ARDHI UNIVERSITY



ASSESSMENT OF THE EFFECT OF URBANIZATION ON WATER SOURCES USING REMOTE SENSING AND GIS.

A Case Study of Kigamboni District

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BSc Geoinformatics

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A Case Study of Kigamboni District

MRUTU, GLADNESS J

A Dissertation Submitted to the Department of Geospatial Sciences and Technology in Partially Fulfilment of the Requirements for the Award of Bachelor of Science in Geoinformatics (BSc. GI) of Ardhi University

CERTIFICATION

The undersigned certify that they have read and hereby recommend for acceptance by the Ardhi University dissertation titled "Assessment of the Effect of Urbanization on water sources using Remote Sensing and GIS" in partial fulfillment of the requirements for the award of degree of Bachelor of Science in Geoinformatics at Ardhi University.

Dr. Zakaria Ngereja	Mr.Method Gwaleba
(Main Supervisor)	(Second Supervisor)
Date	Date

DECLARATION AND COPYRIGHT

I, MRUTU,GLADNESS J hereby declare that, the contents of this dissertation are the results of my own findings through my study and investigation, and to the best of my knowledge they have not been presented anywhere else as a dissertation for diploma, degree or any similar academic award in any institution of higher learning.

.....

MRUTU, GLADNESS J

22720/T.2019

(Candidate)

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I am forever grateful to my dear mother Mrs. Mrutu and to all my friends for their love, wisdom, caring and support financially and ideally during the entire period of my academics.

DEDICATION

Glory and honor is to the creator of heaven and earth, Almighty God for his protection and strength from the beginning of this dissertation up to the end.

I dedicate this research to my late father Mr. Mrutu, my lovely mother Noela Mrutu, my lovely sister Glory Mrutu and my lovely young brother Greyson Mrutu, for their precious support and encouragement throughout this dissertation.

ABSTRACT

This research examined the impact of urbanization on water sources in Kigamboni District, utilizing remote sensing and GIS techniques. The research focuses on land use and land cover changes resulting from urbanization, analyzing data from 2014 to 2020. Results include land cover maps for each year, change detection maps, and population maps to understand the relationship between urbanization and water source dynamics. The study also incorporates a map displaying the distribution of boreholes in the district. The results highlight the impact of urbanization on land cover and population growth, leading to increased water demand and the need for effective water resource management. The outcomes have implications for urban planners, aiding decision-making regarding urban development. Municipal authorities can utilize the findings to regulate land development, while researchers can refer to the study in assessing urbanization's effects on water sources. This research underscores the urgent need for water resource management and conservation strategies in Kigamboni District.

Keywords: Urbanization, water sources, Remote Sensing(RS), Geographic Information System(GIS)

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ACRONYMS AND ABBREVIATIONS

AA Accuracy Assessment

C Classification

CD Change Detection

CM Change Maps

ESA European Space Agency

GEE Goggle Earth Engine

GIS Geographic Information System

LULC Land Use Land Cover

P Pre-Processing

RA Results Analysis

RS Remote Sensing

SM Statistics Mapping

USGS United States Geological Survey

CHAPTER ONE

INTRODUCTION

1.0 Introduction

Water is a very important and crucial resource needed for human existence; especially freshwater is a very essential resource for all life on earth. Freshwater constitutes only 3% of the total water available on the planet. The remaining water is saline water in nature which reduces its usability to a great extent (David & Tamara, 2014). Freshwater is utilized by human beings for drinking, farming and for day-to-day activities. The freshwater is available in the form of glaciers, groundwater and surface water. A vast amount of freshwater is frozen in glaciers and as ice. It is vital not to exploit those sources because of their ecological and environmental impacts. The surface water sources of freshwater include rivers, lakes, ponds and streams. The surface water bodies are the main source of freshwater for all human beings. Therefore, it is of prime importance to safeguard and utilizes the surface water responsibly and efficiently. The water bodies help in maintaining the greeneries around them and also, play a vital part in reducing the surface temperature of the urbanized cities. The urban heat island effect on the cities can be minimized by the presence of water bodies (Sridhar & Sathyanathan, 2020).

The biggest urban growth in history is causing the globe to reach its most extreme point. Urbanization is the process of people moving from rural to urban regions, and the subsequent rise in the percentage of people living in urban areas in a nation or region (Xiaohu & Hongyan, 2019). It typically happens when people relocate from rural to urban regions in search of better employment prospects, educational possibilities, and a higher standard of living. As more people migrate into cities and the urban impact increases, urbanization may also lead to the physical growth of metropolitan areas (Florida, 2019). As more and more people move to cities around the world, urbanization is a historical trend that is expected to continue in the following decades. In 2008, for the first time in history, more than half of the world's population was living in towns and cities (Xiaohu & Hongyan, 2019). Nevertheless, not all regions of the world have reached this level of urbanization. It is expected that half of the population of Asia will live in urban areas by 2020, while Africa is likely to reach a 50% urbanization rate only in 2035 (United Nations, 2012). Each year, the number of human beings increases, but the number of natural resources with which to sustain this population, to improve the quality of human lives and to eliminate mass poverty remains finite (Brundtland, 1987). This means that, rapid urbanization process also affects the management and distribution of available natural resources for the urban population and it cannot grow as fast as human population. Urban sprawl results in intensive demands on the environmental resources and poses problems by penetrating the valuable natural habitats of their hinterlands (OECD, 1990).

With the increase in population and economic development, urbanized areas are expanding spatially and creating an ecological imbalance (Gupta & Gupta, 2020). The cities while expanding convert the cultivable lands, water bodies and forest into the urban structure thus leading to ecological imbalance. The immigration of people to urban areas leads to a drastic increase in the population of the cities thereby creating additional demand for land, freshwater and other infrastructure facilities (Jaysawal & Saha, 2014). Urbanization can have a significant impact on the water source. Urbanization can lead to the destruction of natural habitats and the loss of vegetation, which can disrupt the natural water cycle and lead to changes in the availability and quality of water resources. Some of the ways in which urbanization can affect water resources include: Increased demand for water; as cities grow, the demand for water also increases. This can lead to overuse of water resources and depletion of groundwater reserves. Pollution of water sources; urbanization can lead to pollution of water sources due to the release of untreated sewage and other industrial and agricultural waste into rivers and streams. Alteration of hydrological cycle; urbanization can alter the natural hydrological cycle by changing the way the water moves through an ecosystem. For example, the use of impermeable surfaces such as concrete and asphalt and can prevent rain water from infiltrating the ground and recharging groundwater reserves. Loss of wetland habitats; urbanization can also lead to loss of wetland habitat which can have negative impact on the ecosystem. Wetlands provide important ecosystem services, such as water purification, flood control and habitat for variety of species (Alazba, 2019).

GIS can be used to map the extent of urbanization and identify areas where water resources are vulnerable to depletion or pollution. For example, GIS can be used to identify areas where impervious surface such as roads and buildings reduce infiltration and increase runoff, leading to decreased groundwater recharge and increase flooding. Remote sensing can be used to monitor changes in land cover and vegetation, which can affect water availability and quality. For example, remote sensing can be used to detect changes in forest cover which can lead to decreased water infiltration and increased erosion. GIS and remote sensing can be also be used to assess the impact of urbanization on water quality. For example, GIS can be used

to identify sources of pollution such as industrial facilities or wastewater treatment plants, while remote sensing can be used to detect changes in water color or turbidity that may indicate pollution (Tempfli, 2015).

1.1 Statement of the research problem

Urbanization in cities has significant impacts on water sources leading to water scarcity, changes in water quality, and the quantity of water from water sources. Urbanization can result in numerous environmental problems such as water pollution, altered hydrological cycles, and decreased water availability. Thus, an increase in impervious surface reduces the infiltration of water into the ground leading to increased surface runoff. This results in high peak flows and increased flood risk, which can cause erosion and sedimentation in streams and rivers.

The trend of increased urbanization and urban growth in Kigamboni calls for research to assess how urbanization has impacted water sources that affect people's livelihood, which also has been caused by land use change as a result of increased urbanization.

1.2 Objectives

1.2.1 Main Objective

To assess the effect of urbanization on water sources in the Kigamboni district using remote sensing and GIS.

1.2.2 Specific Objectives

- i) To determine the extent of urbanization and urban growth coverage from 2014-2020
- ii) To determine the changes in water quantity anf availability.
- iii) To determine the relationship between urbanization and water sources

1.3 Research Questions

- i. What is the spatial extent of the urban area in Kigamboni from the year 2014-2020?
- ii. How does urbanization affect water sources in the Kigamboni district?

1.4 Significance of the Study

This study will help urban planners to make decisions on urban growth and development and better management of water sources at Kigamboni. Also, the municipal authorities can manage land development activities through this study and researchers can use this study in reviewing the urbanization of water sources.

1.5 Beneficiaries

Beneficiaries of this research are as follows:

- i) Government agencies: They can use the information to plan and regulate urban development in a way that protects and conserves water sources.
- ii) Environmental organizations: They can use the data to advocate for the preservation of water sources and to hold government accountable for their actions.
- iii) Scientists and researchers: They can use the results of the assessment to expand their understanding of the impact of urbanization on water sources and to inform their future research.
- iv) Communities and residents: They can use the information to raise awareness about the importance of protecting water sources and to take action to preserve them.
- v) Water resource managers: They can use the data to prioritize their efforts to conserve and protect water sources and to make informed decisions about water management practices.
- vi) Developers and urban planners: They can use the data to make informed decisions about the design and location of new developments projects, taking into account the potential impact on water sources.
- vii) Policymakers: They can use the results of the assessment to develop policies that support sustainable urban development and protect water sources.

1.6 Description of the study area.

Kigamboni is small district and a part of Dar es Salaam area in eastern Tanzania. Kigamboni was formerly an administrative ward within Temeke District of Dar es Salaam. It had two administrative parts and the total population of the district is close to 317,902 people. Kigamboni District is divided into 9 administrative wards which are Tungi, Vijibweni, Kimbiji, Kisarawe II, Kigamboni, Mjimwema, Kibada, Somangila, and Pemba Mnazi. Kigamboni District is bordered with Indian Ocean in the east, Mkuranga District in the south, and Temeke Municipal Council in the northern part.

Kigamboni is located at latitude 6.8227°S and longitude 39.3024°E.

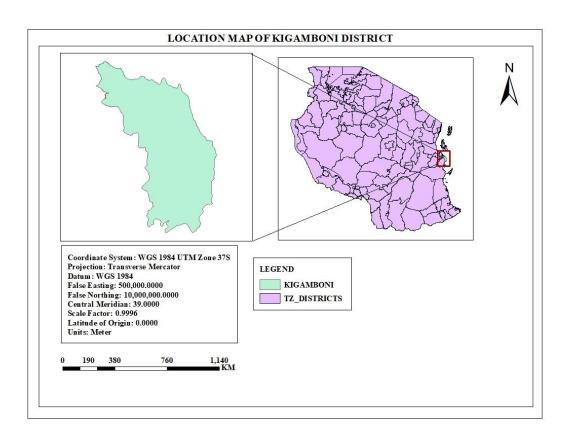


Figure 1.1: Location map of Kigamboni District

CHAPTER TWO

LITERATURE REVIEW

2.0 OVERVIEW

This section will provide the sources cited throughout the report. It will offer information on the range of other studies cited and referenced too, it can be just a summary of the source of particular information and it usually has an organization pattern. In addition, the literature review discusses the published information on a subject area within a certain period.

2.1 Urbanization

Urbanization is the process of people moving from rural to urban regions, and the subsequent rise in the percentage of people living in urban areas in a nation or region. It typically happens when people relocate from rural to urban regions in search of better employment prospects, educational possibilities, and a higher standard of living, hence the size of urban population increases and thus more urban impact increases. These changes in population lead to other changes in land use land cover, economic activity and culture.

Urbanization has been identified as a major cause of water resources degradation, particularly in developing countries (Rahman, Islam, & Hasan, 2018). The rapid growth of urban areas has led to increase demand of water resources, which has resulted in the depletion of available water sources and increased pollution (Wu, Liu, Wang, & Zhang, 2019). The use of GIS and remote sensing has become an important tool for assessing the impact of urbanization on water resources.

2.2 Remote Sensing

Remote Sensing is the science and art of obtaining information about an object, area, or phenomenon through the analysis of data acquired by a device that is not in contact with the object, area, or phenomenon under investigation (Singh, 2013). Remote sensing is performed from a platform (satellite, airplane or ship) using instruments (sensors) which measure electromagnetic radiation reflected or emitted from the terrain. It consists of analysis and interpretation of measurements of electromagnetic radiation that is reflected from or emitted by targets (Gernt, 2001).

Sensor

A sensor is a device that measures and records electromagnetic energy of an object and it is divided into two groups which are.

- Passive sensors are sensors which depend on an external source of energy to collect external source of energy reflected or emitted from a target/object to the sensor. Examples Landsat 1, Camera, Film 1, Radiometers, SPOT 1, Charged coupled devices.
- Active sensors are sensors which generates its own energy where the sensor transmits
 a signal to the target and the signal is backscattered and then receives the reflected
 response from the target. Examples RADARSAT, LISS, Sentinel, Sonar, GPS and
 LIDAR

Platforms

Platforms are a vehicle such as a satellite or aircraft which is used for a particular activity or purpose to carry a specific kind of equipment or instruments. They are categorized into three categories which are ground based platform such as Mobile Hydraulic Platform, Airborne based platform, and Space borne platform (Wolf, 2000).

2.2.1 Image Pre-Processing

Preparation of data for subsequent analysis, correction of deficiencies and Removal of flaws which make the part of preprocessing is important because it improves the quality of image as the basis for later analyses that will extract information from the image (Mather & Needle, 2000).

Image pre-processing operations are also referred to as image restoration and rectification. The pre-processing techniques are concerned with the removal of data errors and of unwanted or distracting elements of the image

There are various pre-processing processes which are.

- i) Inspecting characteristics and quality of data by displaying, summarizing and presenting histograms and other statistical summaries
- ii) Compensate for radiometric errors.
- iii) Geometric corrections.

2.2.2 Radiometric Corrections

Radiometric error is affecting the Digital Number (DN) stored in an image. Radiometric corrections involve improving the surface spectral reflectance, emittance, or backscattered measurements obtained using remote sensing system. They are caused by sensor Errors which are due to mechanical, electronic or communication failures of sensors and due to atmospheric errors, which are caused due to atmospheric constituents' interaction with EMR. Radiometric errors affect the digital number (DN) stored in an image (Mather & Needle, 2000).

The Radiometric errors are:

i. Sensor Errors

Due to mechanical, electronic or communication failures of sensors. Sensor induced errors are dropped line, noise and stripping.

ii. Atmospheric Errors

Due to atmospheric constituent's interaction with EMR. Atmospheric errors involve haze, skylight and sun angle.

Generally radiometric errors result from

- i) Defects from sensor operations
- ii) Atmospheric absorption and scattering
- iii) Variations in scan angle
- iv) Variations in illumination
- v) Systematic noise

2.2.3 Geometric Corrections

Geometric errors change the position of a Digital Number (DN) value and it involves placing the corrected pixels in their proper locations or reference system. Geometric corrections correct positional errors resulting from Variations in the orientation of the platform motion of the instrument. And geometric transformation Alter locational reference system with no regard on the presence of errors (Mather & Needle, 2000)

Two approaches are used which are:

- i) **Geo-referencing;** this relates the image coordinates to map coordinates by a set of transformation
- ii) **Geocoding;** is a process of changing the pixel size value of a given raster map (image) by resampling the raster map such that the resolution of a given picture element(pixel) is changed to any desired size to suit a particular use (Florine, 2001).

2.2.4 Image Classification

Image classification is the process of assigning land cover classes to pixels. For example, classes include water, urban, forest, agriculture and grassland (Dimyati & Mizuno, 1996)

There are three main image classification techniques in remote sensing which are;

i) Unsupervised Image Classification

Unsupervised classification is the most basic technique. Because you don't need samples for unsupervised classification, it's an easy way to segment and understand an image. In unsupervised classification, it first groups pixels into "clusters" based on their properties. Then, you classify each cluster with a land cover class. The two basic steps for unsupervised classification are:

- Generate clusters
- Assign class

The algorithm of unsupervised classification;

- Iso Data classification
- K -Means classification
- ii) Supervised Image Classification

It is based on the idea that a user can select sample pixels in an image that are representative of specific classes and then direct the image processing software to use these training sites as references for the classification of all other pixels in the image (Dimyati & Mizuno, 1996).

The three basic steps for supervised classification are;

- Select training samples
- Generate signature file
- Object-based image analysis

Some of algorithms of supervised classification are;

- The Maximum Likelihood (ML) classifier considers not only the cluster centres but also the shape, size and orientation of the clusters. This is achieved by calculating a statistical distance based on the mean values and covariance matrix of the clusters.
- Minimum distance to mean classifier is the one that classifies the data depending on the mean vector of each spectral class. Its emphasis on the location of cluster center, class labeling by considering minimum distance to the cluster centers.
- Random Forest is a classification algorithm that combines multiple decision trees to make predictions. It works by constructing a collection of decision trees, each trained on a different subset of the data, and then aggregating their predictions to reach a final classification. The randomness introduced in the sampling and feature selection processes helps to reduce overfitting and improve generalization. Random Forest is known for its accuracy, ability to handle large datasets, and providing feature importance measures. It is widely used in various domains for classification tasks.

Supervised and unsupervised classification is pixel-based. In other words, it creates square pixels and each pixel has a class. But object-based image classification groups pixels into representative vector shapes with size and geometry (Singh A., 1989).

Selection of Training Samples

The minimum number of pixels required for a signature when using a Maximum Likelihood classifier is the number of bands plus one (1). Check the Count field in the Cell Array below to confirm the size of a signature. The minimum number of pixels of a sample size used to estimate the mean vector and covariance matrix for an N-dimensional normal distribution is (N+1), which is the necessary condition for the matrix to be positive definite. For a 35-band image, if you choose five (5) bands for your Maximum Likelihood classification, the theoretical minimum number of pixels for a signature is Four (4). However, in actual practice, a larger sample size is needed for statistical significance (Sky, 2001)

Selection of Classes

One of the better-known classification schemes for existing vegetation is known as the Anderson scheme which was developed for use with remote sensing data (both aircraft and satellite based). Note that Anderson's classification (level 1) is hierarchical, so it can be used for many different applications by selecting the level of detail desired (Sky, 2001).

Accuracy Assessment

These target accuracies often tend to be based upon the influential work of Anderson. Typically, the specified requirements take the form of a minimum level of overall accuracy, expressed numerically by some index such as the percentage of cases correctly allocated, and a desire for each class to be classified to comparable accuracy. For an overall accuracy should be greater than 70% to classification to be accurate. Additional features typically called for are the provision of more than one measure of classification accuracy (Muller & Walker, 1998).

2.2.5 Classification Schemes

Image classification is the process of assigning land cover classes to pixels. For example, classes include water, urban, forest, agriculture, and grassland. This shows how the classes will be chosen during the process of image classification. There are several classification schemes these are Anderson's classification schemes. This was developed for the use with remote sensing data both aircraft and satellite based (Mather & Needle, 2000)

The advantages of this are:

- Can be used for many applications by selecting the level of the detail desired.
- Many of the classes are not separable over large areas using remote sensing observations.

Levels of Anderson classification scheme.

- Level one; Urban built up areas, Agriculture, Rangeland, forest, water areas
- Level two; Residential commercial, industrial, croplands, and pasture.
- Level three; Single family units and multifamily units.

Classes chosen during the process of image classification. The classes can be chosen;

- *i.* Based on pixel information Based on pixel information and are classified as pre-pixel classification, sub pixel classification, pre-field classification, contextual classification, knowledge based classification and combination of multiple classifications.
- ii. Based on training samples

Based on use of training samples and are classified as supervised classification and unsupervised classification.

Supervised classification methods require input from an analyst. The input from analyst is known as training set. All the supervised classifications usually have a sequence of operations that must be followed

- Defining of the Training Sites.
- Extraction of Signatures.
- Classification of the Image.

Unsupervised Classification technique uses clustering mechanisms to group satellite image pixels into unlabeled classes/clusters. Later analyst assigns meaningful labels to the clusters and produces well classified satellite image. Unsupervised methods are usually very fast and computationally efficient.

Unsupervised involve the following approaches.

- ISODATA (Iterative Self-Organizing Data Analysis Technique)
- Support Vector Machine (SVM)
- K-Means

2.2.6 Land Cover

Land cover refers to the surface cover on the ground, whether vegetation, urban infrastructure, water, bare soil or other; it does not describe the use of land, and the use of land may be different for lands with the same cover type. For instance, a land cover type of forest may be used for timber production, wildlife management or recreation; it might be private land, a protected watershed or a popular state park. Land cover is commonly defined as the vegetation (natural or planted) or man-made constructions (buildings, etc.) which occur on the earth surface. Water, ice, bare rock, sand and similar surfaces also count as land cover (Ryan, 2013)

2.2.7 Land Use

Land use refers to the purpose the land serves, for example, recreation, wildlife habitat or agriculture, residence; it does not describe the surface cover the ground. For example, a recreational land use could occur in a forest, shrub land, grasslands or on manicured lawns. Land use is commonly defined as a series of operations on land, carried out by humans, with the intention to obtain products and/or benefits through using land resources. (Ryan, 2013)

2.2.8 Change Detection

Change detection is the process of identifying differences in the state of an object or phenomenon by it at different times(Lillesand et al., 2007). Some typical change detection includes land use land cover (LULC) change, Forest or vegetation change, landscape change, urban change and environmental change. Remote Sensing data, opportunely processed and elaborated, can be really useful in change detection tasks to monitor the differences of LC at different times (Singh A., 1989) There are many methods of change detection available and each has variations depending on the imagery type, final purpose for the change image and the type of change to be detected.

There are many techniques which are used in performing change detection. Some of them are.

- i. Map algebra methods which use a reference/threshold to detect change and involve some techniques such as image differencing, image regression, image rationing and vegetation index differencing.
- ii. Classification methods which based on the classified images and some of the techniques used are post-classification comparison and artificial neural networks.
- iii. Advanced models which convert image reflectance values into physically based parameters or fractions which are easy to interpret and some of the techniques used is the spectral mixture analysis.
- iv. Transformation"s method which reduces data redundancy and some of the techniques used are Principal component analysis (PCA) and tasseled cap transformation.

The output of change detection should provide information about;

- i. Area changes and change rate
- ii. Spatial distribution of changed types
- iii. Change trajectories of land-cover types
- iv. Accuracy assessment of change detection results

2.3 Geographical Information System (GIS)

It can be defined as a computer-based system which provides four sets of capabilities to handle geo-referenced data:

- i. Data input
- ii. Data management (storage and retrieval)
- iii. Data manipulation and analysis
- iv. Data output or visualization (Arronoff, 1989)

GIS is a set of tools for collection, retrieving, transformation and displaying spatial data from the real world for a particular set of purposes (McDonnell, 1998)

Geographical referenced data describes both the location and characteristics of spatial features such as parks, forest, river etc. The ability of GIS to handle and process both location and attribute data distinguishes GIS ffrom other information system and established GIS as technology for wide variety of application. GIS has become a powerful tool for handling spatial and non-spatial geo-referenced data for preparation and visualization of input store, manipulate and analyses layers of geo-referenced data to produce interpretable information. In their totality, remote sensing and GIS are the tools to assess temporal spatial dynamic (Nzunda, 2011).

2.4 General Overview on Water Supply

2.4.1 Water supply

Water supply is the provision of water by public utilities, commercial organisations, community endeavors or by individuals, usually via a system of pumps and pipes or other constructed conveyances to the public for human consumption that has 15 or more service connections or regularly serves at least 25 individuals daily. Water supply system includes the following;

- Any collection, treatment, storage and distribution facilities under control of the operator of the system that are used primarily in connection with the system.
- Anay collection or pretreatment storage facilities not under the control of the operator that are used primarily in connection with the system.
- Any water system that treats water on behalf of one or more public water systems for the purpose of rendering it safe for human consumption (Woods, 2011)

In 2010, about 85% of the global population had access to piped water supply through house connections or to an improved water source through other means than house, including the standpipes, water kiosks, spring supplies and protected wells. However about 14% did not have access to an improved water source and had to use unprotected wells or springs, canals, lakes or rivers for their water needs((Woods, 2011)

Water supply is part of the water services cycle which itself is a component of the water cycle.

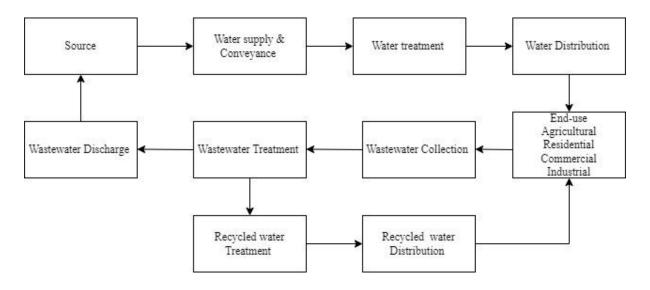


Figure 2.1: Water service cycle (Woods, 2011)

2.4.2 Water Demand

Water Demand is the measure of the total amount of water used by the customers within the water system. There are several things that can influence the amount of water demanded of your system. One of the most importany jobs of a water system is to continually meet this demand without interruption, rain or sun.

Water demand = Average water consumption per person \times Population size of the area

There are different variables you will encounter in the system's water demand which are explained below:

Peak demand

This refers to the times when water consumption is at the highest. This occurs especially ata times when most people arrive home from their jobs and use watervvin different activities such as in bathing, cooking, washing, and many more. This can also be observed during weekends where most people are staying at their homes.

Seasonal demand

This refers to water demand which occurs at cerain periods/ seasonal demands such as during constructions and agricultural activities.((Waterhelp.Org, 2016)

2.4.3 Water for Consumption

Unlike water demand, water for consumption is the amount of water present at the time either enough or not enough according to the demand of the people, for instance a family may demand four buckets of water for bathing but the amount present for consumption becomes only three buckets. The consumption of water may be divided into the following general categories;

- Domestic- Household purposes (including car washing and garden watering)
- Trade- Industries, factories, businesses, shops, offices, hotels, institutions, etc
- Agriculture- Farms, livwstocks, irrigation, dairies, greenhouse etc
- Public-Fire-fighting, swimming pools, street watering, fountains, parks etc
- Losses- Leakage from mains, connections, service pipes, service reservoirs, water used for flushing mains etc (Woods, 2011).

CHAPTER THREE METHODOLOGY

3.1 Introduction

This chapter presents the data used, the overall methods, techniques and materials used to achieve the research objectives. It mainly explains the characteristics of data used in this research, image classification techniques employed, change detection method used, accuracy assessment and list of software packages used in this research.

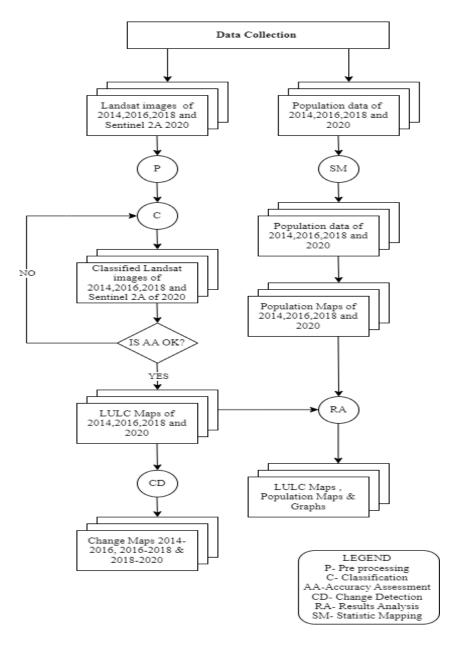


Figure 3.1: General workflow

3.2 Data Acquisition

Based on research objectives, data identified to respond to the research question are in (Table 3.1). The study involved collection of required data from the web archives and from government agencies. The collected data involved satellite images (Landsat 5/7 and Sentinel 2) of path 165 and row 65. Satellite images were freely downloaded from USGS archives and used to generate land cover and change detection maps. Also, the other data used was shape-file which was used for extracting area of interest (AOI).

Table 3.1: Data that are going to utilize this research

SN	DATA TYPE	SCALE/RESOLUTION	SOURCE	USES
1	Landsat 8	30m	GEE	For land cover and
				change analysis
2	Sentinel 2A	10m	GEE	For land cover and
				change analysis
3	Water sources		DAWASA	For monitoring
				changes in water
				quantity and
				availability
4	Population data		NBS	For water demand
				estimation and to track
				the urban growth of the
				urban area over time

3.3 Image pre-processing

This involves the removal of deficiencies and flaws that may reduce the quality and utilization of information extracted from remote sensing data. The downloaded images followed the following pre-processing stages to remove radiometric and geometric errors using Google Earth Engine.

3.3.1 Layer Stacking

This process involved the combination of bands to produce on combined band image. This allows different RGB band combinations during processing for image interpretation. This process was done by considering the band with the same resolution for the case of Landsat was 30m resolution and for the sake of Sentinel2A was 10m resolution. Landsat 8 bands that

were used were band 1,2,3,4,5 and 7 these bands were stacked together except for band 6 which is a thermal band, for Sentinel2A bands that were used were band 2,3,4 and 8 this was done in ERDAS imagine software using layer stacking tool.

3.3.2 Image re-projection

The stacked images were re-projected to the geographical coordinate system, the datum used was WGS 1984 this was done in ERDAS imagine software using the re-projection tool. The aim of this process was to make the images to have the same spatial reference as the coordinate system of the study area.

3.3.3 Image masking

This technique is used in order to reduce the size the data set, improve processing speed, and focus analysis on the specific area of interest. The re-projected images were masked so as to obtain area of interest only, which was Kigamboni district. This was successfully by using a shapefile of Kigamboni District.

3.4 Classification.

The software used for classification was Google Earth Engine and supervised classification was the method employed. There are several image classification techniques used but for my research I opted to use supervised classification which involves controlling the process by the selection of classes based on the nature of the area, collecting training samples for ground-truthing data and for the purpose of accessing the accuracy assessment. The general workflow is composed of three main steps, implemented in two GEE scripts, the composition of the initial dataset, the LULC classification, and the accuracy assessment. The first step was implemented in a separate script to speed up the classification and accuracy assessment procedures, as the base composite image requires fewer adjustments than the subsequent steps. The classification and accuracy evaluation steps were combined into a single GEE script. The process of classification was done by using Random Forest (RF) classifier. Then the accuracy assessment was done through confusion matrix

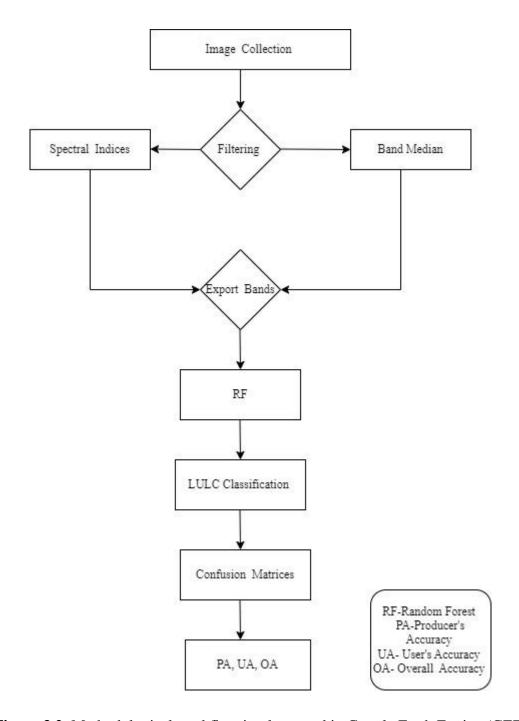


Figure 3.2: Methodological workflow implemented in Google Earth Engine (GEE)

3.4.1 Dataset Composition

The generation of the base dataset is a critical step in any LULC classification. The composition of this dataset for the L8 and S2 data in this application began in GEE with a filtered and cloud-masked image collection. It followed the following steps

Accessing to Satellite data This involved creating of a box in my study area by using GEE tool which is "draw a rectangle". Then followed by browsing the satellite data (sentinel 2 and landsat 8)

- Cloud masking
- Making a cloudless image mosaic
- Image sub setting for the area of interest

3.4.2 Image Classification

1. Image acquisition.

The images used in this research were loaded from the Google Earth engine data catalog and uploaded into the Google Earth engine code editor, where they were filtered to the area of interest and the appropriate date (to an interval of one year). The images were ranked by cloud cover percentage after being filtered, and the one with the least amount of cloud was chosen. After loading, the image was represented in visible band and displayed in the map. After the image was loaded, it was represented in the visible band and displayed on the map.

2. Preprocessing.

Cloud masking was used to remove clouds from the QA PIXEL and QA PIXEL Bitmask bands in images with clouds within the area of interest, yielding a cloud-free image. Because the QA PIXEL and QA PIXEL Bitmask are bands that include cloud pixels, the cloud masking function is used to mask pixels that include clouds.

3. Training and Validation Sample Data

The study area is featured by a landscape mosaic composed of four LULC classes:

- a. Built up areas: that included settlements and other artificial surfaces
- b. Bare land: represents an area with no vegetation or any plant on it
- c. Vegetation: included areas with grass, tress and other plantations
- d. Waterbodies: included areas covered by water such lakes and rivers

Table 3.2: The number of validation points for each Land Use–Land Cover (LULC) class.

S/N	Class	Number of samples
1	Bareland	100
2	Builtup	100
3	Vegetation	116
4	Water	100
	TOTAL	416

A total of 416 samples were collected and divided into validation points (30%) and training samples (70%) which were 125 points and 291 points respectively.

The following changes were carried out on sample points in order to train the classifier and validate the classification findings;

• Merging sample points together into one feature collection.

For the classifier training process, the sample points were combined into a single feature collection. When sample points were combined into a feature collection, they were arranged according to class property value.

• Bands selection.

Bands to be used for training classifier and performing classification were selected from the image that was loaded, where bands 1, 2, 3, 4, 5, 6, 7, 10 and 11 used for Landsat 8 images, and bands 2, 3, 4, 5, 6, 7, 8, 8A, 11 and 12 used in Sentinel 2 images. Selected bands are those that have the same spatial resolution of 30m for Landsat 8 bands and resolution of 10m for sentinel 2 bands.

• Sampling the input imagery

To obtain the feature collection for the training data, samples of the input imagery were taken. The classifier's training pixels were collected throughout this operation. Input imagery, bands that were chosen, and combined sample points are all inputs used in the extraction of pixel values. The pixel spectral values at each sample point's position were therefore collected for each band that was chosen.

• Training classifier.

The sample pixels values extracted from the input imagery sampling step were used to train the RF classifier. Seventy percent of the sample points were used for training, and 300 trees were used by the RF classifier. The trained pixels represented the kinds of land cover: water body, bare land, built-up and vegetation. The model that would be used as the basis for classifying the entire image was created in this step. The majority vote is used to determine the pixel value to be utilized as a representative class during the training of the classifier using 100 trees. The mathematical model that was utilized to train the classifier is shown below.

Random forest = DT (base learner) + bagging (Row sampling with replacement) + feature bagging (column sampling) + aggregation (mean/median, majority vote). (Singh, 2019).

• Classification of the input imagery.

Using the trained classifier, the input images was classified. The incoming imagery was classified in this method using the data the classifier had collected as a base. The categories included bare land, built-up areas, water bodies and vegetation Images and the trained classifier are used as inputs in this process.

Accuracy assessment.

After getting a classified image, the accuracy of classification was determined in order to determine how well it correlates to realities on the ground. The other part of the sample, which was 30 percent of the sample were used to determine the accuracy the classification.

• Change detection.

The post classification approach, which involves comparing the land cover of two successive photos to produce change maps this was done using QGIS software, these change maps were used to calculate the change in area coverage of each class. Change detection was carried out using the two classified photos as input. The locations and the quantity of area where one class changed to another are the information collected from this stage.

3.5 Population data

Population data were obtained from the bureau of statistics, National census report of 2002 and 2012. These data were used to justify the link between boreholes data and the population increase at Kigamboni District. With this population data were used to calculate water

demand for kigamboni distict where the population size of each ward or sub-ward were multiplied by the average water consumption per person of kigamboni which is 120l/day. Increase in residential areas is an evidence of population growth and increase of water demand in Kigamboni District. After getting population data from the National Bureau of Statistics census report and the borehole data from Kigamboni District Council the data were prepared in the excel sheet, the population maps were prepared by adding data in Arc GIS software through the growth rate processing and the population map overlayed with the boreholes data.

Table 3.3: Demographic data of Kigamboni District in the year 2014, 2016, 2018, and 2020.

Year	2014	2016	2018	2020
Population data	181,691	202,611	225,938	

(**Source**: National Bureau of Statistics, Population and Housing Census 2002 and 2012)

Table 3.4: Show Kigamboni District wards population data 2014

STN	KIGAMBONI WARDS	POPULATION DATA	%VALUES
1	Kigamboni	34,007	19
2	Vijibweni	32,350	18
3	Kibada	9,573	5
4	Kisarawe II	9,262	5
5	Somangila	21,503	12
6	Kimbiji	7,149	4
7	Pembamnazi	10,786	6
8	Mjimwema	30,989	17
9	Tungi	26,072	14
	TOTAL	181,691	100

(**Source**: National Bureau of Statistics, Population and Housing Census 2014)

Table 3.5: Show Kigamboni District wards population data 2016

STN	KIGAMBONI WARDS	POPULATION DATA	%VALUES
1	Kigamboni	37,923	19
2	Vijibweni	36,075	18
3	Kibada	10,676	5
4	Kisarawe II	10,329	5
5	Somangila	23,979	12
6	Kimbiji	7,972	4
7	Pembamnazi	12,027	6
8	Mjimwema	34,556	17
9	Tungi	29,074	14
	TOTAL	202,611	100

(Source: National Bureau of Statistics, Population and Housing Census 2016)

Table 3.6: Show Kigamboni District wards population data 2018

SN	KIGAMBONI WARDS	POPULATION DATA	%VALUES
1	Kigamboni	42,289	19
2	Vijibweni	40,228	18
3	Kibada	11,905	5
4	Kisarawe II	11,518	5
5	Somangila	26,740	12
6	Kimbiji	8,890	4
7	Pembamnazi	13,412	6
8	Mjimwema	38,535	17
9	Tungi	32,421	14
	TOTAL	225,938	100

(Source: National Bureau of Statistics, Population and Housing Census 2018)

Table 3.7: Show Kigamboni District wards population data 2020

STN	KIGAMBONI WARDS	POPULATION DATA	%VALUES
1	Kigamboni	47337	19
2	Vijibweni	45030	18
3	Kibada	13326	5
4	Kisarawe II	12893	5
5	Somangila	29931	12
6	Kimbiji	9951	4
7	Pembamnazi	15013	6
8	Mjimwema	43135	17
9	Tungi	36291	14
	TOTAL	252907	100

3.6 Borehole data

These boreholes data were obtained from Kigamboni District Council. These borehole data show the water capacity of each borehole in Kigamboni District.

Table 3.8: Show Kigamboni District boreholes data in Kisarawe II ward

STN	CAPACITY (L)
K3	100,000
K5	250,000
К9	450,000
K11	450,000
K13	420,000
K14	300,000
K15	420,000

Table 3.9: Show Kigamboni District boreholes data in Somangila ward

STN	CAPACITY(L)
Geza	2500
Minondo	1500
Sara	33,000

Table 4.0: Show Kigamboni District boreholes data in Mjimwema ward

STN	CAPACITY(L)
Ungindoni-Kisanduku	20,000
Ungindoni-Magengeni	2512
Maweni No 1	5625
Maweni No 2	5625
Saranga	30000
Mjimwema	2500

CHAPTER FOUR

RESULTS AND ANALYSIS

4.1 RESULTS

This chapter involves data presentation, interpretation and analysis of the products results. It consists of the outputs which were land cover maps of 2014, 2016, 2018 and 2020 as shown in the figures (4.1- 4.4) that are obtained from classified images, land cover change maps for change detection between (2014-2016), (2016-2018) and (2018-2020) as shown in figures (4.5-4.7).

4.1.1 Image Classification Results

Classification was done fully based on the classification scheme, selecting of training sample, and generation of signature files. The different number of pixels were assigned to the high probability specific class in order to determine the accuracy of the process.

4.1.2 Accuracy Assessment Results

Accuracy assessment was performed by computations of union matrices (see tables 4.1 to 4.4). The accuracy assessment of Landsat 8 of 2014 was 68% of 2016 was 68% of 2018 was 66% and of Sentinel 2A of 2020 was 85%. The table below represents total accuracy for the Landsat 8 and Sentinel 2A images.

Table 4.1: Total Accuracy of Classified Image of 2014

Class Name	Producer Accuracy	User Accuracy
BareLand	75.00%	85.71%
BuiltUp	78.00%	85.71%
Vegetation	100.00%	79.31%
Water	85.71%	100.00%
Overall Accuracy		
86.00%		

Table 4.2: Total Accuracy of Classified Image of 2016

Class Name	Producer Accuracy	User Accuracy
BareLand	71.43%	76.92%
BuiltUp	100.00%	92.31%
Vegetation	91.67%	84.62%
Water	78.57%	84.62%
Overall Accuracy		
84.62%		

Table 4.3: Total Accuracy of Classified Image of 2018

Class Name	Producer Accuracy	User Accuracy
BareLand	71.43%	76.29%
BuiltUp	100.00%	92.31%
Vegetation	91.67%	84.62%
Water	78.57%	84.62%
Overall Accuracy		
83.33%		

Table 4.4: Total Accuracy of Classified Image of 2020

Class Name	Producer Accuracy	User Accuracy
BareLand	80.00%	100.00%
BuiltUp	66.67%	63.33%
Vegetation	81.25%	92.86%
Water	100.00%	100.00%
Overall Accuracy		
82.00%		

4.1.3 Land cover maps

Land cover maps provide information about the physical characteristics of the Earth's surface, specifically describing the different types of land cover or land use present in a study area. Land cover mapping involves analyzing satellite imagery to identify and classify different land cover types. The resulting land cover maps offer valuable insights into the spatial distribution and extent of different land cover types within the study area.

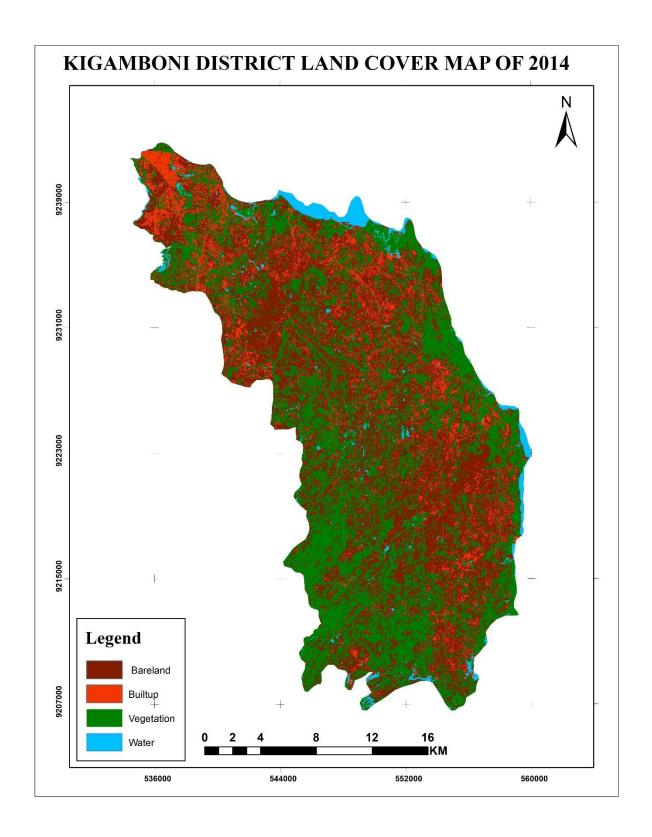


Figure 4.1: Land cover map of Kigamboni District 2014

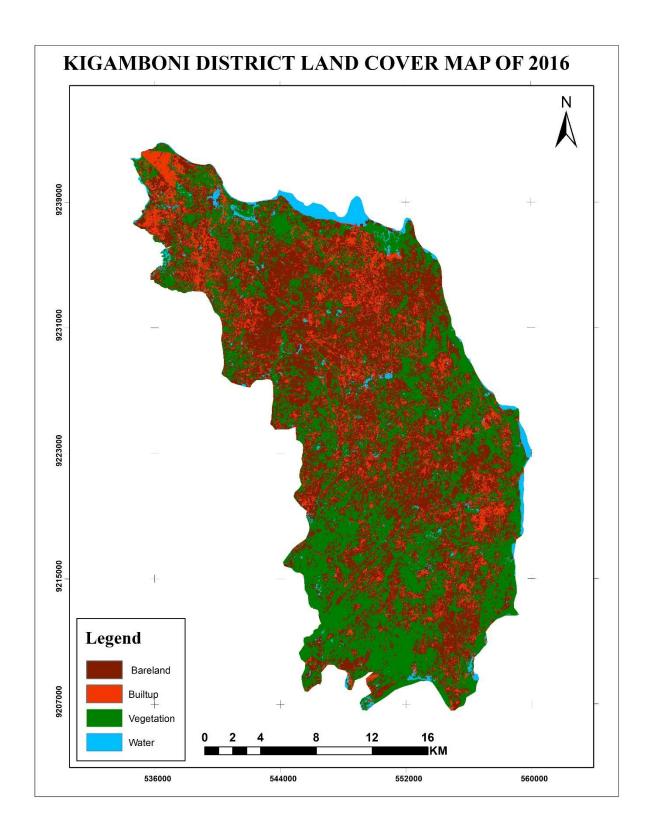


Figure 4.2: Land cover map of Kigamboni District 2016

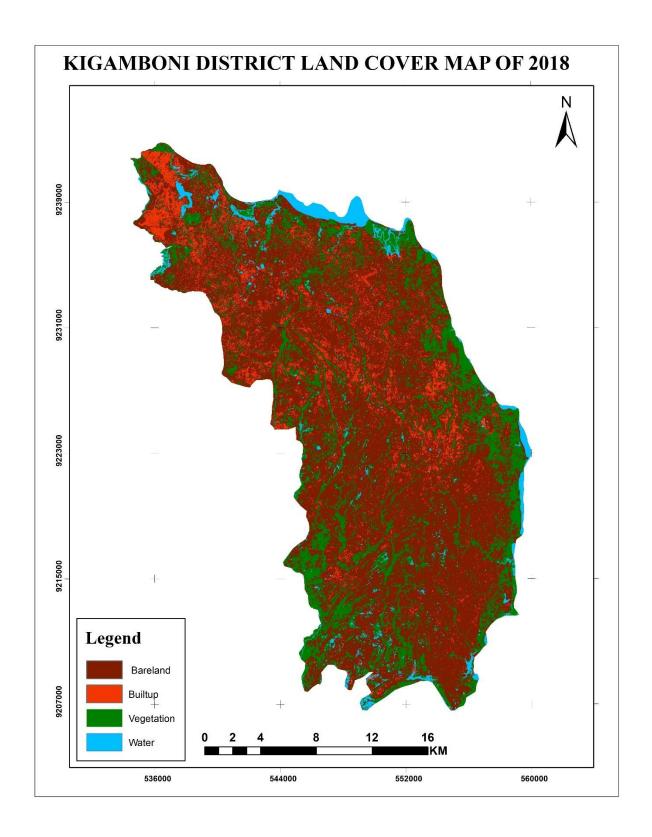


Figure 4.3: Land cover map of Kigamboni District 2018

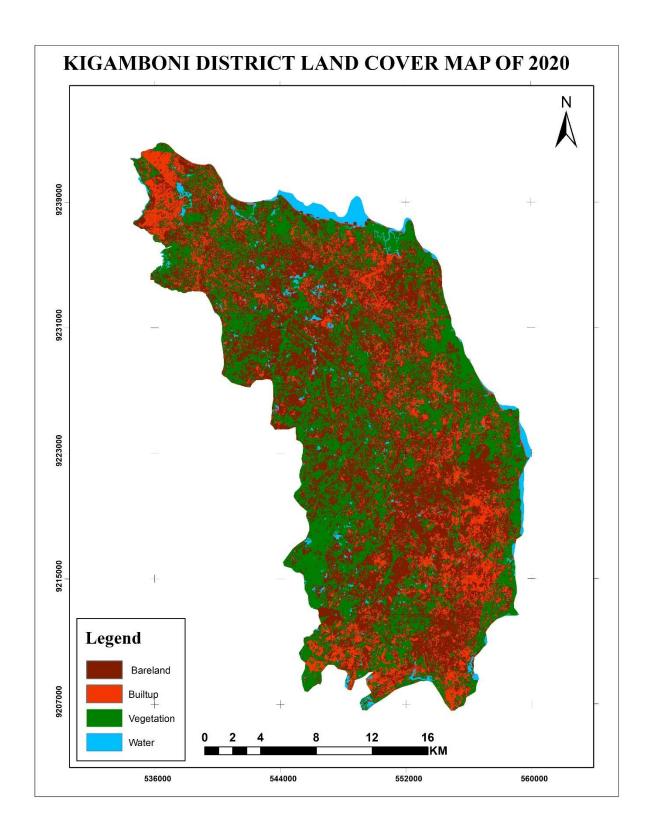


Figure 4.4: Land cover map of Kigamboni District 2020

4.1.4 Change Detection Map

The land cover maps were prepared from the results of classified images The map and graphs were obtained to describe the changes in different land covers at different years on the same seasons in every epoch.

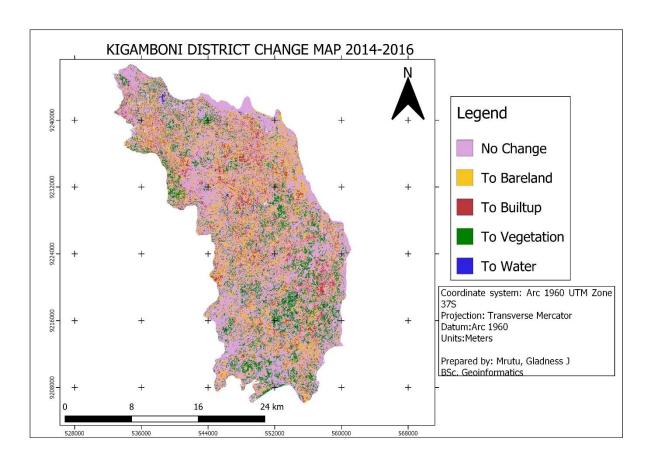


Figure 4.5: Land cover change map of Kigamboni District between 2014 and 2016

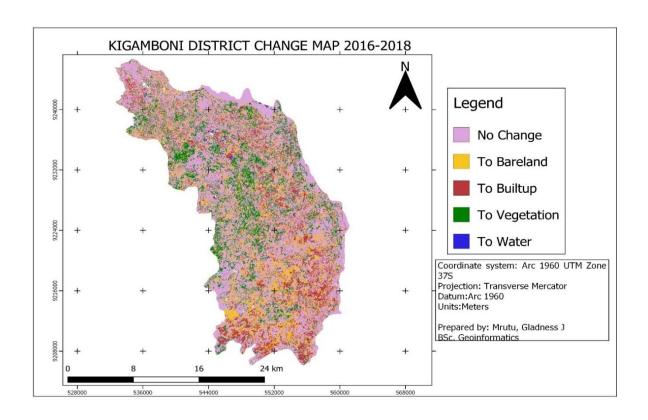


Figure 4.6: Land cover change map of Kigamboni District between 2016 and 2018.

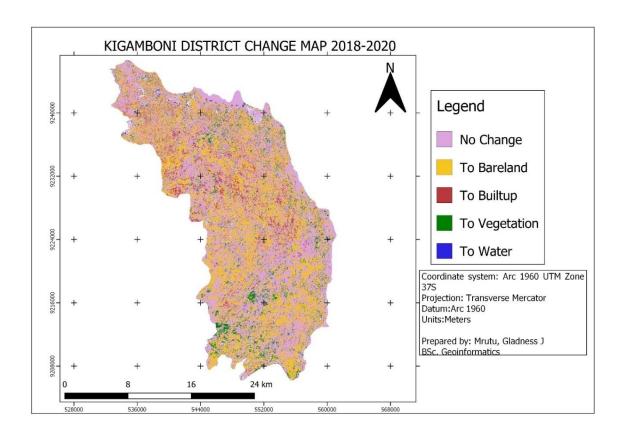


Figure 4.7: Land cover change map of Kigamboni District between 2018 and 2020

4.1.5 Population maps

These are the maps which show population distribution which occurred in Kigamboni District in the year 2014,2016,2018, and 2020.

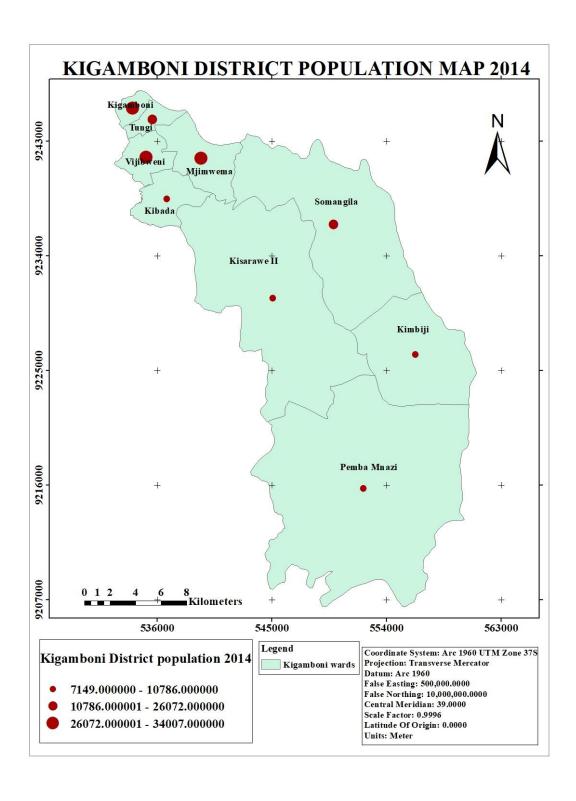


Figure 4.8: Population map of Kigamboni District 2014

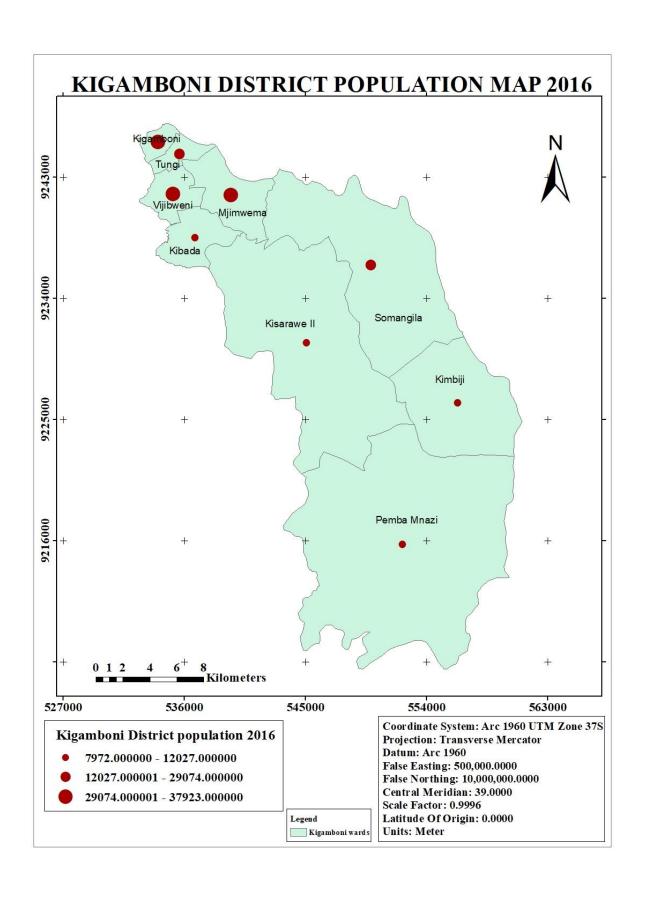


Figure 4.9: Population map of Kigamboni District 2016

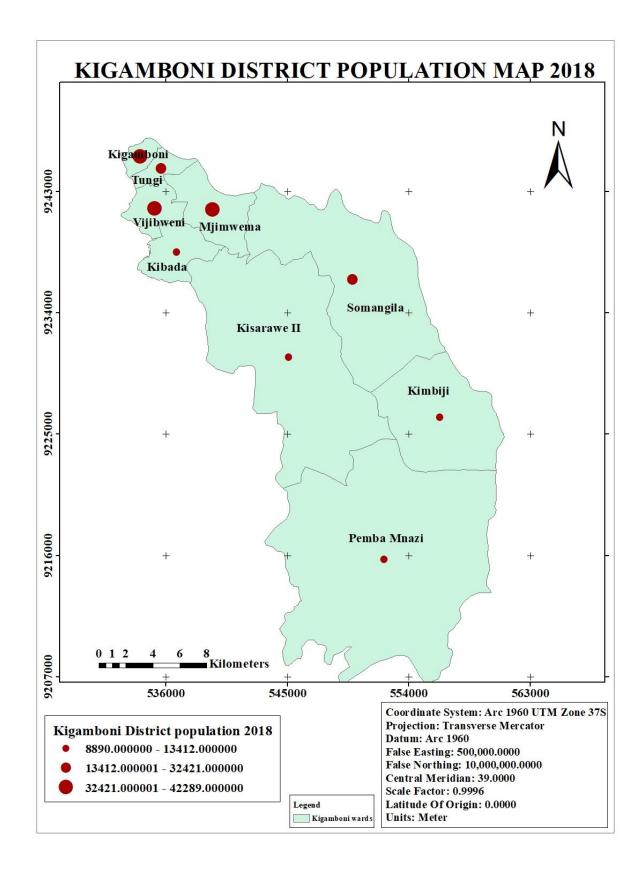


Figure 5.0: Population map of Kigamboni District 2016

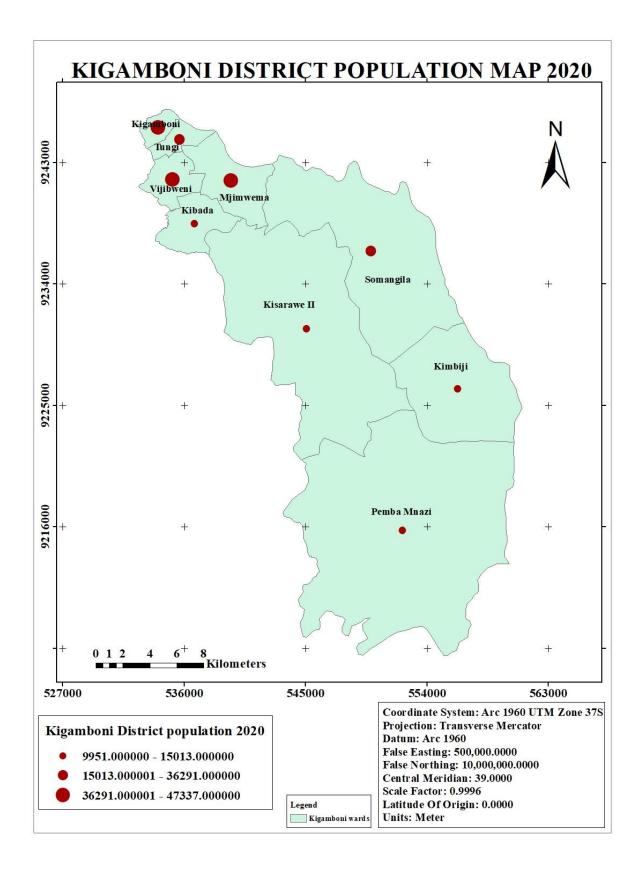


Figure 5.1: Population map of Kigamboni District 2020

4.1.6 Borehole map

This is the map which shows borehole distribution which are found in Kigamboni District in the year 2020.

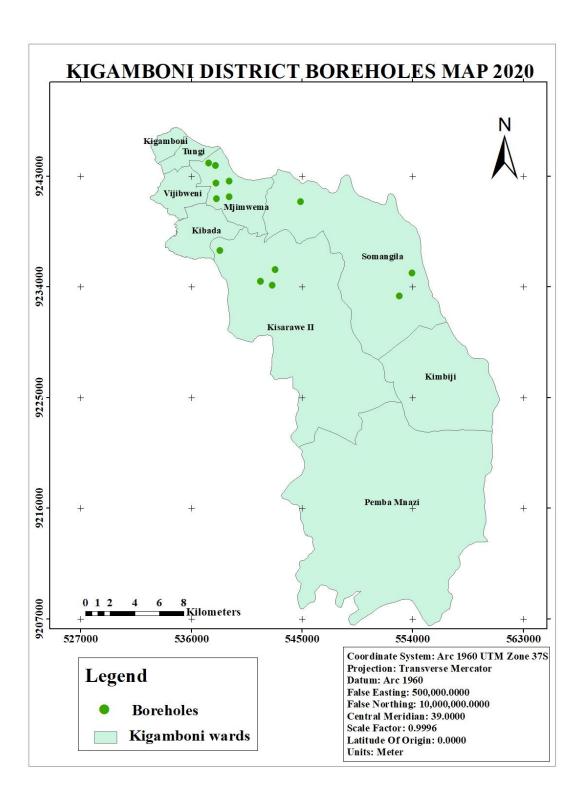


Figure 5.2: Borehole map of Kigamboni District 2020

4.2 ANAYSIS OF RESULTS

4.2.1 Land Use Land Cover Changes analysis

Analysis on the change detections of Kigamboni District from 2014 to 2020 based on changes on Bareland, Built-up, Vegetation, and Water land cover classes. All land cover and change detection studies are based on the prepared land cover maps of 2014, 2016, 2018 and 2020 and histogram based graph of land cover changes from 2014 to 2020.

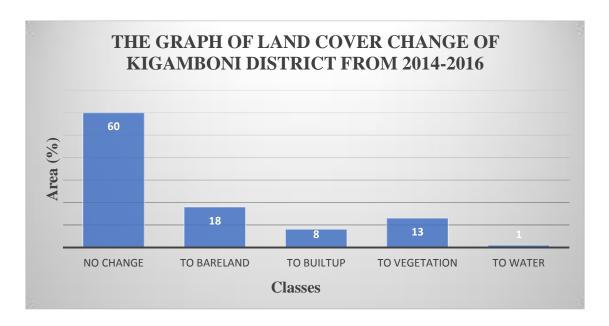


Figure 5.1: Graph of Land Cover Change of Kigamboni District from 2014-2016

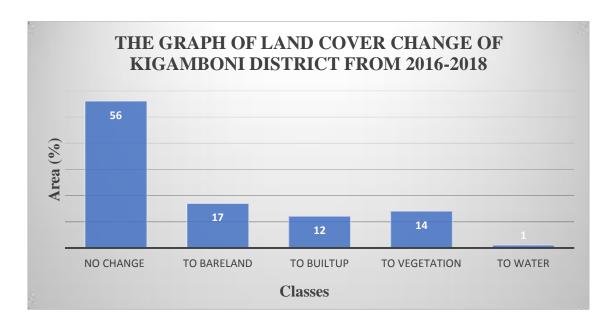


Figure 5.2: Graph of Land Cover Change of Kigamboni District from 2016-2018

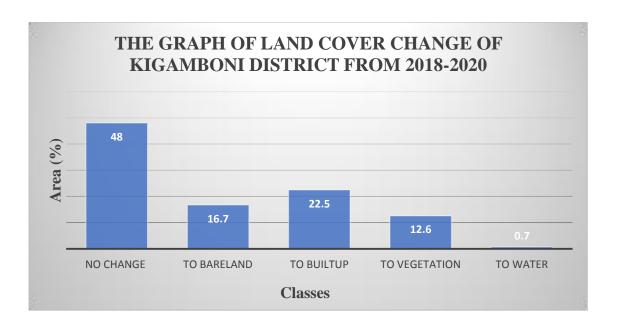


Figure 5.3: Graph of Land Cover Change of Kigamboni District from 2018-2020

From figure 5.1-5.3 as shown above, the year 2014-2016 the areas that didn't change covered 60% while for the year 2016-2018 was 56% and for 2018-2020 was 48%. The other area was covered by other classes such as those that changed to bareland for the year 2014-2016 was 18%, for the year 2016-2018 was 17% and for the year 2018-2020 was 16.7%, were the area changed due to various natural or human-induced factors such erosion, landslides, deforestation, urbanization and many others. Those that changed to builtup for the year 2014-2016 was 8%, for the year 2016-2018 was 12% and for the year 2018-2020 was 22.5%, the area changed due to urbanization. Those that changed to vegetation for the year 2014-2016 was 13%, for the year 2016-2018 was 14% and for the year 2018-2020 was 12.6%, the area changed through natural processes such as growth of plants and trees as well as through human intervention such as reforestation efforts or landscaping. Those that changed to water for the year 2014-2016 was 1%, for the year 2016-2018 was 1% and for the year 2018-2020 was 0.7%.

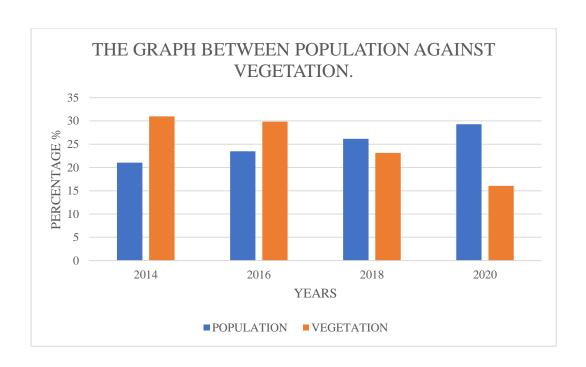


Figure 5.4: Graph of population against vegetation for Kigamboni District

From figure 5.4 it shows the relationship between population and vegetation which occurred in Kigamboni district from 2014, 2016, 2018 and 2020. Results shows that vegetation has decreased as the years go since population has increased.

Table 4.4: Show the amount of water demand against borehole capacity for 2020

SUB-WARD	WATER DEMAND (L/d)	BOREHOLE CAPACITY(L/d)
Kisarawe II	1547160	1590000
Minondo	409440	1500
Sara	75240	33000
Ungindoni	1213920	22512
Maweni	1796040	11250
Mjimwema	1380840	2500

THE GRAPH BETWEEN WATER DEMAND AGAINST BOREHOLE CAPACITY

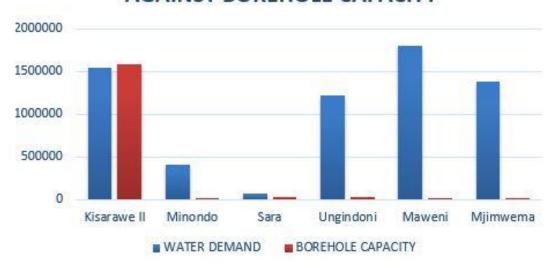


Figure 5.4: The relationship between water demand and borehole capacity

Figure 4.5 represents the relationship between water demand of a particular population in each subward in terms of average water consumption per person and the capacity which each borehole in subward can accumulate per day in liters in 2020. Result show that the water demand at Kisarawe II matches with the bore capacity while with the other areas as seen from the graph there is high demand of water as the boreholes capacity present did not meet the water demand of those areas.

CHAPTER FIVE

CONCLUSION AND RECOMMENDATIONS

5.1 CONCLUSION

This research has been able to produce the Land cover maps of 2014, 2016, 2018 and 2020, change maps between 2014-2016, 2016-2018 and 2018-2020 as well as population maps of 2014, 2016, 2018 and 2020 and a map showing the distribution of boreholes in Kigamboni District. The research shows that there is an impact of urbanization on land cover of Kigamboni District leading to an increase in population thus an impact on water sources hence increase of water demand. This highlights the urgent need for effective management and conservation of water resources in Kigamboni District.

5.2 RECOMMENDATION

Further studies should be conducted to gather information on the impacts of urbanization on water sources. Also, policymakees and the government should prioritize investment in water infrastructure, such as drilling new boreholes and expanding water treatment facilities, to meet the growing demand for water in Kigamboni District.

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