULC data to actual LULC data on the ground (Campbell and Wynne, 2011, Lillesand, et al., 2015).

One of the most common tools used to assess the accuracy of the classification process is the confusion (or error) matrix. The matrix is represented using a table where columns represent LULC classes of actual test data, while rows represent what is assigned by the classifier/predictor (or vice-versa, as both variations exist in the literature (Jensen, 2005, Lillesand, et al., 2015). The matrix shows the relationship between column values and row values, or in simple terms between the sampled actual measurement/classes on the ground and the classified/predicted result by comparing the nth column to the corresponding nth row for agreement (Jensen, 2005, Lillesand, Kefer et al., 2015).

Several descriptive measures can be obtained from the error matrix including,

- Overall accuracy- the proportion of study that is correctly classified. This is computed by dividing the total number of correctly classified pixels by the total number of reference pixels;
- Producers' accuracy- how well the values of any given category are classified. This is computed as the total number of correct pixels in a category divided by the total number of pixels of that category from the reference data/column total;
- Users' accuracy- indicates the probability that a pixel classified into a given category actually represents that category on the ground. This is computed by dividing the number of correctly classified pixels in each category by the total number of pixels that were classified in that category (the row total) (Lillesand, et al., 2015).

Apart from the above descriptive statistics, the accuracy of image classification is also measured using Kappa Coefficient statistics. Fielding and Bell (1997) described Kappa as the "proportion of specific agreement". Lillesand et al., (2015) define it as a measure of the difference between the actual agreement between reference data and an automated classifier and the chance agreement between the reference data and a random classifier. In other words, Kappa seeks to measure and discount the chance agreement of predicted and ground values (Jensen, 2005). Kappa measures the difference between the actual agreement of classification/prediction and the chance agreement to variable, in this case, whether the classification result actually agrees between the map and the ground, and how likely this is due to chance (Jensen, 2005). Kappa scores are usually reported as a value between 0 and 1, where a true agreement (observed) is closer to 1 and chance agreement approaches 0 (Lillesand, et al., 2015).

2.3 LULC Change Detection

One of the most common uses of remotely sensed images is change detection studies. Change detection involves the "identification and characterization of changes over time" (Lillesand, et al., 2015). The state of an object or phenomena is recorded or observed over a period to identify and assess any possible changes by comparing previous and later status (Sigh, 1989). In the case of remotely sensed imagery, the repetitive collection of data over the same space, also known as temporal resolution, is important as it provides historical data for reference. Remotely sensed data are used in change detection studies because the recorded reflectance values over time will show variation that will indicate that change has occurred without image variations being attributed to other factors such as differences in atmospheric conditions, and other remote sensing conditions or processing factors (Singh, 1989, Lu and Weng, 2007).

The ideal requirements for accurate change detection include the use of data acquired by the same or a similar sensor (Lillesand, et al., 2015). This will allow comparison of similar imagery characteristics unaffected by a sensor's technical differences. The second ideal requirement is that the data are recorded using the same spatial resolution, viewing geometry, spectral bands, radiometric resolution, and at the same time of day (Lillesand, et al., 2015). Anniversary dates (same date in different years) and accurate spatial registration are some of the most important factors referenced (Jensen, 2015, Lillesand, et al., 2015). While it is not always possible to meet all these conditions, the literature shows that these are some of the important considerations for accurate change-detecting results. Images with different recording parameters may need to be re-processed to bring them closer to each other. Overall, the successful use of remote sensing for LULC change detection largely depends on an adequate understanding of the study objective and study area, an understanding of the available satellite imaging system, as well as available change detection techniques (Attri, et al., 2015, Hamad, et al., 2018).

There are various change detection algorithms with varied complexity of use and results. Other change detection techniques only output a "change or no change" result while alternative techniques produce more detailed output, including the type of change and spatial distribution of changes. Lu, et al., (2004) posits that change detection should provide results on the area of change and change rate, spatial distribution of changed classes, change trajectory, and the accuracy assessment results of the change detection process.

2.4 Drivers of LULC Changes

Natural as well as anthropogenic activities lead to LULC changes. It is the LULC changes brought about by anthropogenic activities that are the focus of this study because of their highly detrimental impact. An appreciation of the drivers of the LULC changes is thus important for policymakers and for the effectiveness of environmental protection programs. Drivers to LULC changes can be understood as the factors that cause change in the attributes of land cover or use (Bürgi, et al., 2017).

Agriculture plays a major role in the economies of developing countries and will continue to do so for the foreseeable future (Agidew, et al., 2017). Expansion of agricultural land is one of the drivers of LULC change, but at the same time, agricultural produce is also most affected by climate change as a result of LULC. The increase of agricultural land has been cited as a major driver in the literature, itself driven by the loss of soil fertility leading to lessened production and, increase in population leading to increased demand for agricultural produce and land (Munthali and Murayama, 2015, Ngwira and Watanabe, 2019, Munthali, et al., 2020)

Increase in population has also been cited as a major driver of LULC change (Wilson, 2015, Berihun, et al., 2019). The increase in population puts extra strain on natural resources thus human settlements are increasing, as well as industrial production and agricultural production. The increased population also fuels other drivers of LULC change such as deforestation for charcoal making and wood harvesting (Munthali, et al., 2020, Nkwanda, et al., 2021).

Looking at the interlinkages of the drivers of LULC change indicates that one driver cannot independently fully explain LULC changes. One LULC change driver may also be a motivation to other LULC change drivers just as much as they work together to effect LULC changes. Other literature has sought to further categorize the LULC change drivers to separate those drivers that directly lead to LULC changes from those that influence other factors. Lambin, et al., (2003) categorized LULC change drivers into underlying and proximate drivers. Proximate drivers are the actions that local people take that lead directly to LULC changes, while underlying drivers are the main issues that influence people’s actions. In this case, an underlying driver might be the economic situation of a country, or a city's policy towards rural-to-urban migration. The proximate driver would be the local person's reaction to the economic situation, for instance due to lack of jobs people might resort to cutting down trees to make and sell charcoal.

2.5 Predicting LULC Changes Using CA-Markov

Extending the idea of LULC change detection, is the idea of LULC change prediction or modelling. LULC prediction involves measuring LULC changes between two specified periods and then extrapolating these changes into the future (Munthali, et al., 2020). LULC change models are based on the input of factors of change and historical LULC change transitions, which are then used for the model to provide probabilistic predictions of possible future changes (Halmy, et al., 2015, Hua, et al., 2017).

Several models are used to predict LULC changes. These models have a varied range of strengths and weaknesses, and no single model is capable of calculating and modelling all the factors involved in LULC change dynamics. The challenge in LULC change modelling is to fully capture the complexity of the integration of different phenomena related to LULC changes (Arsanjani, et al., 2013, Prestele, et al., 2016). This among other considerations includes the spatio-temporal trends and socio-biophysical processes. In other words, the models processing includes not only how the land is changing, but also why, where, and when the land is changing (Camara, et al., 2020). Recently, many studies have opted to use hybrid models to leverage the advantages of the various individual models (Arsanjani, et al., 2013, Liping, et al., 2018, Camara, et al., 2020). One of the most commonly used hybrid models is the Cellular Automata–Markov Chain (CA-Markov) model (Guan, et al., 2011, Hua, et al., 2017, Munthali, et al., 2020). The CA-Markov chain model is a hybrid combination of Markov model and the Cellular Automata model.

The Markov chain model is a discrete and stochastic model that describes the probability of LULC transitioning from one mutually exclusive state to another state over a specified period of time (Lu, et al., 2019, Camara, et al., 2020). The model provides a transition probability matrix for the LULC states. The model is therefore also referred to as status of states at a defined time, where S = {S0, S1, S2,. . ., Sn}(Camara, et al., 2020). The probability of a given state at a time transitioning to the next state is noted in the model by the transition probability matrix. The major disadvantage with the Markov chain model is that it does not produce the spatial distribution of occurrences of LULC changes as it only estimates and predicts the magnitude of these changes based on the calculated change probability matrix (Hua, et al., 2017, Munthali, et al., 2020, Matlhodi, et al., 2021).

Cellular Automata, is an “agent-based model” that runs based on the collection of cells arranged in a grid-like fashion to form a specific shape (Maithani, 2010). Each cell in the grid at any given time has a particular LULC state, and this state has a possibility of change based on the LULC state of neighboring cells based on application of existing transition rules (Guan, et al., 2011).

The CA-Markov chain model combines the abilities of the Markov model and the Cellular Automata models, such that the probability matrix which is an output of the Markov model is used as an input for the Cellular Automata part of the model (Singh, et al., 2015). The hybrid model solves the Markov chain’s limitation by adding the spatial dimension offered by Cellular Automata models (Matlhodi, et al., 2021). The CA-Markov model is therefore able to predict LULC changes and also to accurately simulate and predict future spatiotemporal LULC changes (Munthali, et al., 2020). Singh (2015) posits that the CA-Markov model is “efficient and simple to calibrate, and has a high ability to simulate multiple LULC and intricate patterns”. The hybrid model enables a more comprehensive simulation as compared to other LULC change models because it takes into consideration the spatial and temporal components of land-cover dynamics (Arsanjani, et al., 2013, Liping, et al., 2018, Ruben, et al., 2020).

2.6 Land Use Land Cover Relationship with Water Quality

Water quality can be understood as a general terminology that is used when describing the suitability of water for an intended use. This quality is described based on the physical, chemical, thermal, and biological properties of the water as compared with the expected standard for each particular use (Ritchie, et al., 2000). Physical properties of water include pH, turbidity, and total suspended solids (TSS), chemical properties of water include the measure of Nitrate, Phosphate, Biochemical Oxygen Demand (BOD), Chemical Oxygen Demand (COD), Electrical Conductivity

(EC) and Total Dissolved Solids (TDS) among others, while the biological properties of water refer to the measure of the presence of fecal coliform.

pH is a measure of the concentration of hydrogen ions in the water. It is also referred to as the "potential of hydrogen". This measurement indicates how acidic or alkaline the water is. It is measured on a scale of 0-14, with readings below 7 indicating acidic conditions, and readings above 7 indicating alkaline or basic conditions. The expected pH range of fresh surface water is between 6 and 8. Turbidity is measured in Nephelometric Turbidity Units (NTU) and refers to how clear the water is. Higher NTU values indicate unclear water or cloudy water such as when silt, mud, or other particles are deposited in water. TSS refers to the quantity of materials that are suspended in a given volume of water, and TSS is the quantity of solid materials that have been dissolved and are now a solution in the water. Both TSS and TDS are measured in milligrams per liter (mg/l) where milligram is the weight of the suspended or dissolved material, and liters refers to the amount of water. Nitrate and Phosphate are both important nutrients for plant growth and are therefore also an important component of farm fertilizers. They are both expressed in milligrams per liter (mg/l) where milligram is the quantity of nitrate or phosphate concentration within the specified liter of water. BOD measures the amount of oxygen utilized by microorganisms to break down matter in water, while COD measures the amount of oxygen needed to oxidise pollutants in water chemically without the involvement of microbes. Both parameters are expressed in milligrams per liter (mg/l). Values above 5mg/l indicate possible water pollution (Harrison, 1992). EC measures the ability of water to conduct electricity and is expressed in Micro Siemens per centimetre (μS/cm). EC is related to TDS and water temperatute, such that EC increases in higher TDS. Faecal coliform is measured and expressed as the number of organisms per 100 ml sample of water (Number/100ml). It may indicate the presence of pathogens in the water body. These are organisms that ordinarily live in the intestines of humans and animals, but can also be transported into water bodies through human and animal excrete (Carr, et al., 2008, Nyasulu, 2010).

Various studies have shown that there is a significant relationship between LULC changes and water quality (Maillard, et al., 2008, Huang, et al., 2013, Wilson, 2015, Hua, 2017, de Mello, et al., 2018, Wang, et al., 2021). Anthropogenic activities directly lead to changes in LULC, which consequently has impact on the environment, including on quality of surface water. This relationship between LULC changes and surface water quality has been assessed at various spatial scales and temporal variations. Other studies have focused on LULC changes at the local scale by looking at LULC at the water sampling point, other studies have analyzed the relationship based on the riparian scale by focusing on land along the water body (this can be at various buffer sizes) and other studies have based the assessment on the entire watershed (Ullah, et al., 2018, Huang, et al., 2020).

For instance, urbanization is known to increase impervious surfaces thus affecting surface water runoff, evaporation rate and reduced ground infiltration rate (Ullah, et al., 2018, Matlhodi, et al., 2021). Increased agricultural activities in catchment areas are associated with nutrient loading and changes to the rate of evaporation due to associated cases of deforestation (Chimwanza, et al., 2006, Nyasulu, 2010, Song, et al., 2020) while industrialization and residence, are associated with increased waste discharge into rivers (Nyasulu, 2010, Song, et al., 2020).

Studies on LULC in Malawi have likewise found that anthropogenic activities such as rapid population growth, poverty, environmental degradation from poor waste disposal, unsustainable use of forest resources, and poor agricultural activities are some of the major causes of increased pollution in Malawi's water bodies (Palamuleni, et al., 2002, Phiri, et al., 2005, Chimwanza, et al., 2006, Nyasulu, 2010, Pullanikkatil, et al., 2016, Ngwira et al., 2019, Nkwanda, et al., 2021). For instance, small scale industries and markets are identified as the biggest polluter of Lilongwe River (Phiri, et al., 2005, Nkwanda, et al., 2021). Agricultural activities also contribute negatively to river water quality due to the use of fertilizers (Lenat, 1984, Palamuleni, et al., 2011, Nkwanda, et al., 2021). The most recent study on the Lilongwe River was done by Nkwanda, et al., (2021), where they analyzed the impact that land use and land cover dynamics have on water quality in the upper Lilongwe River basin. The study looked at temporal LULC change through Landsat imagery and found that "it correlated positively with major nutrient loading, electrical conductivity (EC), fecal coliform, Total Dissolved Solids (TDS), Biochemical Oxygen Demand (BOD), Chemical Oxygen Demand (COD), and Total Suspended Solids (TSS)". The study concluded that LULC changes along the river, to an extent, contributed to the water pollution in the river.

Surface waters can be contaminated by human activities through point sources, such as sewage treatment discharge, that is where the source of pollution can be defined to a specific point in space, and by non-point sources, such as runoff from urban and agricultural areas, that is where the pollution source cannot be defined as coming from a single location but rather an area coverage. This distinction has an impact on the development of environmental management initiatives. Studies that have assessed the impact of LULC changes on water quality on various scales, riparian or watershed scale, have produced varied results. Omernik, et al., (1981) did not find any impact on the variation in scale, while other studies found a greater LULC impact on water quality at riparian buffer zones of 100m (Sliva and Williams, 2001, Pratt and Chang, 2012) and others on the watershed scale (Hunsaker and Levine, 1995). This study looks at the impact of the entire watershed.

2.7 Measurement of Relationship Between LULC and Water Quality

Various methods have traditionally been used to show the strength of correlation between LULC and water quality. These include Pearson Correlation and Ordinary Least Squares (OLS) regression. Recently the use of Geographic Weighted Regression (GWR) or Multi-scale Geographic Weighted Regression (M-GWR) has also increased. This section will discuss the OLS and GWR tools available in the ArcMap software.

2.7.1 Ordinary Least Squares Regression

One of the commonly used methods in GIS to show correlation between LULC and water quality has been the Ordinary Least Squares (OLS) regression. OLS estimates a single regression coefficient for each independent variable, which is constant over space. The method assumes spatial stationarity of the regression relationship and generates a regression equation that best fits the variables for the entire study area regardless of local factors (Ullah, et al., 2018, Wang, et al., 2018, https://pro.ArcMap .com/en/pro-app/latest/tool-reference/spatial-statistics/how-ols-regression-works.htm). It is for this reason that OLS is defined as a global estimation technique since the equation does not consider local spatial variations.

OLS is beset by two major issues when applied to such spatial correlation analysis. These are spatial autocorrelation and spatial non-stationarity (Brunsdon, et al., 1998, Fotheringham, et al., 2003, Tu, et al., 2008). Spatial autocorrelation is when the value of a variable at a location is related to the values of the same variable at the locations nearby (Brunsdon, et al., 1998). In the case of LULC impact on water quality, a sampling site may display similarity in water quality with a site nearer to it than to another site far away. This is of course in agreement with Waddo Tobler's statement and first law of Geography, "nearer things are more related than distant things" (Tobler, 1970).

Spatial non-stationarity means that the relationships between the independent and dependent variables are not constant over space, but rather vary with the local conditions and thus cannot be explained by a global model (Fotheringham, et al., 2003). OLS as a global model applied to LULC's relationship to water quality, assumes that the relationship between a land use type and water quality does not change over space and remains unaffected by varying local LULC conditions. This assumption is not true, because research has shown that watershed characteristics are not the same in different regions within a local watershed.

2.7.2 Geographical Weighted Regression

Geographically weighted regression (GWR) is a regression equation that allows for local rather than global parameters to be estimated (Fotheringham, et al., 2003). GWR produces a set of local parameter estimates showing how a relationship varies over space and then to examine the spatial pattern of the local estimates. Recent studies have employed the use of GWR and indicate that it has higher predictive power than traditional OLS regression models (Brunsdon, et al., 1998, Tu and Xia, 2008, Gao and Li, 2011, Su, et al., 2012).

GWR attempts to capture spatial variations by allowing regression model parameters to change over space. The local estimation of model parameters is obtained by weighting all neighboring observations using a distance decay function, assuming that the observations nearby have more influence on the regression point than the observations further away. GWR models produce a set of local regression results including local parameter estimates, the values of t-test on the local parameter estimates, the local R^2 values, and the local residuals, which can all be mapped to show their spatial variability (Brunsdon, et al., 1998, https://desktop.ArcMap .com/en/ArcMap

/latest/tools/spatial-statistics-toolbox/how-gwr-regression-works.htm). This suggests that GWR models, by taking into account spatial autocorrelation provide a depth of understanding to the relationship between the independent and dependent variables. The GWR models therefore better suggest how the relation between water quality and each explanatory variable might vary at a local (Fotheringham, et al., 2003, Tu and Xia, 2008, Pratt and Chang, 2012).

3. Chapter Three: Data and Research Methodology

The study analyzed changes to LULC for land along the upper Lilongwe River by studying the LULC change for the years 1990, 2000, and 2010. A CA-Markov model was then used to project LULC to the year 2050. Water quality for the same period was also analyzed to determine the trend. Geographically Weighted Regression was used to assess the relationship between water quality and LULC for the same period. Using the projected 2050 LULC, inference was made as to the state of the water quality in Lilongwe River at that time. The study used various tools including Ms Excel, ArcMap , QGIS, Google Earth, and Terrset Idriss.

3.1 Data

3.1.1 LULC Maps

Already classified LULC maps used in this study were downloaded from Malawi Spatial Data Portal (MASDAP). The portal is hosted on https://masdap.com as a web-based data sharing tool managed by the National Spatial Data Center in the Department of Surveys, in collaboration with the National Statistics Office. The portal has been active since 2012, and hosts freely downloadable data.

The data used for this study are for the years 1990, 2000, and 2010. Metadata on the portal indicates that these map products were generated from Landsat Thematic Mapper (Landsat 5), with a preference towards images captured in the dry season. Classification was done using a supervised classification method and maximum likelihood algorithm. Other post-classification procedures such as filtering, pixel/cell editing, and density slicing were also utilized. The accuracy assessment for the images was based on an assessment of Overall Accuracy and the KAPPA coefficient.

The accuracy assessment results are as follows;

a. 1990 LULC Classification: Overall Accuracy = 85.81%
Kappa Coefficient = 0.7899
b. 2000 LULC Classification: Overall Accuracy = 84.88%
Kappa Coefficient = 0.7945
c. 2010 LULC Classification: Overall Accuracy = 83.09%
Kappa Coefficient = 0.7744

3.1.2 Water Quality Data

Water quality data were sourced from Lilongwe Water Board's (LWB) Water Quality & Environmental Management (WQEM) Division. LWB monitors raw water and treated water quality through its WQEM division which has a laboratory for testing samples. The water samples are analysed according to international standards in LWB WQEM laboratory which is accredited by the Malawi Bureau of Standards (MBS). Permanent water quality monitoring points are established since the 1980's along the Lilongwe River for purpose of collecting samples. Historical data up to the year 2011 is kept in hardcopy files and thus some data are no longer legible, while some pages are missing or tattered, and in some cases, complete books have been lost. Further to this, LWB has not been consistent in sampling and testing as evidenced by various gaps in the data where in some cases some months in the year were sometimes skipped or in some cases some parameters not analyzed. The early data of 1989 to 2000 has the most gaps, while data from 2005 are comparable because despite the gaps, there is a sample from each season. To limit bias, and the effect of the data gaps, only those parameters that were sampled and measured across all the sampling points in the same period are used when comparing water quality at different sampling locations. Further to this, only water quality data for turbidity, nitrate, fecal coliform and total suspended solid were used for the geographically weighted regression. The location of the sampling sites, frequency of sampling and the method of sampling and testing are not specifically designed for this study, such that the study relies only on available data.

The water quality data were analysed using MsExcel to identify statistical values of min, max, mean, mean standard error, standard deviation for the various sampling locations as well as the differences in water quality values of the water in the Lilongwe River as shown in table 9 and table 10.

The analysis of the water quality parameters first provides an overview of Lilongwe River's water quality by summarizing the minimum and maximum reported values, as well as the mean of the values. This is intended to provide a generalized view of the quality of water in the upper part of Lilongwe River. Secondly, a comparison of the water quality of the most upstream sampling point (Katete) to the most downstream sampling point (LWB Treatment plant intake) is made because these two points offer the most varied LULC conditions. Thirdly, the water quality at all the sampling points is then compared in relation to the LULC classes, to ascertain whether there is indeed any pattern to the water quality variation as the water moves downstream in relation to the LULC classes.

3.1.3 Secondary Data

Secondary data included vector files of LULC from Google Earth and Open Street Map (OSM), road network, Lilongwe River and tributaries that were sourced from Department of Surveys and Department of Physical Planning. Google Earth historical imagery files were used for cross comparison and a digital elevation model (DEM) sourced from Shuttle Radar Topography Mission (SRTM) was used to delineate Lilongwe River watershed.

3.2 Methodology

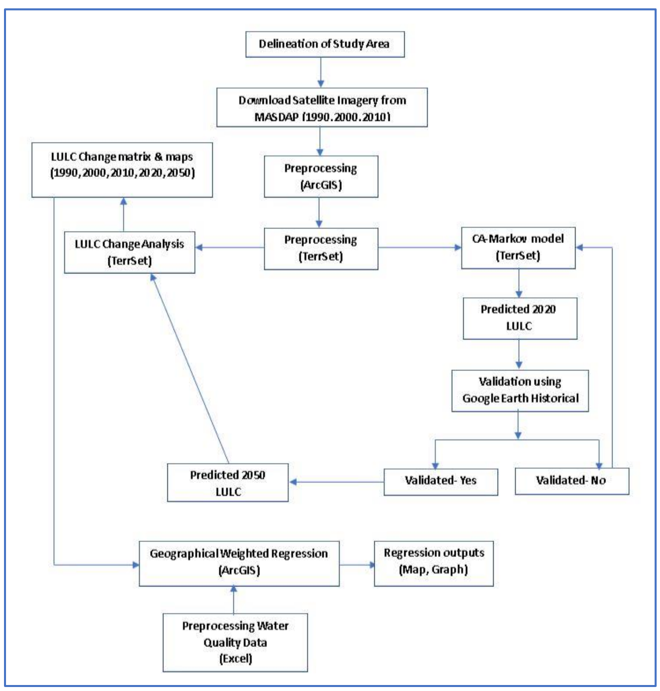

Figure 2- Research Workflow

Figure 2 provides a summary of this research workflow. The first process was to delineate the study area. To this end, shapefile data of Lilongwe River and its major attributes were downloaded from MASDAP and from Department of Surveys office. This data were processed in ArcMap and overlaid on top of a DEM (sourced from SRTM) with the river end point highlighted. ArcMap was used to project the DEM file to local coordinate system, WGS 84 UTM Zone 36, and to extract the Lilongwe River watershed, which is the study area. The extracted raster file of Lilongwe River watershed was also converted into a shapefile.

LULC maps downloaded from MASDAP were processed in ArcMap, and then used to clip out the study area. The delineated watershed was overlaid and used to extract the area of interest from all the raster LULC files. The files were all projected into the local coordinate system, and exported with similar parameters (cell size, no data value, number of columns and rows, etc.). The files have to have similar parameters for the purpose of processing and matching in Terrset Idriss software. A copy of each file was converted to a vector file to calculate LULC area and percentage. The value of percentage was used to compare temporal change in LULC.

The Land Change Modeller (LCM) in Terrset was used to compare the LULC raster files, and produce LULC change maps. Transition models for the study years were generated using the Markovian change model and used as input in Cellular Automata model to simulate LULC spatial distribution for the year 2020. The 2020 LULC map was further used to assess accuracy of the CA-Markov simulation (Overall Accuracy and KAPPA Statistics), and later to also produce the projected 2050 LULC map.

Cellular Automata (CA)-Markov chain model was used for purpose of estimating future LULC within the study area. The LULC classified maps of 1990 and 2000 were used to produce a simulated 2020 LULC map which was compared to the Google Earth 2020 historical image as a means to validate the projection output. A final LULC projection to the 2050 year was made based on the 2000 and 2020 LULC maps.

The ArcMap GWR tool was used to assess the relationship between water quality and LULC. Water quality sampling points were used to delineate sub-watersheds within the main Lilongwe River watershed. The sub-watersheds were created so as to align each water sampling point to a particular sub-watershed LULC characteristics. In this case the implication is that the water quality status at a particular sampling point is then related to the LULC characteristic of that watershed and the GWR was run to assess whether there is any spatial relationship between the water quality parameters of this sampling point to the LULC distribution within the related sub-watershed. Three sub-watersheds were identified coinciding with a majority of LULC class such as forest class in the upper part of Lilongwe River, cultivation in the middle part of the river, and mix of cultivation and settlement in the lower part of the river. The water quality data were summarized for the sampling points that represent the watersheds, and likewise the water parameter at that sampling point was understood to indicate the value for that watershed. As much as possible, the summary of water quality values was for the same year as the LULC map, or in cases where the data were not sufficient, allowance was made for a difference of one year. A LULC shapefile for each year, with sub-watershed delineated, were joined to the summarized water quality values and used as input in running GWR.

4. Chapter Four: Analysis and Results

4.1 Land Use Land Cover Change

The assessment of LULC change was done using LULC classified maps sourced from Malawi Spatial Data Portal (MASDAP) as shown in Figure 3. Classified maps of the study area for the years 1990, 2000 and 2010 were used. Metadata for all the maps indicates that the maps were developed from Landsat Imagery (30m by 30m) resolution using a supervised classification method. LULC classes scheme were defined based on the Intergovernmental Panel on Climate Change (IPCC) 6 land over categories as follows: Forestland, Grassland, Wetland, Cropland, Settlement and Other (which includes land obscured by clouds).

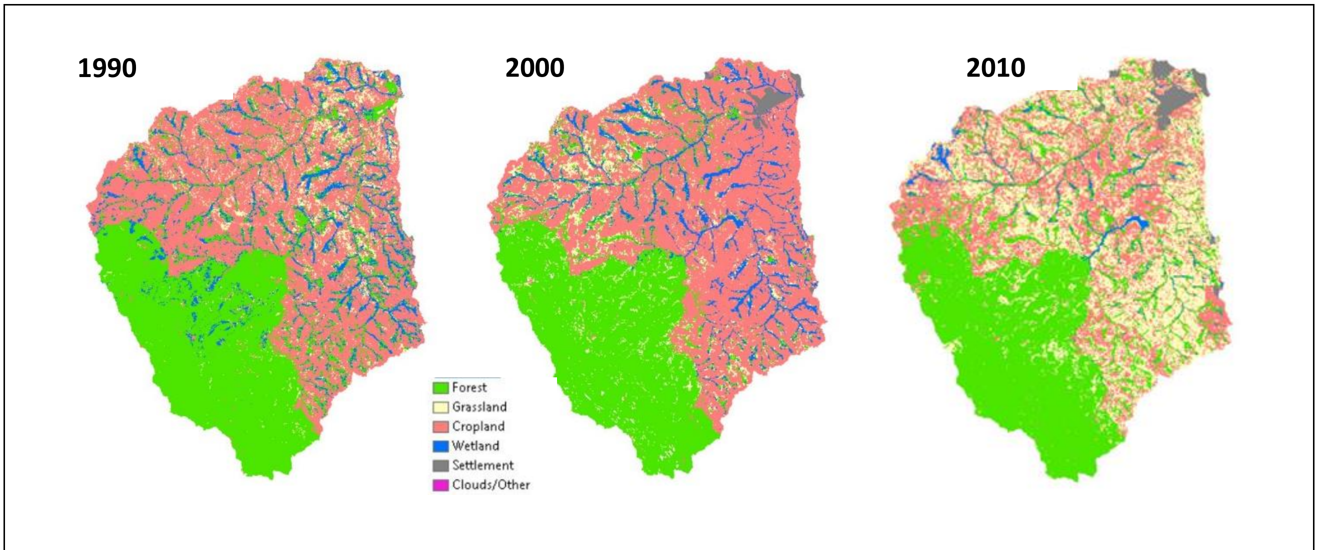

Figure 3- Classified Images of Lilongwe River Catchment (Source: MASDAP)

Analysis of the images indicates that the two dominant LULC categories are forest and cropland, with grassland dominant in the year 2010 only. While forest and cropland remain the dominant category, it is interesting to note that the coverage for these LULC categories is lower in the last year than in the initial year, while on the other hand settlement is the only category that has shown consistent increase through the period. Another notable change is the increase of grassland for the period 2000 to 2010 with a total of 24%, and a decrease in cropland by 22%. This is a surprising change considering that subsistence farming is an annual and continuous activity for the majority of Malawians as it is the major source of maize, Malawi's staple food. With increase in population, it would be expected likewise that there would be a continued increase in cropland. Factors that led to the decline of cropland for the year 2010 are beyond the scope of this research. Nevertheless, the research also looked at other LULC classification post 2010 and found that the percentage of cropland continues to rise (Phiri, et al., 2005, Nyasulu, 2010, Nkwanda, et al., 2021). When comparing the initial year to the last year, cropland and wetland indicate the highest decline in land coverage by percentage. Wetland category indicates a substantial and consistent decline from the initial year coverage of 8.5% to 2.2% coverage at end year 2010. Wetland lost a substantial area to cropland due to the use of dambo land (seasonally waterlogged wetlands) and riverbanks for winter cropping or vegetable gardening. The majority of the forest in the study area is within the Malingunde protected area which despite continued encroachment by people looking for firewood, illegal felling of trees for making charcoal, and hunters continues to receive government support to ensure the forest is not depleted. The increase in settlement can be attributed to the increased coverage of Lilongwe city in the north-western part of the study area, but also due to increased population in the rural areas as evidenced by expanded village areas (Munthali, 2015, Pullanikkatil, et al., 2016). This information is also illustrated in Figure 4 and in Table 1.

Table 1- Comparison of LULC Coverage

	Year							
	1990		**2000**		**LULC Change 1990-2000**	**2010**		**LULC Change 2000-2010**
LULC Category	**LULC Area (Ha)**	**LULC %**	**LULC Area (Ha)**	**LULC %**		**LULC Area (Ha)**	**LULC %**	
Forest	69602.82	39.44%	61656.13	34.94%	-4.5	67830.63	38.43%	3.49
Grassland	10057.19	5.70%	10225.44	5.79%	0.09	52762.44	29.90%	24.11
Cropland	81786.96	46.34%	89170.49	50.53%	4.19	48734.46	27.61%	-22.92
Wetland	14951.87	8.47%	12835.84	7.27%	-1.2	3899.95	2.21%	-5.06
Settlement	44.99	0.03%	1768.49	1.00%	0.97	3258.02	1.85%	0.85
Other	40.16	0.02%	827.81	0.47%	0.45	0.44	0.00%	

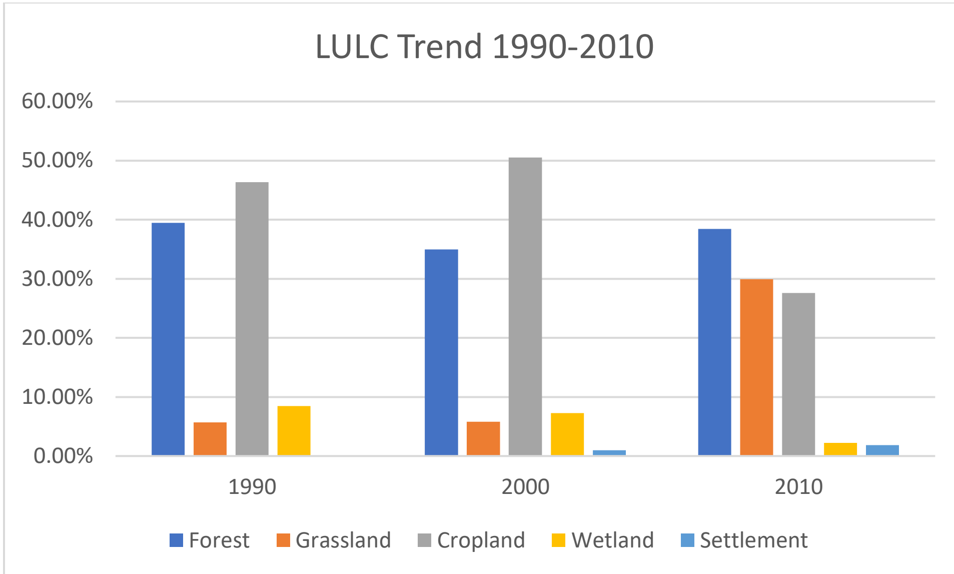

Figure 4- LULC Trend 1990-2010

Further analysis was done to ascertain the LULC change by category for each time period as shown in Table 1 and Table 2 as well as Figure 5. The first analysis covers the period 1990 to 2000. In this period, the highest category change was from grassland to cropland at a total of 8000Ha, followed by forest to cropland at 6000Ha. This would also be in agreement with the noted increase of coverage of cropland to 50.5%. Settlement is the land category that has the least amount of change into another category, but earns 100Ha from cropland. Forest is the LULC category that has lost the most coverage to other LULC categories including cropland, wetland and grassland. Wetland lost the highest proportion of its coverage to cropland at 3700Ha.

Table 2 - LULC Category Area Change (Ha) 1990-2000

LULC Change 1990-2000	**Area Change (Ha)**
Cropland-Cropland	70,268.68
Forest-Forest	54,703.01
Grassland-Cropland	8,078.87
Forest-Cropland	6,993.23
Wetland-Wetland	6,767.32
Cropland-Grassland	5,634.07
Forest-Wetland	4,335.15

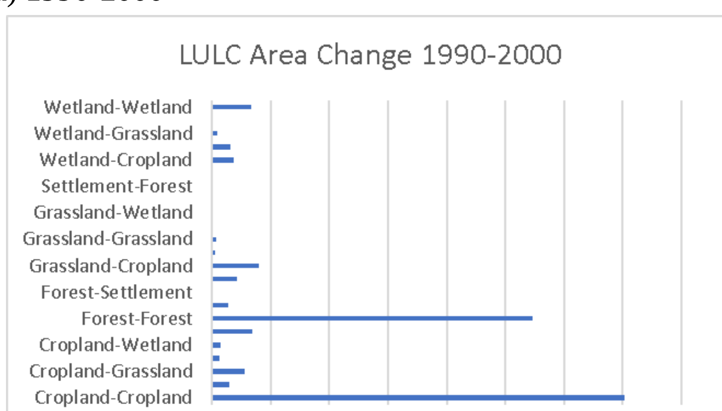

Figure 5- LULC Area Change by Category 1990-2000

Wetland-Cropland	3,746.88
Wetland-Forest	3,234.62
Cropland-Forest	3,027.67
Forest-Grassland	2,772.27
Cropland-Wetland	1,474.98
Cropland-Settlement	1,276.63
Wetland-Grassland	982.71
Grassland-Grassland	832.81
Grassland-Forest	637.03
Grassland-Wetland	255.04
Grassland-Settlement	235.10
Wetland-Settlement	163.11
Forest-Settlement	86.37
Settlement-Cropland	24.63
Settlement-Forest	20.03
Settlement-Grassland	0.10

The second period is from 2000 to 2010 illustrated in Table 3 and Figure 6. In this period, the highest category change was a reverse of the change that happened in the initial period, namely a change from cropland to grassland at a total of 43,000Ha. This is also in agreement with the noted increase of coverage of grassland to 29%. Settlement continued to be the category with the least loss of coverage but gained a notable 13,000Ha from cropland and 43Ha from forest. In this period, wetland lost the highest proportion to forest at 6,800Ha.

Table 3- LULC Category Area Changes (Ha) 2000-2010

LULC Change 2000-2010	**Area Change (Ha)**
Forest -Forest	53921.35
Cropland -Grassland	43167.39
Cropland -Cropland	40671.56
Wetland -Forest	6848.42
Grassland -Grassland	4123.98
Forest -Grassland	4087.40
Cropland -Forest	3711.98

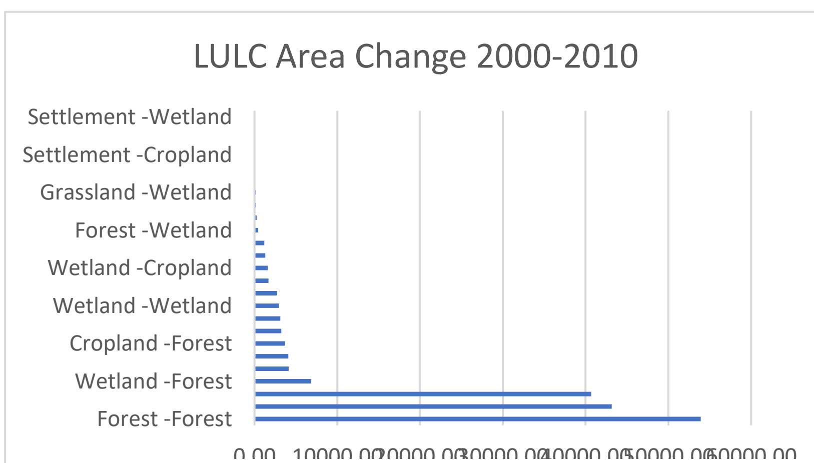

Figure 6- LULC Area Change (Ha) by Category 2000-2010

Grassland -Cropland	3213.21
Forest -Cropland	3124.12
Wetland -Wetland	2977.82
Grassland -Forest	2710.53
Settlement - Settlement	1696.56
Wetland -Cropland	1618.72
Cropland -Settlement	1306.76
Wetland -Grassland	1200.53
Forest -Wetland	460.24
Cropland -Wetland	268.71
Wetland -Settlement	188.83
Grassland -Wetland	161.02
Forest -Settlement	43.61
Settlement - Grassland	37.93
Settlement -Cropland	27.85
Grassland - Settlement	15.20
Settlement -Forest	3.85
Settlement -Wetland	0.23

4.2 LULC Projection with CA-Markov

A Cellular Automata (CA)-Markov chain model was used for purpose of estimating future LULC within the study area. The Markov module produces transition probability files which are used as an input in the Cellular Automata model to spatially distribute the transitions. The LULC classified maps of 1990 and 2000 were used to produce a simulated 2020 LULC map as shown in Figure 7 which was compared with Google Earth 2020 historical image as a means to validate the projection output. The results of this accuracy assessment are presented using Overall Accuracy based on the error matrix in Table 5 and Kappa Coefficient below. Table 4 provides LULC class distribution by size for the projected year 2020.

Table 4- Projected 2020 LULC Area

Projected 2020 LULC		
Category	**Hectares**	**Percent Cover**
Forest	52,387.87	30%
Grassland	10,841.77	6%
Cropland	99,682.74	57%
Wetland	10,655.31	6%
Settlement	1,919.75	1%

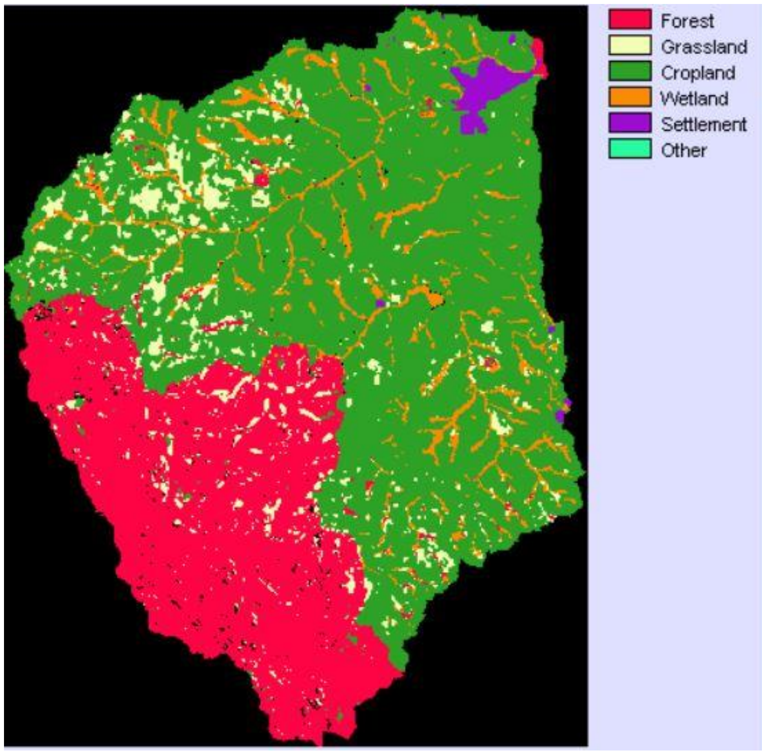

Figure 7- Projected 2020 LULC

Table 5- Error Matrix for 2020 Projected LULC

	Waterbody	**Forest**	**Cropland**	**Grass/Bareland**	**Settlement**	**Total (User)**
Waterbody	**20**	0	0	0	0	20
Forest	0	**12**	0	0	0	12
Cropland	0	4	**16**	2	8	30
Grass/Bareland	0	0	0	**12**	0	12
Settlement	0	0	0	0	**8**	8
Total (Producers)	20	16	16	14	16	82

Where;

Overall Accuracy = Total Number of Correctly Classified (User) / Total Number of Reference Pixels (Producers)) x100

Therefore;

Overall Accuracy = (68/82) * 100= 82.93%

Where;

Kappa =

$$\hat{k} = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r} (x_{i+} \cdot x_{+i})}{N^2 - \sum_{i=1}^{r} (x_{i+} \cdot x_{+i})}$$

Equation 1- Kappa Equation

r= number of rows in the error matrix

Xii = number of observations in row i and column i (on the major diagonal)

Xi+ = total of observations in row i (shown as marginal total to the right of the matrix)

X+i = total of observation in column i (shown as marginal total at the bottom of the matrix)

N = total number of observations included in the matrix.

(Lillesand, et al., 2015)

Therefore; $(82 \ * \ (20 + 12 + 16 + 12 + 8)) - ((20 * 20) + (16 * 12) + (16 * 30) + (14 * 12)) + (16 * 8))\ /$

82^2 - ((20*20)+(16*12)+(16*30)+(14*12))+(16*8))

Therefore, Kappa is 0.78

The level of agreement between the projected map and the validation map using Kappa Coefficient ranges from 1 to 0, with values closer to 1 meaning that the projected map has a high agreement with the reference map that is not based on chance, while values close to 0 indicate poor agreement, and that this agreement is more likely due to chance (Lillesand, et al., 2015). In this case an overall accuracy of 82.9% and a Kappa of 0.78 gives confidence of a well-classified LULC.

A final LULC projection to the year 2050 as shown in Figure 8 was made based on the 2000 and 2020 LULC maps. The 2010 LULC map was not used because of the substantial decline in cropland in this year, which is an outlier due to the heavy reliance on annual subsistence farming in the area. Utilizing this year in the simulation would therefore have possibly led to the under-projection of cropland land use area. Detailed results of the distribution of LULC categories are presented in Table 6, while Table 7 quantifies the LULC change from 1990 to 2050.

.

Table 6- Projected 2050 LULC Area

Projected 2050 LULC		
Category	**Hectares**	**Percent Cover**
Forest	44878.74	25.6%
Grassland	11122.04	6.3%
Cropland	107900.17	61.5%
Wetland	9523.74	5.4%
Settlement	2062.75	1.2%

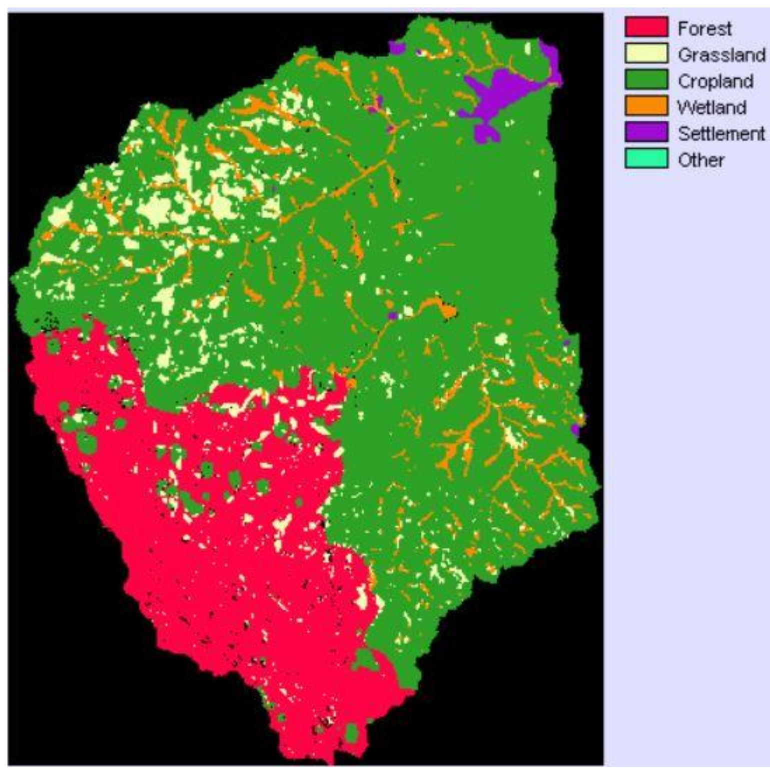

Figure 8- Projected 2050 LULC

Table 7- Comparison of LULC Sizes by Category 1990-2050

LULC Category	Year						LULC Change 1990-2050	LULC Change 2010-2050
	1990		2010		2050			
	LULC Area (Ha)	LULC %	LULC Area (Ha)	LULC %	LULC Area (Ha)	LULC %		
Forest	69602.82	39.44%	67,830.63	38.43%	44,878.74	25.6%	-13.84	-12.83
Grassland	10057.19	5.70%	52,762.44	29.90%	11,122.04	6.3%	0.6	-23.6
Cropland	81786.96	46.34%	48,734.46	27.61%	107,900.18	61.5%	15.6	33.89
Wetland	14951.87	8.47%	3,899.95	2.21%	9,523.74	5.4%	-3.07	3.19
Settlement	44.99	0.03%	3,258.02	1.85%	2,062.75	1.2%	1.17	-0.65

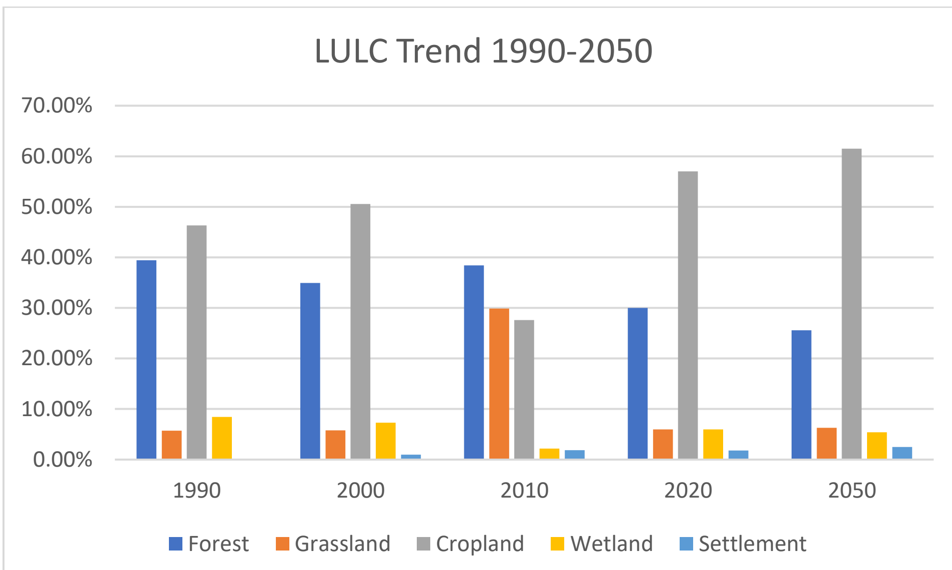

Figure 9-LULC Trend 1990-2050

Results of the LULC projection show that there is a continued decline in forest from year 1990, 69,602.82Ha (39%) to 52,387Ha (30%) in 2020 and 44,878Ha (25%) in 2050. Cropland has the biggest gain as it increases from 48,734Ha (28%) in 2010 to 99,682Ha (57%) in 2020 and 107,900Ha (62%) in 2050. Wetland increased within the period 2010 to 2020, but experiences a slight decline from 2020 to 2050. Grassland experiences the biggest decline for all LULC classes between 2010 and 2020 from 52,762Ha (30%) to 10,841Ha (6%) representing a 24% decline, but increased to 11,122 (6%) in 2050. Settlement is the LULC class that experiences the least amount of change by both percentage and actual size among all the LULC classes. Between the year 2010 and 2020 it declined from 3258Ha (1.8%) to1919Ha (1%) then slightly increased to 2062Ha (1.2%) in 2050. This information is also presented in Figure 9.

The reduction of forest cover in Malawi, and in Dzalanyama specifically, has been raised in other publications as one of the major challenges (Phiri, et al., 2005, Munthali and Murayama 2015, Ngwira and Watanabe, 2019, Munthali, et al., 2020, Nkwanda, et al., 2021). Ngwira and Watanabe (2019) state that globally deforestation is happening at a rate of 13 million hectares per year, while in Malawi forest area reduced from 47% in 1975 to 36% in 2005. Munthali and Murayama (2015) in their study of LULC change detection in Dzalanyama also concluded that the forest area will continue to decline if no specific measures are put in place to protect the forest reserve.

Malawi is a predominantly agriculture-based economy, with the majority of people involved in subsistence agriculture. With increased population, it is thus to be expected that there will also be increased land that is used for farming. Within the Lilongwe River watershed, there is also a noticeable use of wetlands for dry season farming which over time leads to reduction of wetland land cover. Similar findings were noted by Pullanikkatil, et al., (2016) and Nkwanda, et al., (2021).

Human settlement within the catchment is growing mostly due to the expansion of Lilongwe city in the north-eastern part of the study area, which is also downstream of Lilongwe River. Other settlements, mostly small villages, are spread throughout the cropland area, specifically in the middle section of the Lilongwe River. These settlements may possibly be under registered due to the nature of their roofing materials that are made from grass, thus likely to be miscategorized as grassland. With increased population, it can be expected that the growth of Lilongwe city will continue to lead to expansion of human settlement within the watershed, and especially in the northeast part of the watershed where the Lilongwe City is expanding.

4.3 Water Quality

LWB through its WQEM division monitors the quality of water in the Lilongwe River and its major tributaries. Testing is done in LWB’s own laboratory which is duly certified by the Malawi Bureau of Standards (MBS). The spatial distribution of the sampling points used in this study are mapped in Figure 10 while Table 8 describes the sampling locations in their order along Lilongwe River.

Table 8- Description of Sampling Locations

No	Sampling Point	Description of Location	Easting	Northing
1	Katete	• Most upstream sampling point, at the base of the Dzalanyama mountains. • The surrounding is mostly mountainous forest and shrubs.	564293.74	8429722.54
2	Kamuzu Dam 1	• Approx 7.5km from first sampling point. An outlet of Kamuzu Dam 1 (KD 1 bridge), the first Dam on the river. • The surrounding is mostly villages and cultivation areas.	569230.2	8432931.13
3	Lilongwe river-Lisungwi Confluence	• Approx 10km from KD1 sampling point. Lilongwe river and Lisungwi river confluence point. The first major tributary into Lilongwe River. • The surrounding is mostly villages and cultivation areas.	575954.87	8437445.59
4	LL-Malili bridge	• Approx. 6km from previous sampling point at Lilongwe River and Lisungwi River confluence. • The surrounding is mostly villages and cultivation areas.	576852.7	8442757.77
5	LL-Likuni Confluence	• Approx. 7km from previous sampling point. Lilongwe river and Likuni River confluence. This is the second major tributary. • The surrounding is mostly semi-urban settlements and cultivation areas.	577026.02	8448518.29

6	LWB Treatment Plant Intake	• Approx. 6km from the previous sampling point. • The surrounding is an urban settlement area.	581675.3	8451428.88

The distribution of the sampling points was further generalized to agree with the spatial distribution of the LULC classes. The upper most part of Lilongwe River consists of the Dzalanyama mountains which is a protected area and thus is mostly made up of forest and shrubs despite recent anthropogenic activities mostly tree cutting for purpose of making charcoal. Cultivation and sparse human settlement areas start from the base of the mountain and continue downstream up to the 5th sampling point at Lilongwe Likuni Confluence. From this sampling point up to the 6th sampling point LWB Treatment Plant Intake, the LULC share is almost evenly spread between Settlement, Cropland and Shrubs. This area is within the Lilongwe City boundary.

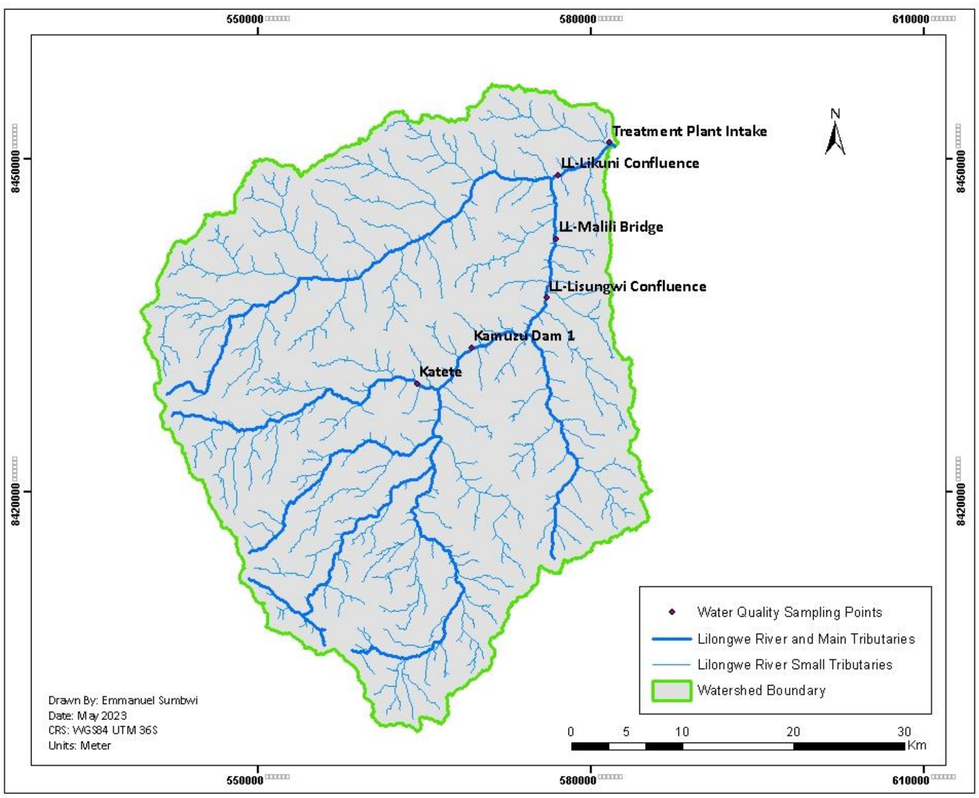

Figure 10- Location of LWB Water Quality Sampling Points

4.3.1 Status of Lilongwe River Water Quality

Other previous studies have concluded that water in Lilongwe River is not safe for drinking as it falls below WHO and MBS requirements for safe drinking water (Phiri, et al., 2005, Nyasulu, 2010, Nkwanda, et al., 2021). An assessment of the downstream water quality of the river, based on samples collected in the year 2000 and 2020 is provided in Table 9.

Table 9- Statistical Description of Lilongwe River Water Quality

Parameter	**Year 2000**		**Year 2020**	
	Dry Season (September)	**Wet Season (December)**	**Dry Season (September)**	**Wet Season (December)**
Turbidity (NTU)	11.7	211	21	1,550
pH	7.7	8.1	7.5	7.6
Fecal Coliform count/100ml	700	8,400	320	9,000
Sodium (mg/l)	18.661	9.81	17.24	9.95
TDS (mg/l)	12	97.3	204	114.8
TSS (mg/l)	70.4	162.4	7	45
Nitrate (mg/l)	2.76	11.3	2.1	11.39
Phosphate (mg/l)	0.04	0.4	0.25	0.31
Sulfate (mg/l)	38	13	53	26
EC µmS/cm	232	139	292	164
Potassium (mg/l)	1.993	Not Available	1.26	2.41

The available sample data from all water quality sampling points indicate a wide variation in the Turbidity, with ranges of 0.4 Nephelometric Turbidity Units (NTU) to 1,550NTU and a mean of 73.5NTU. This also agrees with the wide range of Total Dissolved Solids (TDS) and Total Suspended Solids (TSS) pointing to possible external influences causing the wide variations. Similarly, the wide variations for Phosphate, Sulfate, Potassium and Nitrate indicate external influence. A wide range in Fecal Coliform from 2 to 15,500 further indicates similar possible external influences. The mean pH value of 7.6 indicates that the water is basic, with the lowest pH value recorded at 6.8 and the highest at 8.8. The pH variation on the other hand is generally constant and does not on its own value arouse suspicion of external influence. Considering all these water quality parameter values, and mainly the wide range of results for the sampled water, it indicates that Lilongwe River is possibly being affected by some external factors causing the massive fluctuation in water quality. This external influence could include the use of the river banks for winter vegetable farming resulting in fertilizer and other farm chemicals depositing into the water body, annual cultivation of maize is prevalent in the rural area which could also impact the river with fertilizer and other chemicals as well as increased siltation, and depositing of animal and human waste into the river amongst other possible influences.

4.3.2 Comparison Of Upstream and Downstream Water Quality

A comparative analysis was done to compare Lilongwe River water quality based on most upstream and furthest downstream sampling points, as well as with reference to the middle sub-watersheds sampling point as presented in Table 10-11 and in Figure 11-12. The results indicate minimal fluctuation of the pH, with the minimum values at both sites indicating neutral pH, with maximum values of 8.6pH at Katete and 8.4pH at Treatment Works Intake (TW Intake) both indicating that the water has basic pH, the mean at both sites also indicates there is minimal fluctuations.

All the other values indicate disparities in the water quality at the first sampling point (Katete) to the last sampling point (TW Intake). The maximum turbidity at the downstream sampling point, TW Intake, is 414NTU as compared to 204NTU at upstream point, Katete, while the lowest value is 0.4NTU at Katete as opposed to 2NTU at TW Intake. There are also high disparities in Fecal Coliform, TDS and SS values with increased values at the downstream sampling point. Similarly, there is a higher concentration of Sodium, Nitrate and Sulfate at the last sampling location (TW Intake) with maximum differences of 22, 4.99, and 38 respectively. Phosphate indicates minor difference of 0.07 for the two sites, while it is only Electrical Conductivity that is higher upstream than downstream. It can therefore be concluded that the water quality is indeed deteriorating as the river flows downstream. This is the normal pattern of surface water as the river flows further from its source as there is a possibility of an increase in contamination as the water travels downstream and interacts with the surrounding environment.

Table 10- Statistical Comparison of Water Quality Parameters at Upstream (Katete), Midstream (Malili) and Downstream (TW Intake) Sampling Points

Parameter	Katete				Malili				TW Intake			
	Min	Max	Mean	SE	Min	Max	Mean	SE	Min	Max	Mean	SE
Turbidity	0.4	210	14.47	4.9	3.6	1550	81.19	46.14	2	414	41.49	12.361
pH	7.1	8.6	7.44	0.047	7.3	8	7.66	0.029	6.9	8.4	7.61	0.03
Fecal Coliform	20	2400	460.6	93.7	40	10500	1697.06	403.26	320	9000	2367.71	552.48
Sodium	0.88	38	8.94	0.96	4.92	45	10.79	1.26	1	60	14.31	0.9
TDS	26.82	108.5	54.65	2.7	46.34	883	111.37	21.24	68.29	369	155.8	8.17
TSS	0.4	50	7.8	1.76	3.1	768	53.94	21.24	5	295	56.1	9.33
Nitrate	0.1	6.4	2.15	0.32	0.1	43	4.33	1.47	0.2	11.39	2.76	0.39
Phosphate	0.1	2.3	0.45	0.08	0.07	2.08	0.38	0.058	0.04	2.37	0.41	0.07
Sulfate	1	37	3.48	1.078	3	213	20.33	5.78	13	75	34.84	2.12
EC	42	824	96.12	19.62	0	212	124.64	7.31	110	528	228.58	11.76
Potassium	0.1	10.2	1.85	0.25	0.2	7.7	1.94	0.23	0.2	20.9	3.72	0.45

Table 11- Statistical Difference in Water Quality Values for Upstream (Katete) and Downstream (TW Intake) Sampling Point

	Min Differences	Max differences	Mean Differences	Observation
Turbidity	1.6	204	27.02	Increasing Turbidity downstream
pH	-0.2	-0.2	0.17	Minor difference, increased Ph downstream
Fecal Coliform	300	6600	1907.11	Increased Fecal Coliform downstream
Sodium	0.12	22	5.37	Increased Sodium downstream
TDS	41.48	260.5	101.15	Increased TDS downstream
TSS	4.6	245	48.3	Increased SS downstream,
Nitrate	0.1	4.99	0.61	Increased amount of Nitrates downstream
Phosphate	-0.06	0.07	-0.04	Minor decrease in Phosphate downstream
Sulfate	12	38	31.36	Increased Sulfate content downstream
EC	68	-296	132.46	Increased EC downstream
Potassium	0.1	10.7	1.87	Minor increase in Potassium downstream

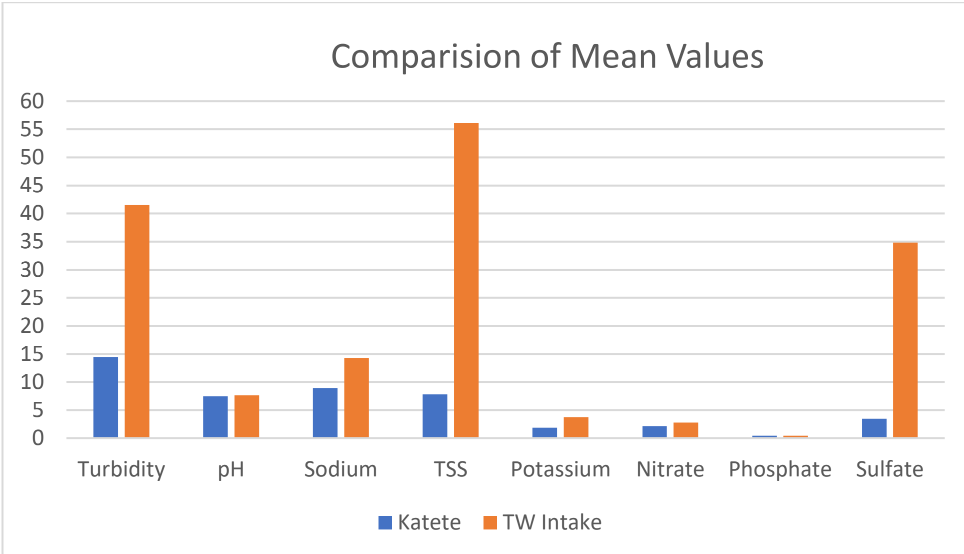

Figure 11- Comparison of Upstream and Downstream Water Quality Mean Values

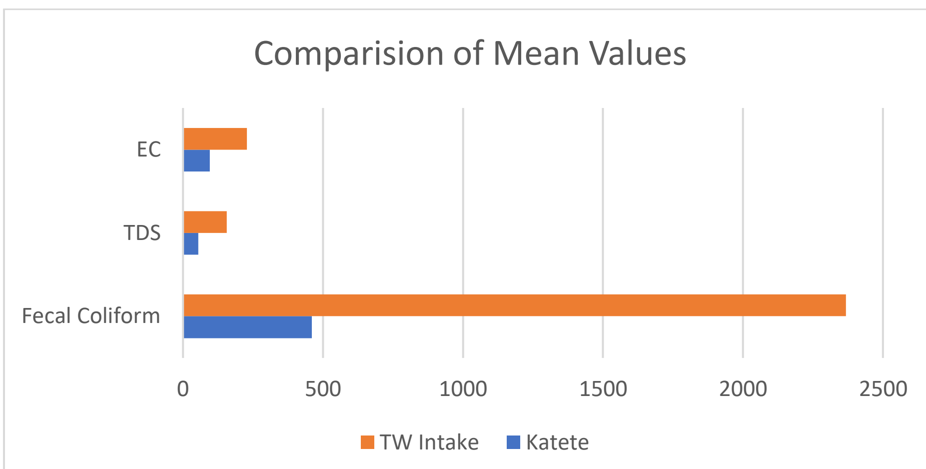

Figure 12- Comparison of Upstream and Downstream Mean Values of Water Quality

It is also interesting to note that despite most water quality parameters registering a higher maximum value at the most downstream sampling point when compared to the most upstream sampling point, it is actually the middle sampling point at Malili that has the majority of highest maximum water quality values for all the sampling points. The maximum turbidity is at 1550NTU, which is 86% and 73% higher than Turbidity values at Katete and TW Intake respectively. Maximum Fecal Coliform of 10,500count/100ml at Malili is 71% and 14% higher than values at

Katete and TW Intake, respectively. Likewise, values for TDS and TSS are noticeably higher within the Malili sub-watershed than both the upper and lower river sampling points. Nitrate and Sulfate also indicate higher maximum values at the Malili sampling point, with Nitrate 85% and 75% above maximum values recorded at Katete and TW Intake respectively. The sulfate maximum recorded value at Malili is 86% and 65 % higher than values recorded at Katete and TW Intake, respectively. Based on findings from previous research, the higher values reported in this sub-watershed might be attributed to runoff due to a large percentage of open land of grass and crops, as well as agricultural chemicals and fertilizer discharge (Ngwira and Watanabe, 2019, Nkwanda, et al., 2021).

Overall, the higher maximum values are mostly concentrated within the middle sub-watershed, while the highest average values are mostly concentrated at the downstream sub-watershed. This could indicate that the middle watershed is the non-point source for the majority of the pollutants, and the downstream watershed is the concentration area for the said pollutants.

4.3.3 Water Quality Relationship with LULC

As explained above, the data on water quality indicates deteriorating quality as the water goes downstream, which is normally the expectation that fresh and good quality water is found near the river source but deteriorates as the water comes into contact with other elements of the environment as the river flows. The LULC distribution above also indicates increased anthropogenic activities as the river flows downstream. The upper part of Lilongwe River is 68% forest, while the middle section is 39% cropland with grassland coming a close second at 38%, and the lower river section is 33% grassland, 29% cropland but settlement is now highest for all sections at 26% of the downstream watershed. This means that the river water is influenced by increased anthropogenic activities in the second and third sub-watersheds. The findings are also in agreement with other studies that have indicated a positive relationship between cropland and water quality parameters such as Nitrate, Phosphate as evidenced by higher values in the middle sub-watershed which have the highest percentage of cropland. Similarly, turbidity, TDS and TSS are also high in this sub-watershed due to increased percentage of grassland and cropland. Fecal coliform value is highest in the sub-watershed with the highest built-up settlement (Phiri, et al., 2005, Nyasulu, 2010, Nkwanda, et al., 2021).

Using the GWR tool in ArcMap 10.7, spatial regression analysis was carried out to ascertain whether there is any spatial relationship between the LULC changes as the river flows downstream to the quality of water in the river. Water quality data and LULC data for the year 2020 was used for this analysis. The year 2020 was selected as this is the most recent year where both the LULC map and the water quality data are available. Other studies have used statistical correlation methods and OLS to conclude that anthropogenic activities such as cultivation and human settlement contribute to poor surface water quality. The use of the GWR here, being a local regression model, is intended to further identify whether this relationship between the water quality parameters and LULC is indeed uniform across the area. Other studies have also utilized the GWR to measure the relationship between water quality and LULC and have concluded that the GWR provides improved results compared to OLS (Tu and Xia, 2008, Gao and Li, 2011, Su, et al., 2012). It is not the scope of this research to provide a detailed comparison of the two regression models.

The output of the GWR model among other output parameters, shows distribution of local R^2 values thus indicating how well the model fits, as well as the regression coefficients providing insight into how much influence if any, the independent variables have. This study analyzed the relationship of the following water quality parameters (parameters with adequate water quality sampling results);

(i) Turbidity

Earlier comparison of turbidity values indicated that turbidity was highest during the onset of rain season, but also high in the middle sub-watershed (Malili) seconded by the downstream sub-watershed (TW-Intake).

The GWR results as presented in Figure 13 indicate that turbidity in this area is most affected by increase in grassland and cropland which are the prevalent LULC classes in the Malili sub-watershed area. Higher local R^2 as well as high positive coefficients are recorded for the cropland and grassland LULC classes. The local R^2 values do not predict well in the south-western part, upstream of Lilongwe River where the majority LULC class is forest, and in some of the north-eastern areas notably in the settlement LULC areas. Research indicates that increase in forest might reduce surface water turbidity, this GWR coefficient output also agrees with this finding, but the low local R^2 does not provide adequate standing to also make a similar conclusion for this area.

The residual output data were assessed to check for spatial autocorrelation as provided in Figure 14 which indicates that residuals are randomly distributed and thus also indicates a well modeled regression (https://pro.ArcMap .com/en/pro-app/latest/tool-reference/spatial-statistics/spatial-autocorrelation.htm).

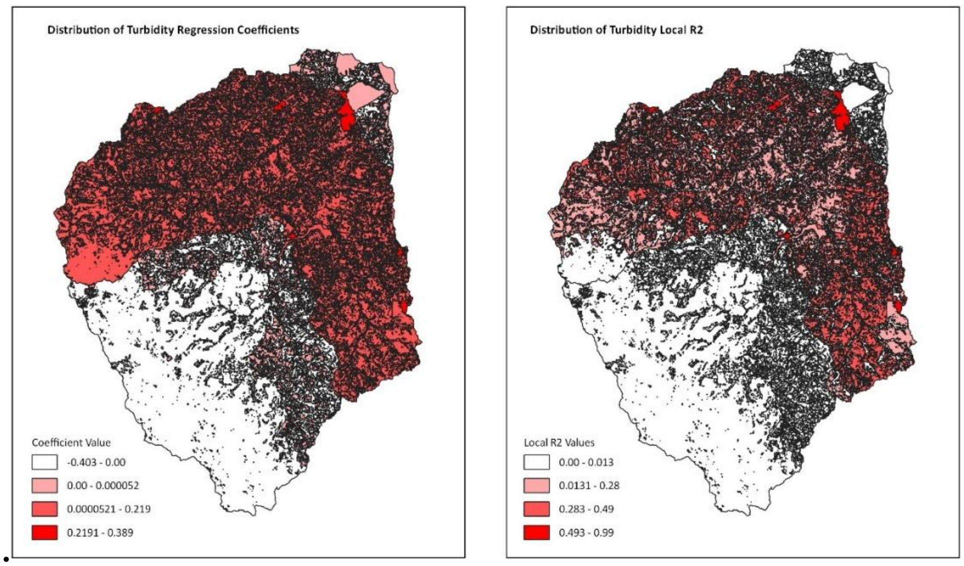

Figure 13- Turbidity Regression Coefficient and Local R^2 Values

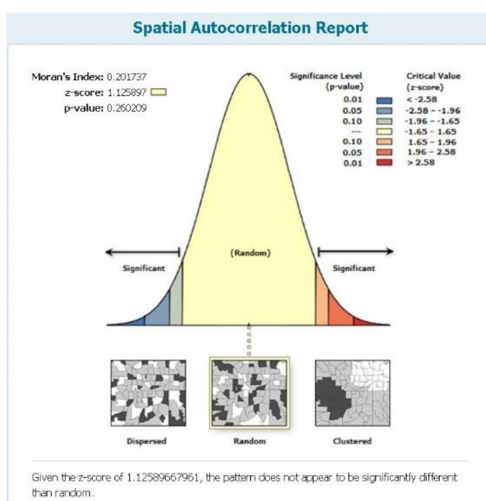

Figure 14- Turbidity Spatial Autocorrelation Report

(ii) Nitrate

The maximum recorded as well as the average nitrate values are both within the middle sub-watershed.

GWR output results as mapped in Figure 15, indicate a negative relationship with grassland but a positive relarelationship with cropland. The regression coeeficient map shows the negative relationship across the cropland LULC areas

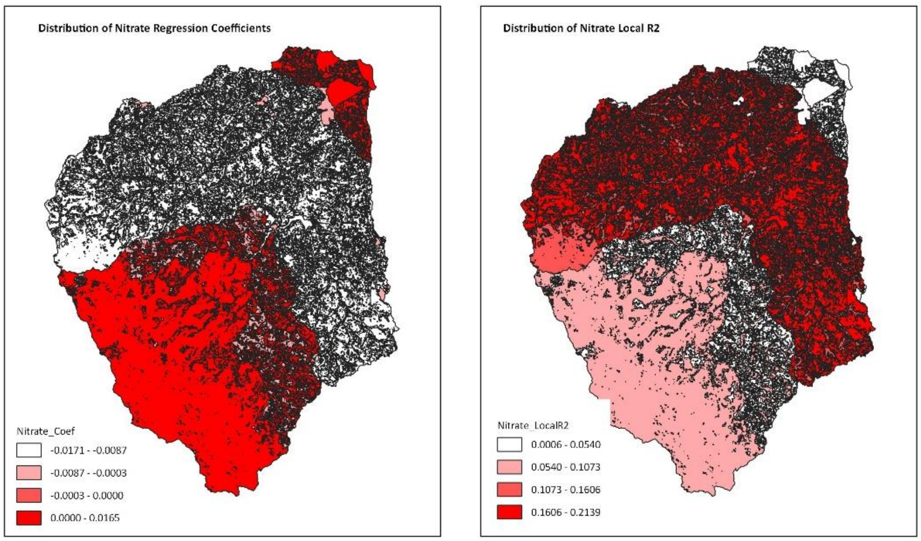

Figure 15- Nitrate Regression Coefficient and Local R^2

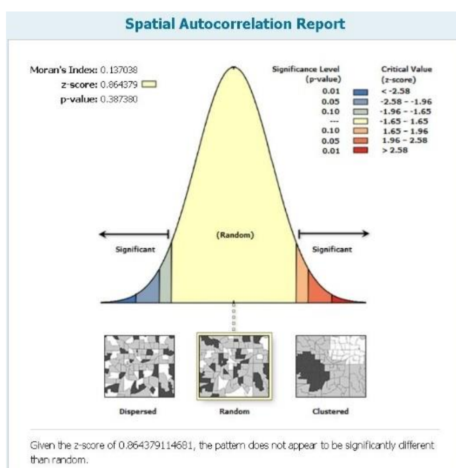

Figure 16- Nitrate Spatial Autocorrelation Report

The residual output data were assessed to check for spatial autocorrelation as provided in Figure 16, which indicates that residuals are randomly distributed and thus also indicates a well modeled regression.

(iii) Fecal Coliform

Comparison of recorded Fecal Coliform values showed that the highest maximum value was recorded in the middle sub-watershed, but the highest averages are in the downstream sub-watershed. The downstream watershed has the highest built-up settlement LULC class amongst the sub-watersheds, and therefore would indicate potential discharge into the Lilongwe River, and possibly discharge from animal waste in the middle watershed.

The GWR output mapped in Figure 17, surprisingly, does not indicate a direct strong relationship between Fecal Coliform and any of the LULC classes. The regression coefficients are negative across all LULC classes, while the local R^2 output indicates low prediction power in the northeast area, that is the downstream sub-watershed. In the year 2010, the built-up area LULC class constituted 1.3%, at about 3000Ha of the watershed. It would be interesting to note whether as the years progressed and the size of built-up area increased, whether a significant relationship could be identified with increased Fecal Coliform.

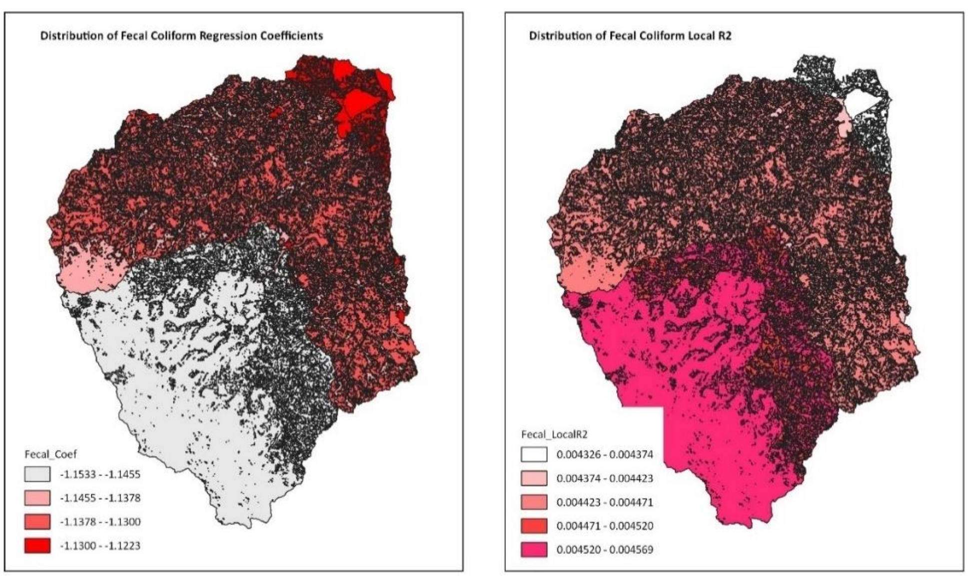

Figure 17- Fecal Coliform Regression Coefficient and Local R² Values

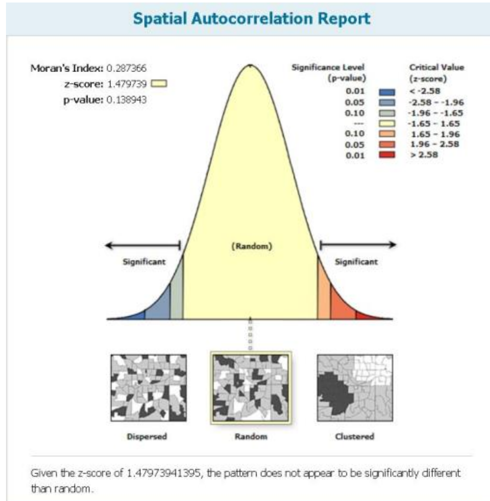

Figure 18- Fecal Coliform Spatial Autocorrelation Report

The residual output data were assessed to check for spatial autocorrelation as provided in Figure 18 which indicates that residuals are randomly distributed and thus also indicates a well modeled regression.

(iv) Total Suspended Solids

The earlier comparison of TSS values in Table 10 above has already shown that the maximum recorded TSS value was in the middle sub-watershed, while the overall mean was highest at the downstream subwatershed.

Results of the GWR mapped in Figure 19 indicate that TSS has positive relationship with increase in grassland and cropland. The higher regression coefficients are recorded along the grassland LULC class below the Dzalanyama forest in the upstream sub-watershed, as well as grassland LULC class in the middle sub-watershed. This could be explained by deforestation activities in the Dzalanyama forest, and increased farming along wetlands that is prevalent for winter vegetable farming in these areas.

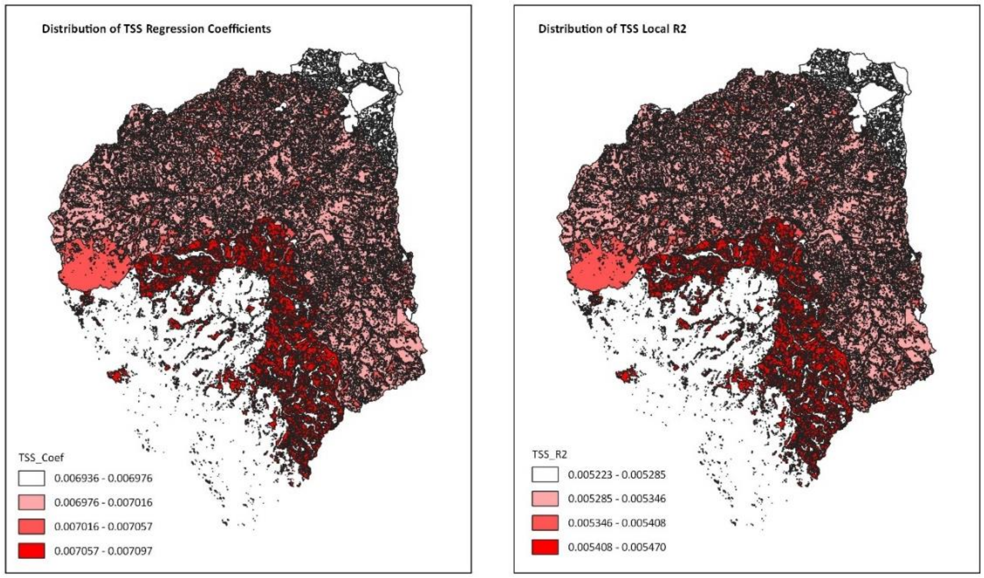

Figure 19- TSS Regression Coefficients and Local R² Values

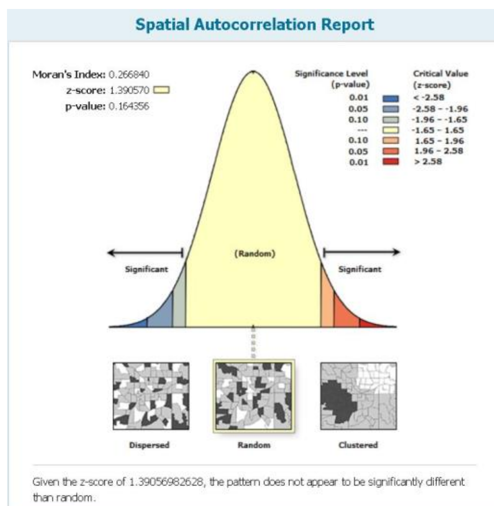

Figure 20- TSS Autocorrelation Report

The residual output data were assessed to check for spatial autocorrelation as provided in Figure 20 which indicates that residuals are randomly distributed and thus also indicates a well modeled regression.

5. Chapter Five: Conclusion

The findings of this study are in agreement with findings from other previous studies on the trend of LULC change for the Lilongwe River watershed. Analysis of the classified images in this study has shown that there is a decrease in waterbody and forest land, where forest land has the highest decrease. On the other hand, built-up and land for cultivation has increased. These changes are in agreement with other studies in Malawi and other developing countries that have found that with increase in population, there is higher demand for land for cultivation, as well as increase in built up areas especially for developing cities and urban areas.

Modelling of 2050 LULC was done to ascertain possible future distribution of LULC classes within the watershed. Projections were based on the historical LULC changes and the results showed a continued decrease in forest land cover and increase in built up and cropland. This is also in agreement with other studies done in Lilongwe River watershed, and for other areas in Malawi.

The study has also showed that the water quality in Lilongwe River has continued to deteriorate with time and with distance from source. Water quality sampling data from Lilongwe Water Board has shown that there is better water quality near the source, based on results of tests of samples captured from the upstream sampling location, Katete, as compared with samples captured at the most downstream sampling point, TW. A temporal comparison of the water quality data also indicates the deteriorating quality of water over time. This was done by comparing historical records of surface water quality. Such findings are also in agreement with other studies on the Lilongwe River, as well as other studies on surface water quality in other areas.

The study used the GWR method to identify the relationship between water quality and LULC. The study was able to show a positive correlation between turbidity to grassland and cropland; TSS to grassland; Nitrate to cropland. One negative relationship was identified between Nitrate and grassland, while no statistically significant correlation was found for fecal coliform and any of the LULC classes.

Considering the projected 2050 LULC distribution, notably the increase in built-up and cropland, with a decrease in forest land, and assuming no deliberate interventions in place, it can be concluded that the water quality in the river will continue to worsen. The literature on the relationship between anthropogenic activities and water quality already indicates that the Lilongwe

River water quality will continue to deteriorate since the future LULC projection indicates increased anthropogenic activities.

Based on these findings, coupled with other relevant literature, recommendations to mitigate the impact on the Lilongwe River water quality and the environment are:

- Devise and implement multi-sectoral and integrated watershed management. Currently efforts to conserve the environment are done independently by various players depending on their interests for instance LWB focuses on conserving Dzalanyama forest because it is the source of the river, Lilongwe City council focuses only on urban waste disposal, the Department of Forestry focuses on forest regeneration and fighting encroachment. The Ministry of Environment should bring all the stakeholders together to ensure a coordinated approach.
- There is need to identify strategies that directly minimize impact of existing anthropogenic activities, for instance protection of the riparian zone for the Lilongwe River and its catchment. Simultaneously, other interventions that would address the long term and root cause of the increased anthropogenic activities should be identified and implemented.
- There is generally non-compliance to existing policies, regulations and laws. There is therefore a need to lobby for strict adherence to requirements as well as meting out punishments.
- LWB should improve its data management practices in relation to water quality data so as to ensure that no data is lost, there are no gaps, and that the sampling and testing schedule is followed. This will allow better monitoring of the water quality for informed decision making.
- There is need for continued study of the drivers of the LULC changes, as this will enable implementation of appropriate interventions. Dissemination of results of studies should be improved to ensure non-academic stakeholders access to findings for their informed decisions.

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