University of Nairobi

School of Engineering

MONITORING THE DISTRIBUTION OF WATER HYACINTH, USING REMOTELY SENSED DATA: CASE STUDY OF LAKE VICTORIA, KENYA

BY

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A Project Report submitted in partial fulfilment of the requirements for the Degree of Master of Science in Geographic Information Systems, in the Department of Geospatial & Space Technology of the University of Nairobi

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Declaration of originality

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Dr. – Ing. Musyoka

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Abstract

The objective of this project was to apply the recent Landsat 8 OLI & TRS Thematic Mapper imagery in mapping the distribution, quantify the area covered by invasive floating vegetation commonly known as water hyacinth as well as assess the changing pattern (change detection) of the weed on the Lake Victoria. Selected period of study was from 2013 to 2019, considering the month of April when the cloud cover is relatively less than 10%. The process involved pre-processing of raw downloaded Landsat 8 OLI/TIRS TM satellite images by radiometric and atmospheric correction, geometric rectification, layer stacking, and sub-setting to extract area of interest. Pre-processed images were then subjected to supervised classification by maximum likelihood, Normalized Difference Vegetation Index (NDVI) and post-classification. In supervised classification, spectral signatures for each image were obtained through data training. Both classification techniques were used to obtain water-vegetation maps followed by quantifying the changes through change detection technique. The results indicated a fluctuating but significant percentage in area occupied by floating vegetation. The highest was in 2014 and lowest in 2015 recording 9.7% and 1.9% corresponding to 33211 and 6435 hectares respectively. The change detection analysis results depicted a massive decline in floating vegetation by about 79.8%. In contrast to the table 17 which points out a strong increment of the floating vegetation by 79.913%. However the general change indicate that the floating vegetation decreased overall from 5.779% in 2013 to 4.693% in 2019. In contrast, water did not change a lot, but it increased by approximately 3.937% between 2013 and 2019.

Dedication

First I wish to dedicate this project to the Lord God Almighty the Creator, who is my strong pillar, my source of knowledge, wisdom, understanding and inspiration. He has been my source of strength during the time of this research and to Him I will always be grateful.

Second, I dedicate this work to my parents, Mr and Mrs Wilfred Wanyonyi who have encouraged me and through financial support making sure I finish that which I have started. Third, to my family members, lovely wife Everlyne Bucheta Mwituyi and my daughter Precious Naliaka Wanyonyi for their moral support. Also without forgetting my friend in deed Oscar Shivaji Mutuva for the financial support and guidance at all levels of my study. Thank you and May God bless you all.

TABLE OF CONTENTS

List of figures

List of tables

List of Abbreviations

GIS	Geographic Information Systems
RS	Remote Sensing
SB	Short Bulbous
TN	Tall Non-bulbous
DN	Digital Numbers
OLI & TIRS	Operational Land Imager and the Thermal Infrared Sensor
KMA	Kenya Maritime Authority
OW	Open water
SV	Sparse Vegetation
FV	Floating Vegetation
MODIS	Moderate Resolution Imaging Spectroradiometer
EIA	Environmental Impact Assessment
USGS & CLI	United States Geological Survey & Clean Lakes, Inc.
NASA	National Aeronautics and Space Administration
LVEMP	Lake Victoria Environmental Management Program
TM	Thematic Mapper
NDVI	Normalized Differential Vegetation Index
ROI	Region of Interest
ENVI	Environment for Visualizing Images

CHAPTER 1: INTRODUCTION

1.1 Background of study

Water hyacinth among other aquatic weeds has become one of the major environmental challenges globally due to its massive infestation in rivers, lakes and fresh ocean water bodies. The weed is associated with many worldwide adverse effects. Such effects according to (Mitchell, 1990; Gallagher and Haller, 1990; Denny, 1991; Harley, 1991; Mailu, Ochiel, and others, 1998), ripple through infested areas and include among other effects: hindrances to; transportation of irrigation and drainage water both in canals and ditches, lake navigation, hydro-electric power schemes, trapping silt particles thereby increasing sedimentation, reduction in human food production in aquatic habitats both fisheries and crops; interfering with both washing and bathing; adversely affecting recreation e.g. angling, swimming and water – skiing (Pieterse, 1990). For proper lake management, continuous observation and monitoring of weed proliferation and its control should be put in place (Albright et al., 2004). Remote sensing and GIS techniques have increasingly become essential and powerful tools for water resource management especially when studying large scale phenomena in aquatic vegetation communities. These capabilities therefore help in delivering timely information unmatched by any other surveying technique (Silva et al., 2008).

However, according to (Govender et al., 2007), accurate and frequent monitoring of aquatic vegetation provides timely and reliable information as well as improving the quality of related studies that rely on this information for their analyses. For example adequately accurate information on both the location and extent of aquatic plants is required when evaluating the effect of nutrient influx on vegetation proliferation. Users' assessment on the accuracy of remotely derived information allows them to ascertain its reliability. This therefore, is a means through which product limitations is communicated to users by the product producers, thereby enabling the use of information appropriately (Latifovic and Olthof, 2004).

1.1.1 Study Area

Lake Victoria is the second largest fresh water lake in the world with an area of approximately 68,800 Km^2. The lake is located in the western Kenya and bordered by five neighbouring counties; Busia, Kisumu, Siaya, Homa Bay and Migori. About 20 million people from Kenya, Uganda and Tanzania benefit from the lake through clean drinking water, hydro-electric power, water transport, ecological stability, fishing activities and food security. The lake lies across the equator at 0° 30' N – 3^0 12'S and 31° 37' E - 34° 53' E at an altitude of about 1135 metres above sea level. It has a mean depth of 40 metres, maximum depth of 80 metres and a shoreline of 3,450km. The Lake's strip, Winam Gulf that extents into the Kenyan part is vulnerable to invasive vegetation due to high levels of eutrophication from river Sondu and Awach. The gulf is shallow and therefore experiences high level of nutrients deposition that favours the massive spread of Water hyacinth. The entire Lake Victoria basin is approximately 258,700km^2 and proportionately shared by three bordering countries as follows: Kenya 6%, Uganda 43% and Tanzania 51%. The lake basin spreads eastwards to Mara, Mori, Suguti, Grumet, Mgono, Mogogo, Mbalageti in Tanzania; Kuja, Awach, Sondu-Miriu, Nyando, Nzoia, Yala, Sio and Gucha in Kenya; Ruizi, Kibale and Katonga in Uganda.

According to (Oguya et al., 1998), the River Nile in Uganda is the only outflow of the entire Lake Victoria basin. The figure 1(a) and (b) shows the whole Lake Victoria basin in relation to the three neighbouring countries and the Kenyan part respectively.

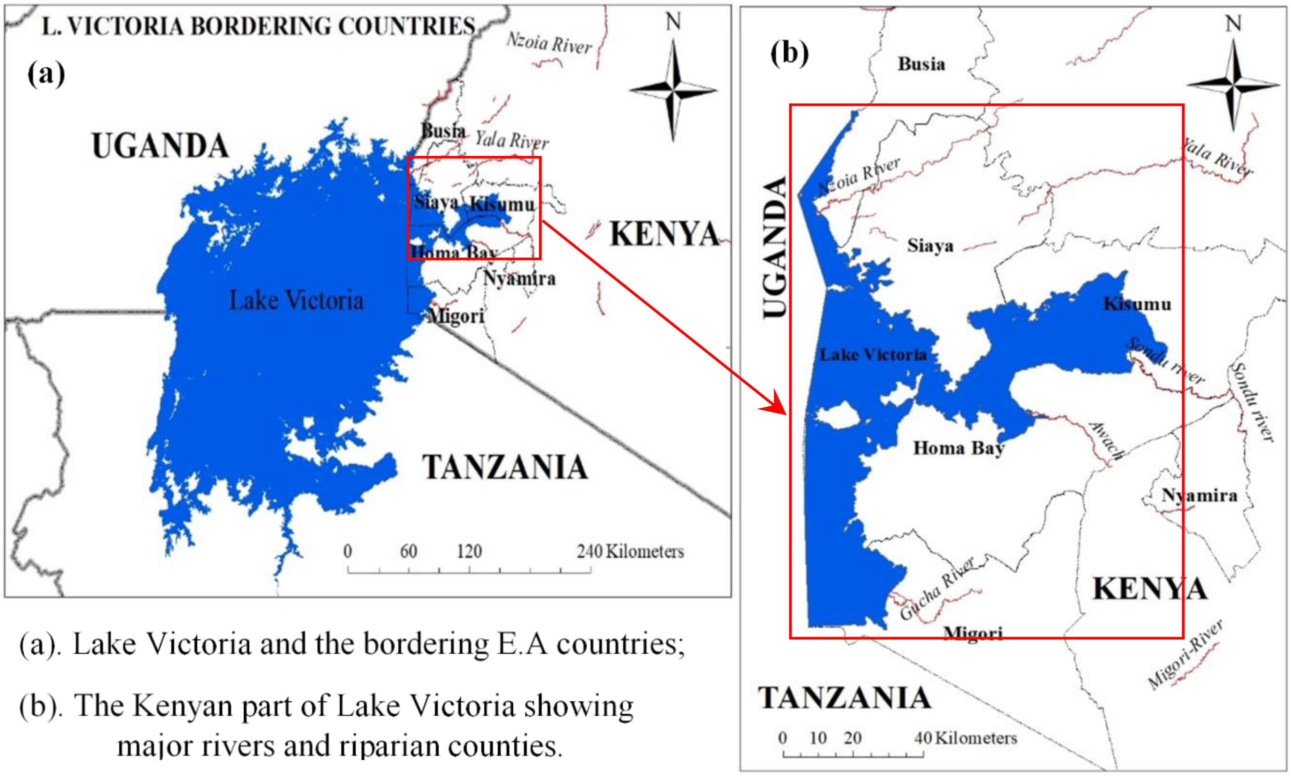


Figure 1: Study Area Showing Lake Victoria basin

1.1.2 Water hyacinth on Lake Victoria

Since 1870s, water hyacinth has existed in Africa, mainly the River Nile in Uganda. According to (Twongo and Balirwa, 1995), the floating macrophyte has been in existence in Lake Victoria from early 1980s. However, the problems associated with it had not become apparent until 1989 when the weed was reported in Lake Victoria. According to the research by (Matagi, 2002), 80% of the Ugandan coastline was inundated with this floating weed by around 1995. In his findings, a fringe of the invasive weed was formed extending out from the shore for about 15 metres in sheltered bays of the lake. The weed later extensively spread further out beyond 50 metres. Moreover, a dense carpet of floating macrophyte occupying about 300 hectares in size formed within the sheltered bays surrounding Lake Victoria as shown in Figure 2.

Figure 2: Carpet of floating water hyacinth on Lake Victoria

Historically, Water hyacinth has been associated with certain names that are used to illustrate its impact, consequences and usefulness to the environment. Such names include: *'Demon,' Blue Devil,' 'Terror of Bengal,' 'Curse of Bengal,' 'Million Dollar weed,' 'Cinderella of the plant world'* and *'Ford.'* Like any other excessive weed, the water hyacinth creates a series of problems particularly related to the use and management of water resources such as fishing and navigation. It impacts severely on the environment and sometimes changes entire ecosystems. The weed's infestation has serious, adverse implications for the economic, social and political relations of the three East African countries (Kenya, Uganda and Tanzania).

Water hyacinth exists in a number of forms differing in morphological structure i.e. leaves, flowers and petioles. In addition, according to (Pieterse, 1978; Center and Spencer, 1981; Watson et al., 1982), clonal groups can also be highly plastic. (Wright and Purcell, 1995; Julien et al., 1999), identified two dominant forms of water hyacinth. The first form that is characterised by short bulbous (SB) and buoyant petioles is typically found in open water or at the edges of plant mats.

The second form on the other hand has tall, slender, non-bulbous (TN) petioles occurring mainly in crowded areas. Since the two forms of water hyacinth are phenotypically adaptive, according to (Pieterse, 1978), the SB form can develop into the TN form if crowding occurs and sufficient nutrients are available.

1.2 Problem Statement

Kenya just like other Lake Victoria riparian countries namely Uganda and Tanzania is facing a number of serious water resource management challenges such as massive population growth due to high birth rate and immigration, climate variability due to changing weather pattern, water scarcity and resource degradation, invasive macrophyte species such as water hyacinth, rivers and water pollution from both agricultural and urban waste.

The infestation of water hyacinth in the lake has severely affected the social-economic activities around the lake such as decline in fish production, tourism, and hydro-electric power, navigation not to mention dangers that are associated with snakes, mosquitoes and crocodile habitat.

1.3 Objectives

The main objective of this project is to quantitatively map the distribution of water hyacinth on the Kenyan part of Lake Victoria with an aim of assessing the impact of the weed as well as analyse the changes in its distribution (change detection) for the period from 2013 to 2019.

1.4 Specific objectives

To achieve the objective above, the following specific objectives must be achieved:

1. Image discrimination of floating vegetation (Water hyacinth) from other constituents in this case water and sparse vegetation i.e. by image classification;
2. Prepare classified time sequence land cover maps covering the period April 2013 – March 2019;
3. Perform change detection analysis in order to draw conclusions on the impacts and implications of water hyacinth on Lake Victoria.

1.5 Justification for study

Blue economy is one of the major plans by the Kenyan Government to help boost its economy. This can only be achieved if the water hyacinth spread in the Kenyan waters such as Lake Victoria is controlled. Various technologies have been used in the past to manage water hyacinth in the Lake Victoria but none has been successful. This failure could be as a result of application of time consuming and labour intensive methods such manual removal by hand picking.

Over years the distribution of water hyacinth in the Lake Victoria has been based on people's speculations during sampling and data collection. Depending on such methods has led to increasing spread of water hyacinth in the lake following that there is no consistency data collection through sampling. Application of remote sensing and GIS techniques therefore aims at providing a faster and sufficient solution in eradication of the water hyacinth in the Lake Victoria. The technique is also suitable in acquiring information from dangerous areas of the lake as well as during stormy days for which manual removal seems impossible. Since remote sensing make use of imagery data of the study area, record of the previous coverage on water hyacinth can easily be obtained and analysed against the current distribution of the weeds in the lake.

Apart from advantages of water hyacinth in the Lake Victoria such as oxygen fixation, and acting as food to the marine animals, a number of demerits are also posed by these alien species to both marine life and human around the lake. The disadvantages are related to lake navigation, hydro-electric power generation, fish harvesting, transport, clean drinking water and malaria infections. Water hyacinth control in the Lake Victoria is a one step to actualisation of Kenya's blue economy aiming at boosting the country's economy in realization of the vision 2030. The results obtained from this study will also help the stakeholders who have been dealing with eradication measures to rate their performance.

1.6 Scope of work

To be able to attain the set objectives, seven Landsat 8 OLI TM images of the area of study were acquired for the period 2013 – 2019. The scope of this project was limited only to the area of study that is the Lake Victoria basin and for the period identified above. Individual image pre-processing (layer stacking, obtaining region of interest as well as masking), classification and NDVI were performed using ENVI 5.3, ArcGis, QGis and Erdas Imagine software. NDVI ranges that were used for classification in this case are; -1.0 - 0, water, 0.2 - 0.3999, sparse vegetation, and 0.4 - 1.0, floating vegetation since these were the classes of interest in this study. Afterwards, vegetation cover map of 2013 to 2019 were overlaid to generate the map of change of vegetation cover for the respective dates and to find out the changing pattern of vegetation cover. To analyze the accuracy, statistics, and the change detection of the images, a post-classification was done to obtain class statistics, change detection, and the confusion matrix statistics data. Analyses of the confusion matrix data giving the overall accuracy and the errors (commission and omission) were also performed to determine the peak period in vegetation cover. The values obtained above were then used to sketch a line graph and the histograms showing the trend in floating vegetation change.

1.7. Organization of the Report

This report is organized into five chapters, list of references and appendices. In chapter one above, gives the background to the study area, water hyacinth introduction to Lake Victoria, scope and objectives to the study. Chapter two presents previous studies or related researches done in mapping floating vegetation like water hyacinth using remote sensing techniques and by use of different satellite imageries. Chapter three elaborates on materials used which includes data sources and tools and methods used to map floating and sparse vegetation on the Lake Victoria basin.

Chapter four contains the results obtained after mapping Vegetation both by supervised classification, NDVI and vegetation change detection techniques using Remote Sensing software such as ENVI 5.3, Erdas imagine and Gis softwares such ArcGis and QGis both applied in this project for various functions. Also in this chapter, discussions are made for the results obtained. In chapter five conclusions are made for results in chapter four and recommendations made for Lake Victoria Environmental Management Program (LVEMP, 1996) to adopt and future researches that are needed in water vegetation management. Lastly, is the reference list indicating the scope of my study and associated knowledge used in compiling this report.

CHAPTER 2: LITERATURE REVIEW

2.1. Definitions

2.1.1. Remote Sensing

Remote sensing can be defined as a science or method used to gather information about objects or phenomena on the surface of the earth without actually being in direct contact with the object. The method uses the characteristics of the electromagnetic radiation that is reflected or emitted by the earth system to identify features on earth. United Nations in a 95th plenary meeting held on 3 December 1986, defined remote sensing as *means of sensing of the earth's surface from space by making use of the properties of the electromagnetic wave emitted, reflected or diffracted by the sensed objects for the purpose of improving natural resources management and protection of the environment* (Joseph, 2005).

Factors that help to differentiate various object using remote sensing depends on composition and nature of materials that show different spectral characteristics or signatures. These spectral characteristics help to understand the signature of the earth objects. According to (Slater, 1980), for a ground object, spectral signature is a set of measured value for reflectance or radiance of the earth objects with each value within specific wavelength interval. Among remote sensing applications is detecting vegetation changes i.e. the process of identifying differences in vegetation or land cover over a given period of time (J.A. Richards and X. Jia, 2006). Vegetation change is a key step in understanding the evolution of the environment and what has changed for a period of time either positively or negatively. Among the methods that have been applied in detecting vegetation changes include but not limited to: image differencing, image rationing, image classification techniques and so on. According to the research by (J.A. Richards, 2012), Vegetation index differencing and post classification are the most widely used in vegetation change.

2.1.2. Mapping

Mapping refers to the operation done to represent an element or an area on a map. Increase in population in the earth has caused many resources to be scarce, floating vegetation (water hyacinth) encroachment replacing surface area initially covered by water. This scarcity and abundance of different resources have been the effect of land conversion over the whole world. Therefore, these resources require timely and accurate information, like the type, quantity, area/

extent and distribution of resources. It is in this effect that mapping of resources is necessary for easy planning and decision-making (Congalton and Green, 2009).

2.2 Landsat 8 Satellite

Landsat 8 was developed by NASA and the United States Geological Survey and was launched in February 2013, California, Vandenberg Air Force Base. Its payload consists of two instruments the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS). Its provides coverage over the landmass at 30 meters (visible) spatial resolution, 100 meters (thermal) and 15 meters (panchromatic) (Landsat 8 Overview, 2018). Landsat 8 bands are used for different applications as specified in table 1.

Table 1: Characteristics of Landsat 8 OLI & TIRS

Band	Wavelength	Useful for mapping
Band 1 – Coastal Aerosol	**0.435 - 0.451**	**Coastal and aerosol studies**
Band 2 – Blue	**0.452 - 0.512**	**Bathymetric mapping, distinguishing soil from vegetation, and deciduous from coniferous vegetation**
Band 3 – Green	**0.533 - 0.590**	**Emphasizes peak vegetation, which is useful for assessing plant vigor**
Band 4 – Red	**0.636 - 0.673**	**Discriminates vegetation slopes**
Band 5 – Near Infrared (NIR)	**0.851 - 0.879**	**Emphasizes biomass content and shorelines**
Band 6 – Shortwave Infrared (SWIR) 1	**1.566 - 1.651**	**Discriminates moisture content of soil and vegetation; penetrates thin clouds**
Band 7 – Shortwave Infrared (SWIR) 2	**2.107 - 2.294**	**Improved moisture content of soil and vegetation and thin cloud penetration**
Band 8 – Panchromatic	**0.503 - 0.676**	**15 meter resolution, sharper image definition**
Band 9 – Cirrus	**1.363 - 1.384**	**Improved detection of cirrus cloud contamination**
Band 10 – TIRS 1	**10.60 – 11.19**	**100 meter resolution, thermal mapping and estimated soil moisture**

2.3 The Water hyacinth mapping

2.3.1 Remote Sensing in Water hyacinth mapping

In mapping, the use of Remote Sensing and Remote Sensing data has been in use for a long time. Remotely sensed data have been in use to identify the status of vegetation and help the users to take action of any disaster at an appropriate time. In sea and lake vegetation mapping, several types of research have been done to monitor the abundance and distribution of water hyacinth in Lake Victoria, change detection assessment and water quality assessment. However, in all those research done, very few studies have focused on the entire Kenyan part of Lake Victoria. Most of the studies have been focusing on small section of the lake mainly the Winam Gulf. In addition those few that have explored entire Lake Victoria, few among them have used Remote Sensing and GIS technology. Attempts using Remote Sensing data and GIS have been used to monitor water hyacinth in the Lake Victoria basin (USGS/CLI, 2000).

A successful research was done by (Fusilli et al., 2013) in assessing the abnormal growth of floating macrophytes in Winam Gulf (Kenya) by using MODIS imagery time series. In this research, NDVI technique was applied in vegetation classification on the images between 13th March 2007 to 29th April 2007 where they established a high explosion of sparse and floating vegetation between 3rd April – 8th April 2007 and 25th April – 21st April 2007 respectively. In their finding, maximum extent reached by the weeds was 440km^2. In my research I have applied the RS and GIS techniques to monitor the recent development in vegetation cover on the Lake Victoria Basin.

2.3.2 Impacts and implications of water hyacinth

The first and most acute impact and implication felt is the interference with the fishing activities of the lake communities. Lake Victoria provides a livelihood to one third of the population living around it, most of whom are dependent on fishing (Mumma et al., 1998).

Considerable revenue is also generated for the national economies of the three countries from fish exports. The water hyacinth problem has long term effects on the economy because the foreign exchange is diminishing. Such a situation has very serious economic implications for the relations of the East African countries. The water hyacinth usually impedes the access of boats to the fishing grounds thereby interfering with fishing activities because it impedes the access of boats to fishing grounds and landing beaches. It also harbours snakes and crocodiles and therefore makes fishing a dangerous activity. It interferes with fish breeding since the dense mat reduces light penetration and oxygen supply to the waters of the breeding grounds. In places where fishing activities have become impossible, whole communities have had to move to areas not yet infested by it. This is because with the increase of the water hyacinth there is a drastic decline in fishing activities since often the fishing boats are trapped in the water hyacinth mats. According to the 2009 census (Kenya National Bureau of Statistics, 2018), the population has increased thereby attracting higher demand for fish consumption in the country. In cases of cross border migrations, different ethnic and cultural groups are propelled together under circumstances associated with deprivation and stress (Ong'ang'a 0. and K. Munyrwa, 1994). In such cases, there is a likelihood of inter-group hostilities.

During such hostilities, a group would emphasize its own identity while denigrating and discriminating against outsiders or even attacking them. It should be noted that the fisheries of the three countries are highly valued as a source of protein, employment for the population and revenue for the government. In Kenya, it is estimated that the fishing business has been reduced to 70 percent because of the problem of the water Hyacinth, (Musoke D. and A. Dianga, 1998). It is estimated that the weed covers 2000 hectares around the Kenyan port of Kisumu (Drunnineh. H et al., 1998). At Kusa Bay, South of Kisumu, the water hyacinth has filled the bay destroying the livelihood of a 2000 strong fishing community. It was reported that at least 52 fishing boats have been marooned and the fishermen have been forced to fish from the rivers where fishing has been reduced drastically.

One estimate puts the economic cost of the exotic invader at 150 million dollars a year. Water hyacinth's infestation has negatively affected Tanzania's fishing industry just like in Kenya and Uganda. During certain seasons, the fishermen from Ukwere islands cannot move to Mwanza to deliver fish to processors. This has led to heavy post-harvest losses for the fishermen and a reduction in the foreign earnings of the country, (Ong'anga, O. and K. Munyrwa, 1998).

The water hyacinth has seriously disrupted lake transport. Ports such as Kisumu and Port Bell are often blocked. It has choked important waterways and landing sites. Commercial transportation and services of people and goods, especially movement by small boats are often obstructed. Docking of steamers is now regularly delayed. This has serious implications for trade and economic activities in the East African region

2.3.3 Water hyacinth as a plant

The water hyacinth is a perennial and free floating, fresh water plant native to South America in Brazil. The weed is classified as Eichhornia Crassipes (Woomer P.L, 1997) belonging to the Pontederiaciae family of eight other genera. The macrophyte often grows among other aquatic weeds such as *Silvinia molesta*. Water hyacinth has also been reported as one of the most productive plants on earth (Alimi T. and O.A. Akinyemyu, 1998). Among its unique characteristics are a high productivity and a tolerance of a wide range of ecological conditions. These features give the water hyacinth a strong competitive ability and enable it to multiple rapidly, often at the expense of its neighbours.

The widespread distribution of the water hyacinth is partly attributed to its attractive, purple flower, prompting its establishment in many botanic gardens during the late 19^{th} century prior to its recognition as a noxious weed (Woomer P.L, 1997). Additionally, the water hyacinth is known to have few natural predators outside its native home. It has a thin, wall capsule root containing up to forty small seeds. On the average, the water hyacinth weighs twenty-five kilograms per square metre or twenty-five tons per hectare. Since the plants are 95% water, they contain 12.5 tons of dry matter per hectare or 237.5 tons of water per hectare. It has a high capability of rapid, vegetative reproduction (Alimi T. and O.A. Akinyemyu, 1998). This is coupled with a remarkable survival mechanism during the period that the seed remains viable. It also has a great ability to survive extreme drought conditions. All these factors combined have made it very successful in invading numerous water systems throughout the world (Cillier et al., 1996). This has created many problems which have either short-term effects or severe long-term repercussions on both the environment and the people.

2.3.4 Origin and movement of Water hyacinth into Lake Victoria

The water hyacinth is widespread throughout the world (Gopal, B.B. and K.E. Sharma, (eds), 1981). It was first clearly spotted in South East Brazil, although it was already widespread in Central and South America. Several conditions were reported in 1929 from Demarara, Guyana, New Granada, Equador, and Buenos Aires in Argentina. In Africa, the water hyacinth was first introduced in Egypt, sometime between 1879 and 1882, and in Natal in the 19th century.

It was reported in Southern Rhodesia in 1937 and near Congo (Zaire) in 1952 (Cillier et al., 1996). It was spotted in Khartoum in 1958. By 1981, the weed was already widespread in Ethiopia, Madagascar, Mozambique, Natal, Eastern Cape, the Okavango Basin in Botswana, Zambia (Kafwe Reservoir), Angola, Guinea and Senegal. The major river basins infested by the water hyacinth are those of the Kagera, Lagone, Niger, Senegal, Zambezi rivers, and their tributaries. The water hyacinth is thought to have been brought to the African continent as a decorative plant by early travellers. In East Africa, the water hyacinth is thought to have entered Lake Naivasha in Kenya between 1982 and 1983, but was out-competed by *Silvinia molesta* (Sambari J.T, 1996). In 1988, the floating weed was subsequently spotted on Lake Victoria, the Ugandan portion. Two years later, it was spotted on the Tanzanian side, and then the Kenyan side in 1992. Since then, the spread of the water hyacinth has been shocking. In 1992, it was a mere passing interest. It has grown so rapidly that in some parts of Lake Victoria, it covers an area of a thousand hectares. Consequently, it has come to occupy centre stage in the debate about the management of Lake Victoria waters.

2.3.5 Factors contributing to growth of Water hyacinth and current coverage in the lake

The water hyacinth survives well in warm waters and because of its attractive flowers, it has been widely spread by man. The water hyacinth cannot tolerate any form of salinity. This explains why it is widespread in Lake Victoria, a fresh water lake and in Lake Naivasha which is also a fresh water lake, but not in any of the Rift-Valley lakes neighbouring Naivasha. It survives in clear waters but does not thrive unless some nutrients are added from agricultural runoff, urban waste or runoff, suspended solid from silt, and some industrial wastes.

To illustrate this (Sambari J.T, 1996), argues that, "The water hyacinth thrives on sewerage from cities such as Kampala and Kisumu, effluents from sugar factories paper mills, tanneries and breweries springing up across the Lake Basin, and silt washing into the Lake as the catchment, forests are chopped down and converted to fields. These nutrients have turned a once clear, well-oxygenated Lake into muddy, stratified water body with no oxygen in its bottom layers. The fish may die but water hyacinth thrives best in the presence of these nutrients (Cillier et al., 1996).

When the environment is conducive it grows very fast, flowers, sets seed and takes root (Kosyan, S.A., V.E. Markosyam, L.S., S. N. Kisyan et al, 1974). In the open waters such as that of Lake Victoria, the water hyacinth just survives but does not proliferate. When it comes to the shores especially to the protected bays where there are added nutrients, it grows faster. This makes the control of the water hyacinth very difficult (Lee B, 1979). In six to seven days, the number of plants can double in conditions of high temperatures and humidity. The plant normally forms a floating mat and can cover large areas of water surface thus polluting the water. The spreading of the water hyacinth is also enhanced by wind (Ong'anga, O. and K. Munyrwa, 1998). There are numerous shallow bays within the shoreline of Lake Victoria which have permanent mats of water hyacinth. However, the extent of the water hyacinth infestation in Lake Victoria is difficult to map out. This is because the plants keep drifting with surface wind from one place to another (Kosyan, S.A., V.E. Markosyam, L.S., S. N. Kisyan et al., 1974).

2.3.6 Water hyacinth control and mitigation measures

Efforts to control water hyacinth in Lake Victoria basin started way back in 1990s where the primary methods were directed at manually removing water hyacinth and public awareness exercises. However the exercise was limited in success following the challenges associated with the immense weight of the water hyacinth that weighs up to and even exceeding 400 tons/ha. In late 1995, upon successful trials of two *Neochetina* weevil species, a biological control release/control program commenced on Lake Victoria through collaborative local and international efforts. In search of a better solution, mechanical removal operations, herbicide trial demonstration and environmental impact assessment (EIA) took effect. From the EIA, both biological control *Neochetina* weevil species, and mechanical control were approved but the herbicide option was reject following its environmental effects to the marine and human life. According to (Ochiel, Mailu, and others, 1999), weevil release started off in Kenya in January 1997, Tanzania in August 1997. This thereafter attracted a noticeable reduction around the lake as from late 1998 to early 1999. Although the reduction coincided with a rapid increase in weevils' population and followed by the El Niño rains of late 1997 to early 1998.

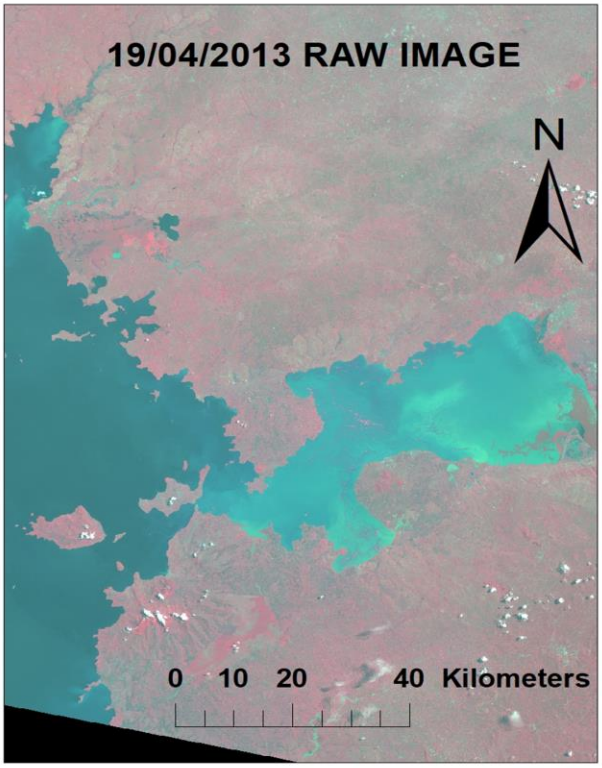
CHAPTER 3: MATERIALS AND METHODS

3.1 Landsat 8 OLI & TIRS Satellite images used in this study

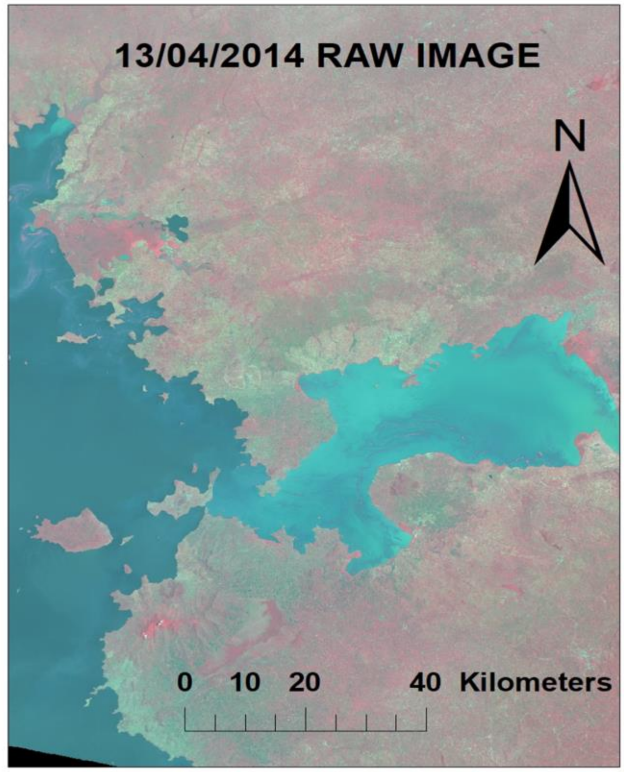
The Landsat 8 satellite images that were used in this study were downloaded from EarthExplorer.usgs.gov website for the study period starting from 2013 to 2019. All the images except 2019 were of the month of April considering the fact that this was the time when the cloud cover was relatively low to about less than 10%. The choice of the month of April also aimed at standardizing results since different months of the year have different climatic conditions. All the images were downloaded under same requirements that include path 170 and row 60 as described in the table below. Both the downloaded data and the Lake Victoria shapefile that was used to extract the area of interest were projected to the same geographical coordinates.

Table 2: Landsat 8 satellite imagery used

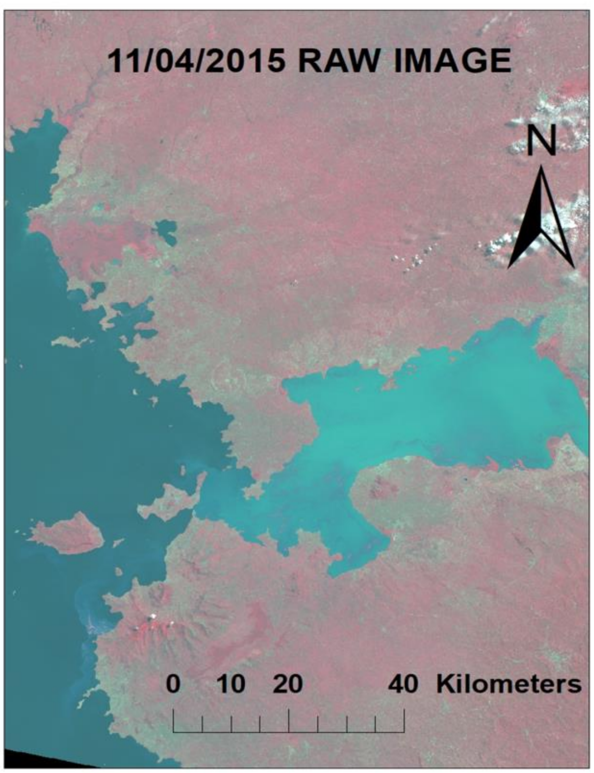
Acquisition date	Sensor/Mode	Cell size	Location
19/04/2013	Landsat 8 OLI/TIRS	30 m	NE Lake Victoria (path 170, row 60)
13/04/2014	Landsat 8 OLI/TIRS	30 m	NE Lake Victoria (path 170, row 60)
11/04/2015	Landsat 8 OLI/TIRS	30 m	NE Lake Victoria (path 170, row 60)
11/04/2016	Landsat 8 OLI/TIRS	30 m	NE Lake Victoria (path 170, row 60)
14/04/2017	Landsat 8 OLI/TIRS	30 m	NE Lake Victoria (path 170, row 60)
13/04/2018	Landsat 8 OLI/TIRS	30 m	NE Lake Victoria (path 170, row 60)
19/03/2019	Landsat 8 OLI/TIRS	30 m	NE Lake Victoria (path 170, row 60)



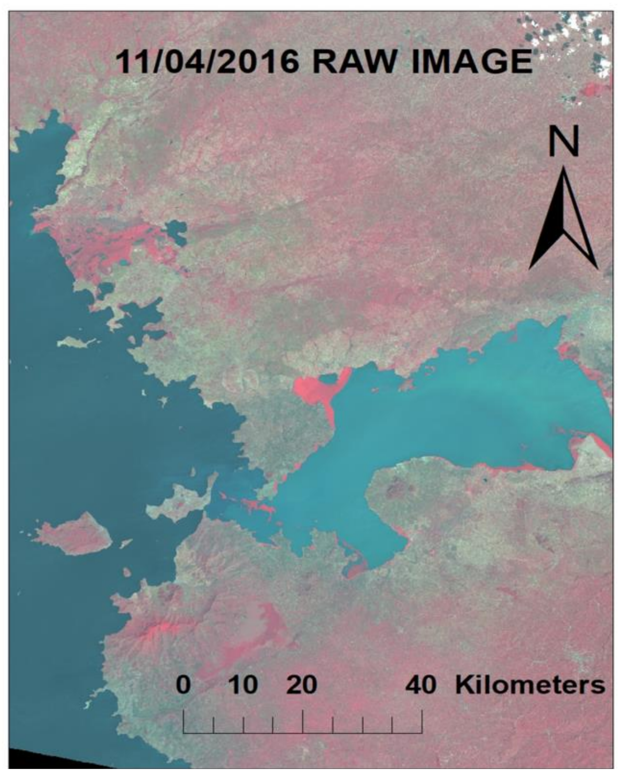
Landsat 8 Raw Image 2013



Landsat 8 Raw Image 2014

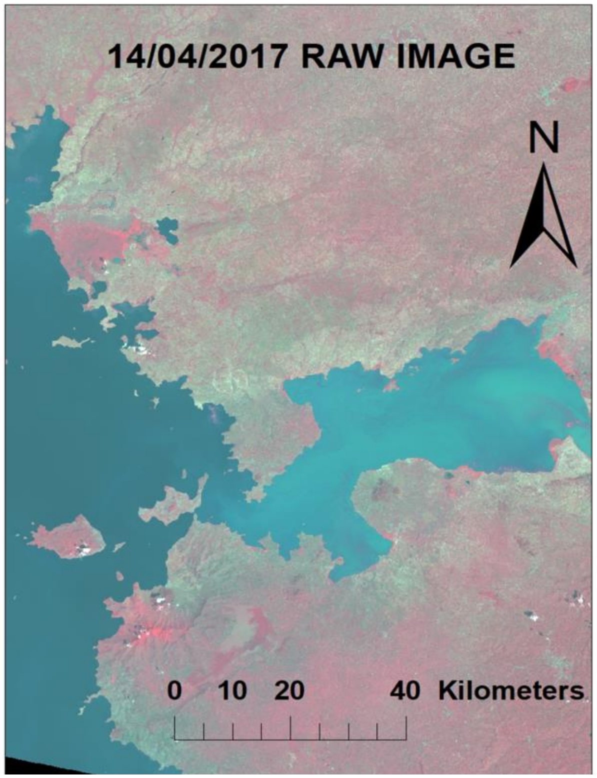


Landsat 8 Raw Image 2015

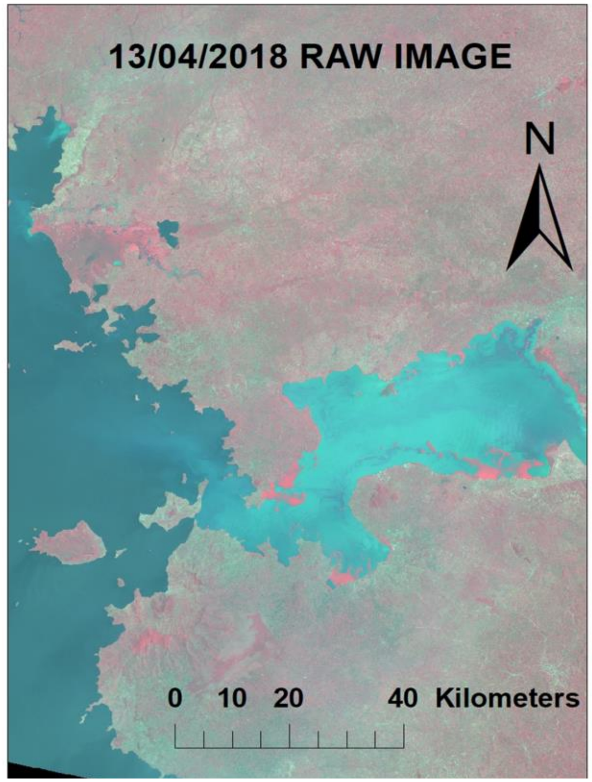


Landsat 8 Raw Image 2016

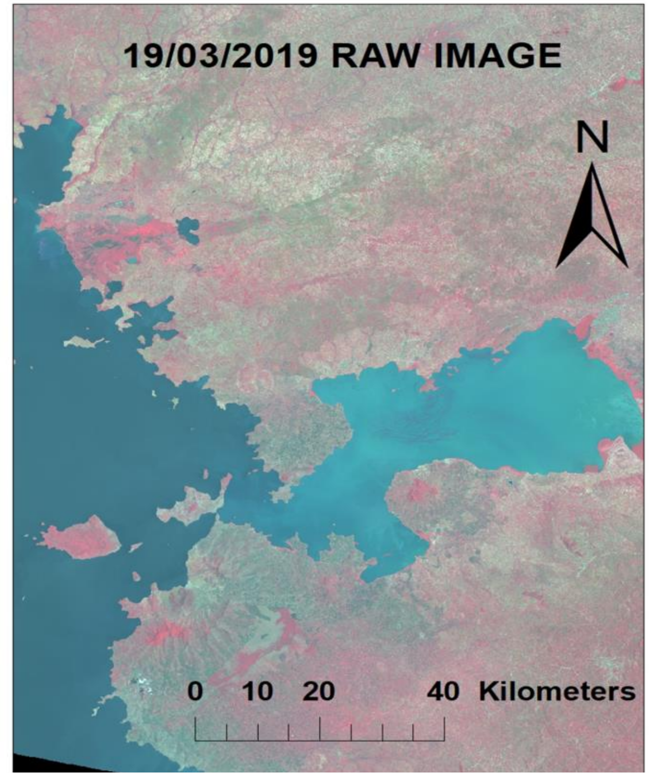
Figure 3: Landsat 8 Raw Images of 2013, 2014, 2015 & 2016



Landsat 8 Raw Image 2017



Landsat 8 Raw Image 2018



Landsat 8 Raw Image 2019

Figure 4: Landsat 8 Raw Images of 2017, 2018 & 2019

3.2 Image pre-processing

3.2.1 Radiometric / Atmospheric correction, Geometric rectification and image Sub-setting

The downloaded images were pre-processed before their analysis. This was so because original data usually come with errors and anomalies associated with radiometric and atmospheric effects that may lead to misinterpretation of digital image during analysis. Radiometric correction is a computer-based technique for reducing noise. The technique enhances the brightness value range in the digital imagery while on the other hand atmospheric correction removes the atmospheric haze through normalization of each frequency band in the image. In this case, the digital numbers (DN) are converted to surface reflectance data (Forkuo EK, Frimpong A, 2012). Since this study was limited to Kenyan part of Lake Victoria basin, instead of using topo sheet to extract region of interest (roi), image resizing was done by sub-setting the downloaded imagery by the Lake Victoria shapefile acquired from National Biodiversity.

3.2.2 Normalized Difference Vegetation Index (NDVI)

NDVI is a vegetation index that is used to estimate the biomass of plant and their condition by measuring the amount and health conditions of the biomass on the land surface. In this work, the processed data were put to Normalized Differential Vegetation Index (NDVI) analysis in ENVI 5.3 to estimate the biomass of water hyacinth over the years in the Lake Victoria and maps based on the vegetation index were developed to distinguish more easily green vegetation from other non-photo-synthetically active surfaces (Rouse et al., 1974; Tucker, 1979). This was achieved through conducting a combined analysis on the near-infrared band and red band.

$$NDVI = \frac{NIR-RED}{NIR+RED} \quad \text{(i)}$$

Normally NDVI value range from – 1.0 to 1.0 with negative values indicating clouds and water, positive values closer to zero indicating bare soil, and higher positive NDVI values ranging from sparse vegetation (0.1 – 0.4) to dense vegetation (0.5 to 1.0).

In this study therefore the following three – level NDVI values ranges were applied to distinguish the three classes namely water, floating vegetation and sparse vegetation.

$$NDVI = \begin{cases} > 0.4 \; Floating\ vegetation\ (FV) \\ 0.2 - 0.3999 \; Sparse\ vegetation\ (SV) \\ < 0.2 \; Open\ water\ (OW) \end{cases} \quad \text{(2)}$$

3.2.3 Supervised classification

Classification is an art of assigning pixels in an image to various classes. The objective of classification is to ensure that all pixels in the image are put into a group or class. There are two methods of image classification. One is image analysis based on the pixel; the other is object-oriented image analysis method. For this research, Supervised Classification pixel-based image analysis method was used to classify the features in the image. During this process, the images for each year were trained by categorizing the pixels in each image through specifying various land cover types present in each image. Sample pixels obtained after training were then used to classify other pixels in the image with similar characteristics (Wiki.landscapetoolbox.org, 2018). Together with Supervised Classification, Maximum Likelihood Classifier was performed in the classified image. Then comparison of results for the seven study years was performed prior to change detection analysis.

3.2.4 Accuracy assessment

Accuracy assessment is described as the process of relating the classified image to what is in existence or the real environment that existed when the image was captured. The process involves ground truthing or by analysis of high-resolution satellite imagery. In this work, accuracy assessment was achieved through computation of error matrix or confusion matrix in which data was represented as row and column. Rows represent classification results while columns represent reference data. From Error Matrix the overall accuracy was obtained which is calculated by dividing the total number of pixels that are correctly classified by the total number of reference pixels. The expected accuracies in this case are: user’s accuracy, producer’s accuracy, kappa, errors of omission and commission.

3.2.5 Change detection

This refers to the process of documenting the physical changes that have occurred over a period of time. This is done by comparing two or more remotely sensed images. The change detection can be given in statistics or maps. This is important as it gives insight to certain trends that cannot be directly identified from a single image. The objective of change detection in this work was to determine how the floating vegetation otherwise known as water hyacinth has spread in the Lake Victoria over a period 7 years from 2013 to 2019. To understand the annually effort put in by the controlling bodies in eliminating water hyacinth, subsequent yearly images were also compared.

3.3 Software used in this study

The following remote sensing tools were used in this study;

3.3.1 Environment for Visualizing Images (ENVI 5.3)

ENVI was used to process, analyze and extract meaningful information from Landsat imagery.

3.3.2 QGIS Desktop 2.16.3

QGIS was used to extract and join X and Y coordinates from the random samples of the classification image and transform to WGS84, ZONE 37S.

3.3.3 ArcGlS

ArcGIS was used in making the land-cover maps through direct export of classified images from ENVI.

3.4 THEORETICAL FRAMEWORK

The overall methodology applied in this study is as outlined below:

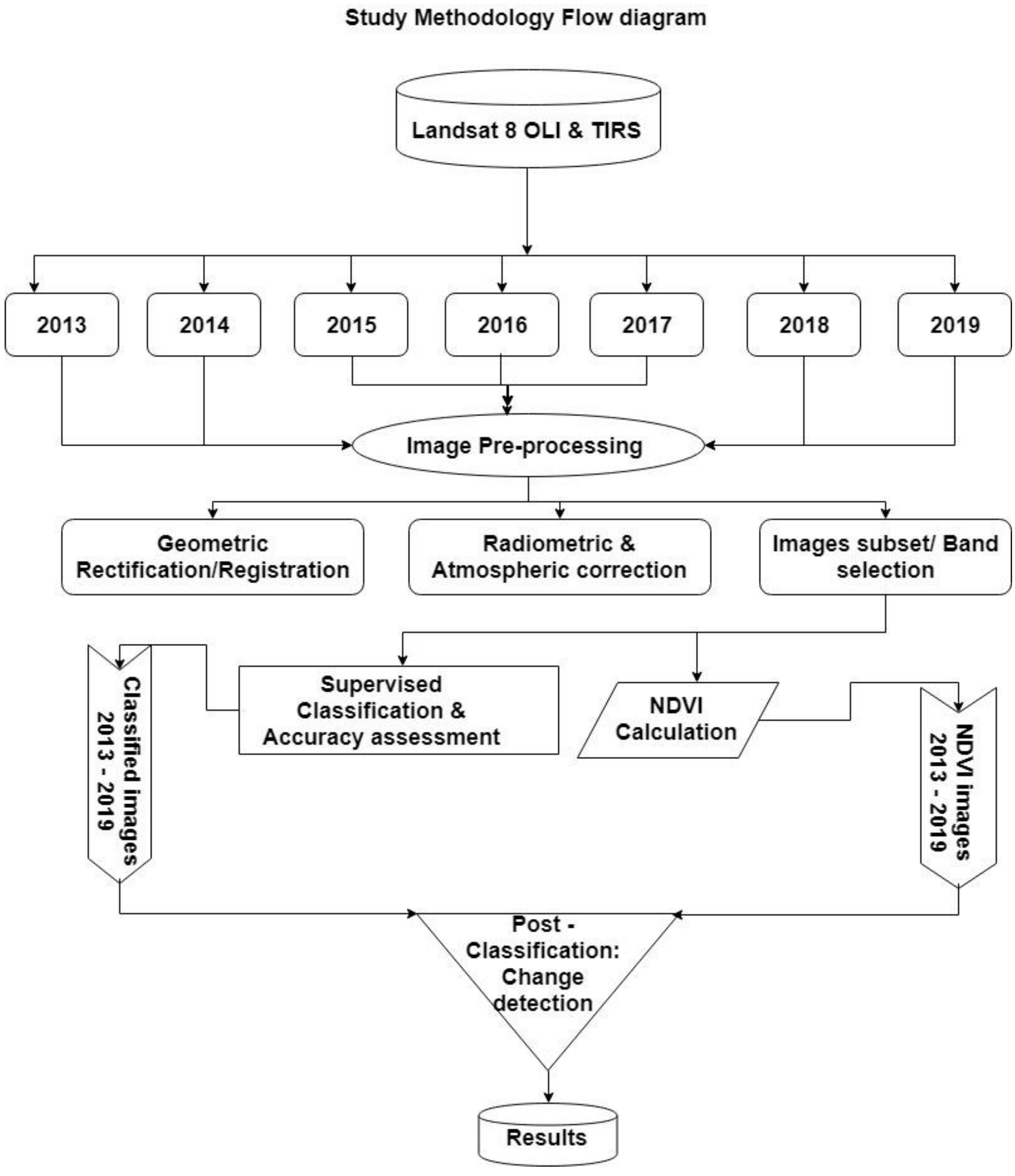


Figure 5: Study methodology flow chart

CHAPTER 4: RESULTS ANALYSIS AND DISCUSSION

4.1 Image classification

This being a process of assigning image pixels into different groups or classes depending on their properties, those with similar properties were grouped together to achieve a set of classes in the image. After performing a supervised classification by training on all the images, the following classes were identified:-

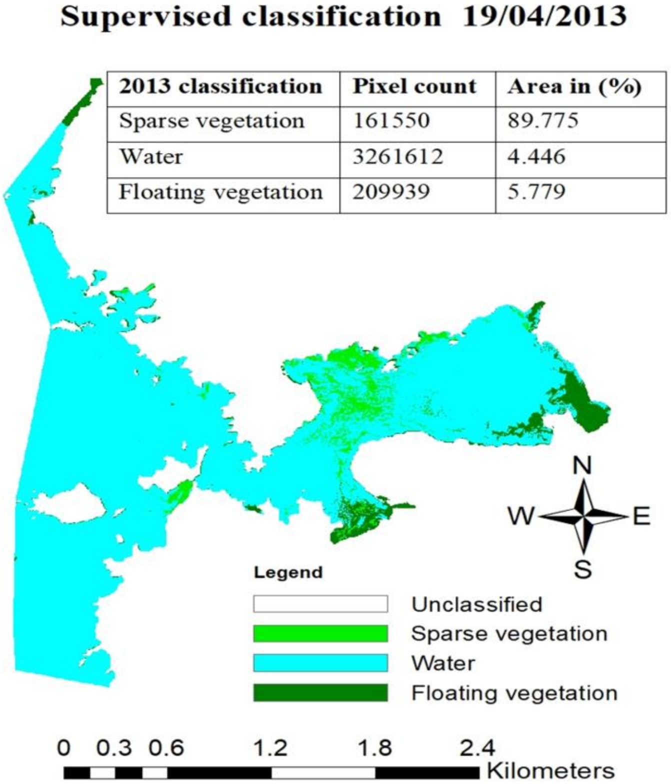
1. Water
2. Water hyacinth identified as floating vegetation
3. Sparse vegetation

Though both floating and sparse vegetation appeared green during image training, the pixels assigned to floating vegetation class were denser than those assigned to the sparse vegetation. This difference could be as a result of the position of vegetation on the lake either floating or submerged. The classification summary of each year together with the zoomed in window and statistical data is provided for and finally an overall summary of change detection in classes throughout the study years.

From the image classification results, it is evident that despite drastic drop in both floating and sparse vegetation between 2013 and 2015, there has been a gradual increase from 2015 to 2019. This increase could be attributed to the increased dumping into rivers and the lake by surrounding industries, homesteads as well as erosion of agricultural fertilizers by rivers into the lake. The eroded fertile deposits around the shoes of the lake provide a conducive environment for faster spread of Water hyacinth.

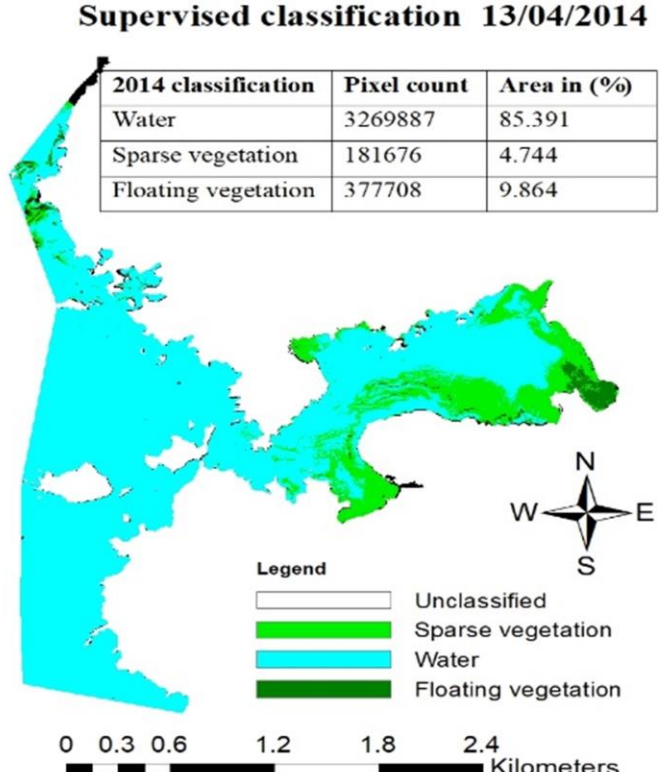
The histogram together with the line graph gives a quick summary of the changes that has occurred in all the three classified classes with emphasis on the Water hyacinth between April 2013 and March 2019 study period.

4.1.1 Supervised classification results



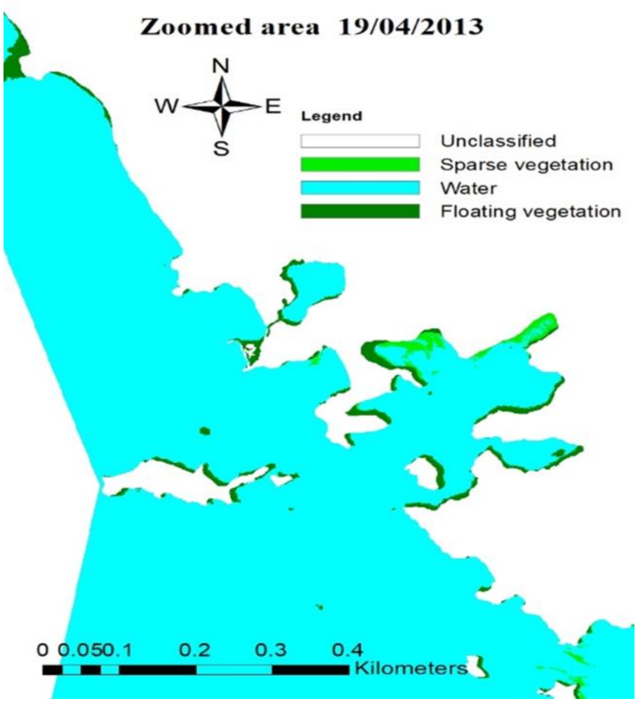
2013 classification	Pixel count	Area in (%)
Sparse vegetation	161550	89.775
Water	3261612	4.446
Floating vegetation	209939	5.779

Classification Map 2013

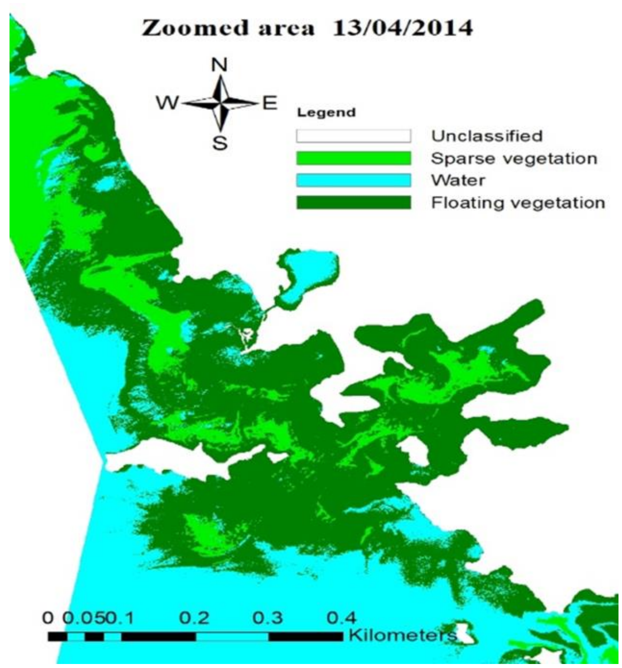


2014 classification	Pixel count	Area in (%)
Water	3269887	85.391
Sparse vegetation	181676	4.744
Floating vegetation	377708	9.864

Classification Map 2014

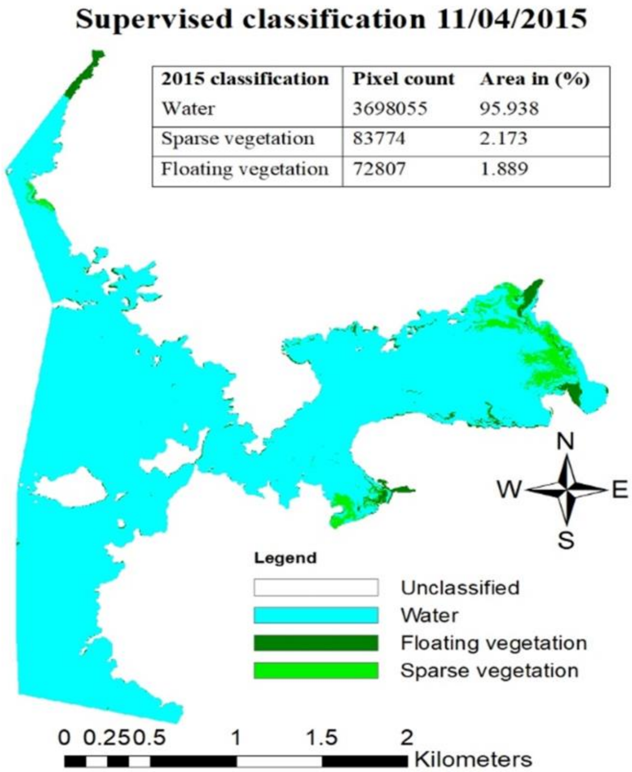


Zoomed in Classification Map 2013



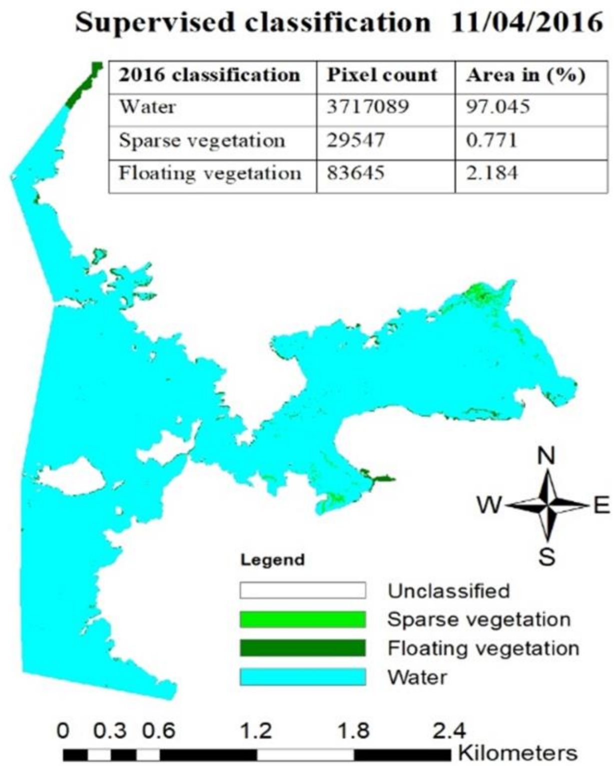
Zoomed in Classification Map 2014

Figure 6: Supervised Classification Maps 2013 & 2014



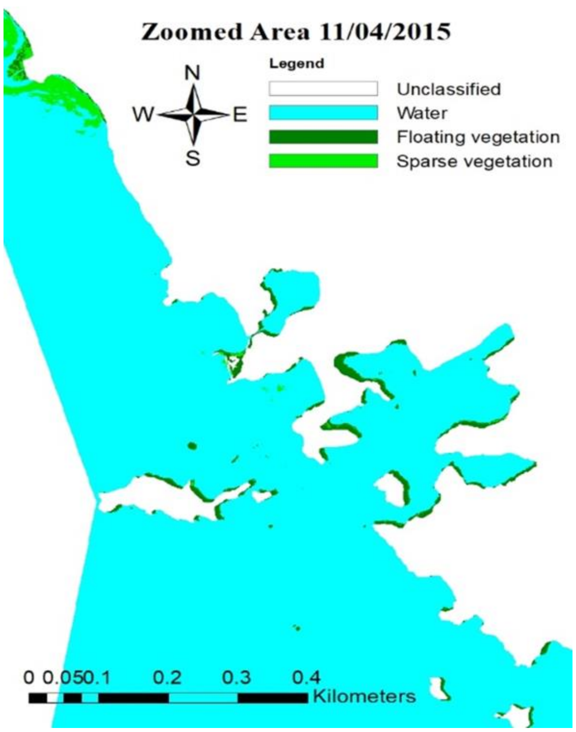
2015 classification	Pixel count	Area in (%)
Water	3698055	95.938
Sparse vegetation	83774	2.173
Floating vegetation	72807	1.889

Classification Map 2015

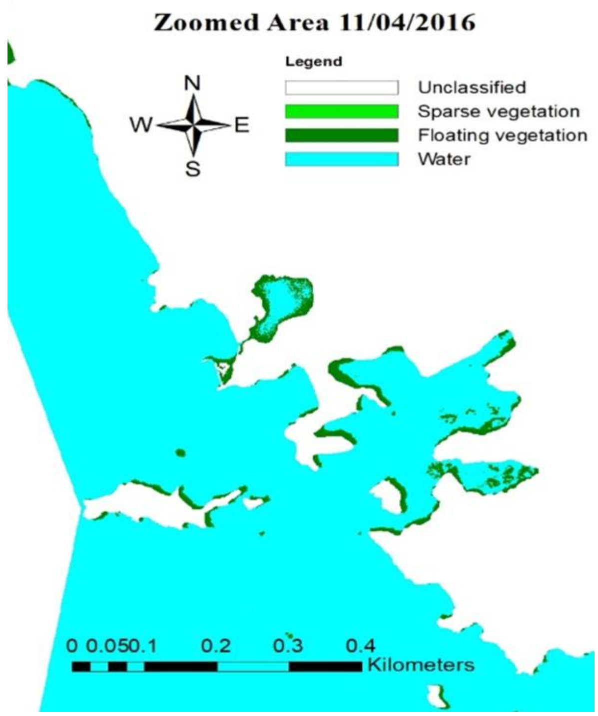


2016 classification	Pixel count	Area in (%)
Water	3717089	97.045
Sparse vegetation	29547	0.771
Floating vegetation	83645	2.184

Classification Map 2016

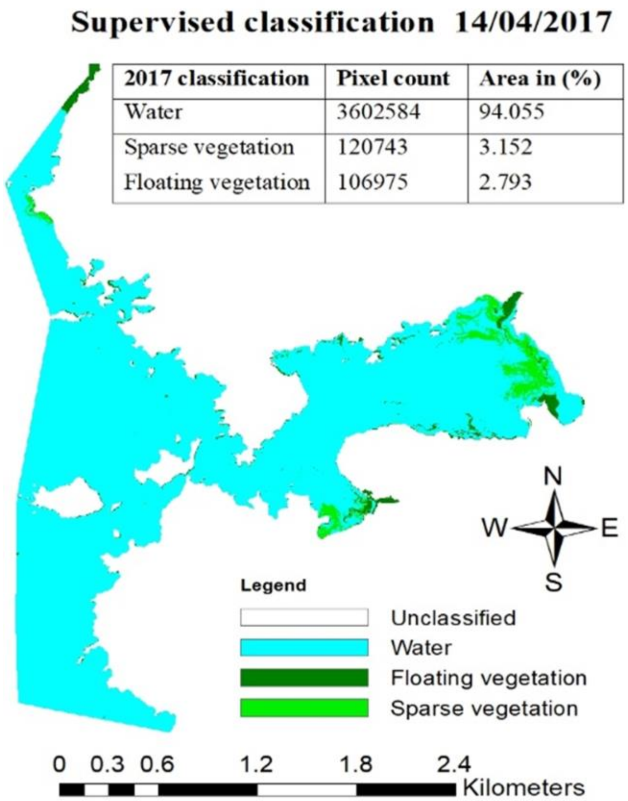


Zoomed in Classification Map 2015

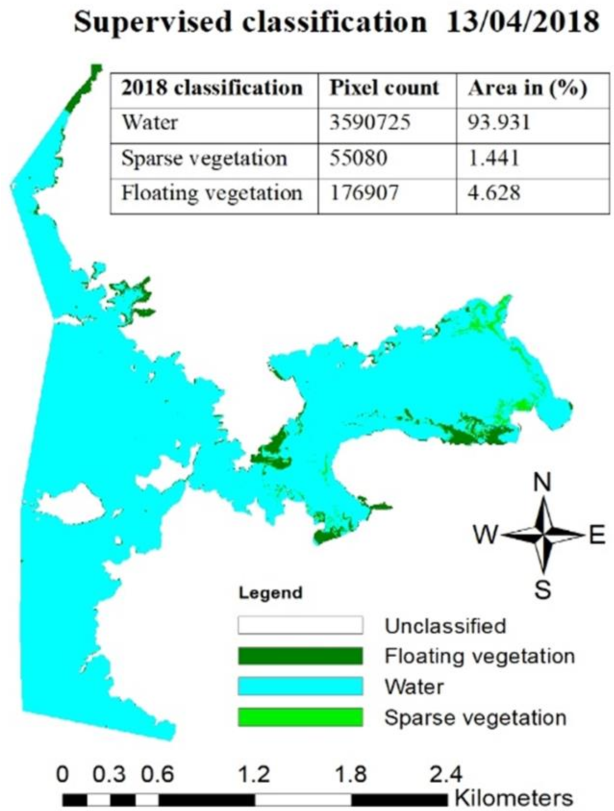


Zoomed in Classification Map 2016

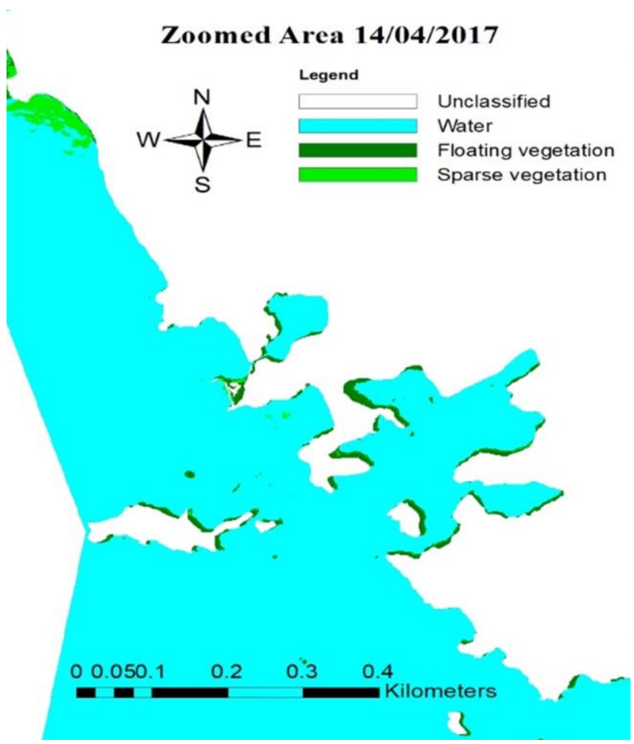
Figure 7: Supervised Classification Maps 2015 & 2016



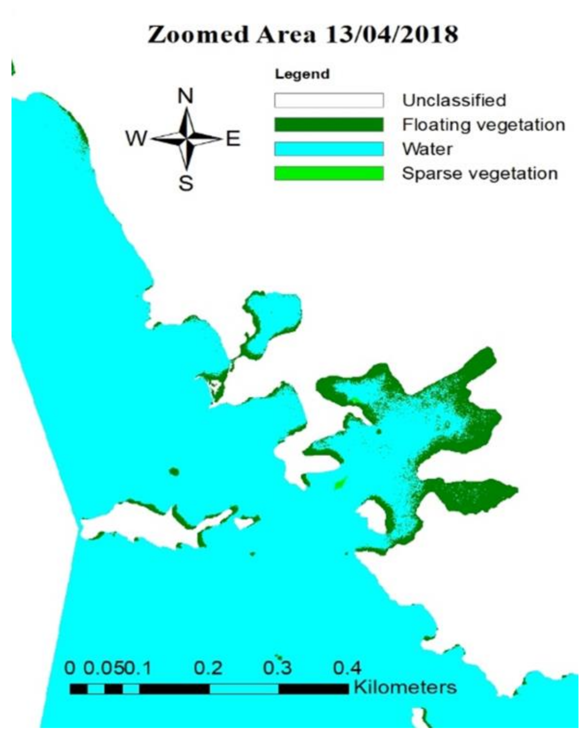
Classification Map 2017



Classification Map 2018

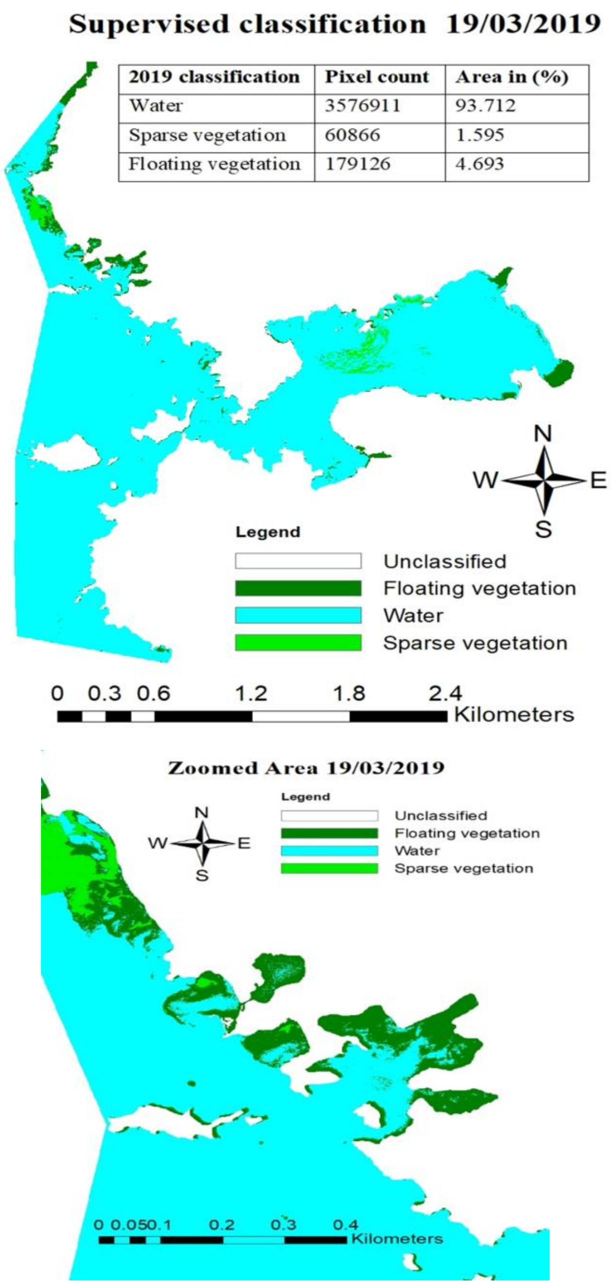


Zoomed in Classification Map 2017



Zoomed in Classification Map 2018

Figure 8: Supervised Classification Maps 2017 & 2019



Zoomed in Classification Map 2019

Figure 9: Supervised Classification Map 2019

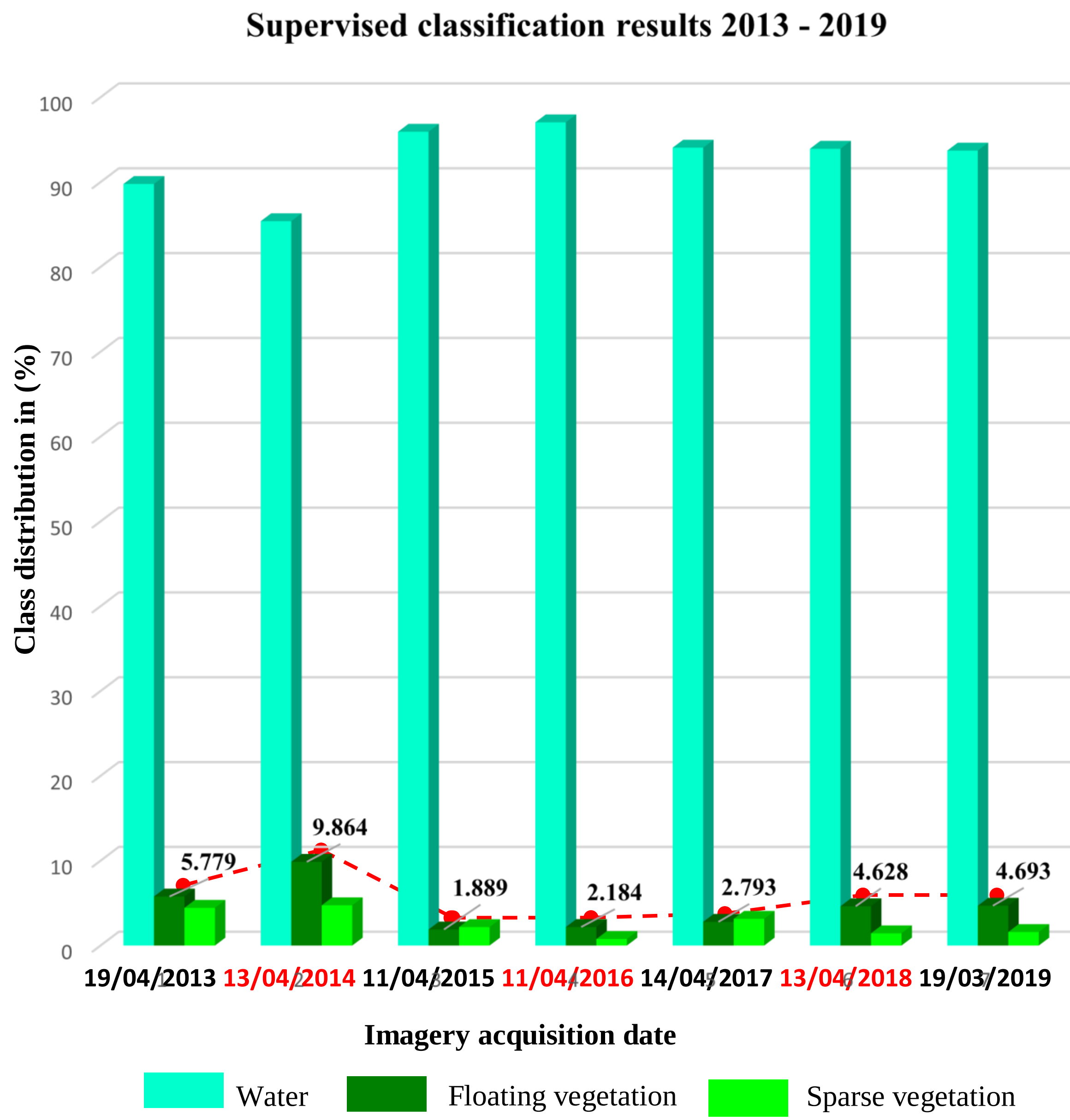


Figure 10: Overall Classification histogram 2013 - 2019

4.1.2 Accuracy assessment: Confusion matrix

According to (Congalton, R.G, 1991), accuracy assessment of remote sensing map products has evolved in four developmental stages. It started with visual assessment of images to determine whether the classification results were good or not. It improved to the stage where overall non-site-specific percentage accuracy was provided, and further to a site-specific accuracy assessment. Finally, a more detailed analysis of the site-specific accuracy assessments emerged, for example the use of error/confusion matrix and kappa coefficients. Error matrix has become one of the most commonly used methods of classification accuracy. A summary of classes and their respective pixels obtained from 2013 – 2019 images are as shown in the tables below.

Table 3: 2013 - Ground Truth (Pixels)

Land cover class	Sparse veg.	Water	Floating veg.	Total
Sparse veg.	109	0	1	110
Water	0	338366	0	338366
Floating veg.	0	0	1597	1597
Total	109	338366	1598	340073

Overall accuracy = 340072/340073 = (99.9997%); kappa coefficient = 0.9891

Table 4: 2013 Producer and user accuracy

Land cover class	Producer Accuracy (%)	User Accuracy (%)	Producer Accuracy (Pixels)	User Accuracy (Pixels)
Sparse veg.	100	99.09	109/109	109/110
Water	100	100	338366/338366	338366/338366
Floating veg.	99.94	100	1597/1598	1597/1597

Table 5: 2014 - Ground Truth (Pixels)

Land cover class	Sparse veg.	Water	Floating veg.	Total
Sparse veg.	111	0	2	113
Water	0	231475	0	231475
Floating veg.	0	0	1261	1261
Total	111	231475	1263	232849

Overall accuracy = 232847/232849 = (99.9999%); kappa coefficient = 0.9832

Table 6: 2014 Producer and user accuracy

Land cover class	Producer Accuracy (%)	User Accuracy (%)	Producer Accuracy (Pixels)	User Accuracy (Pixels)
Sparse veg.	100	98.23	111/111	111/113
Water	100	100	231475/231475	231475/231475
Floating veg.	99.84	100	1261/1263	1261/1261

Table 7: 2015 - Ground Truth (Pixels)

Land cover class	Sparse veg.	Water	Floating veg.	Total
Sparse veg.	202	0	7	209
Water	0	264937	0	264937
Floating veg.	0	5	2438	2443
Total	202	264942	2445	267589

Overall accuracy = 267577/267589 = (99.01%); kappa coefficient = 0.8967

Table 8: 2015 Producer and user accuracy

Land cover class	Producer Accuracy (%)	User Accuracy (%)	Producer Accuracy (Pixels)	User Accuracy (Pixels)
Sparse veg.	100	96.65	202/202	202/209
Water	99.99	100	264937/264942	264937/264937
Floating veg.	99.71	100	2438/2445	2438/2438

Table 9: 2016 - Ground Truth (Pixels)

Land cover class	Sparse veg.	Water	Floating veg.	Total
Sparse veg.	174	0	0	174
Water	0	235772	242	236014
Floating veg.	0	46	1043	2438
Total	174	235818	1287	237279

Overall accuracy = 2366989/237279 = (99.8778%); kappa coefficient = 0.8931

Table 10: 2016 Producer and user accuracy

Land cover class	Producer Accuracy (%)	User Accuracy (%)	Producer Accuracy (Pixels)	User Accuracy (Pixels)
Sparse veg.	100	100	174/174	174/174
Water	99.98	99.90	235772/235818	235772/236014
Floating veg.	81.04	95.78	1043/1287	1043/1089

Table 11: 2017 - Ground Truth (Pixels)

Land cover class	Sparse veg.	Water	Floating veg.	Total
Sparse veg.	785	0	1	786
Water	0	101900	0	101900
Floating veg.	0	0	824	824
Total	785	101900	825	103510

Overall accuracy = 103509/103510 = (99.9990%); kappa coefficient = 0.9997

Table 12: 2017 Producer and user accuracy

Land cover class	Producer Accuracy (%)	User Accuracy (%)	Producer Accuracy (Pixels)	User Accuracy (Pixels)
Sparse veg.	100	99.87	785/784	785/786
Water	100	100	101900/101900	101900/101900
Floating veg.	99.88	100	824/825	824/824

Table 13: 2018 - Ground Truth (Pixels)

Land cover class	Sparse veg.	Water	Floating veg.	Total
Sparse veg.	840	1	0	841
Water	0	348012	525	348537
Floating veg.	0	4	9121	9125
Total	840	348017	9646	358503

Overall accuracy = 357973/358503 = (99.8522%); kappa coefficient = 0.9734

Table 14: 2018 Producer and user accuracy

Land cover class	Producer Accuracy (%)	User Accuracy (%)	Producer Accuracy (Pixels)	User Accuracy (Pixels)
Sparse veg.	100	99.88	840/840	840/841
Water	100	99.85	348012/348017	348012/348537
Floating veg.	94.56	99.96	824/825	824/824

Table 15: 2019 - Ground Truth (Pixels)

Land cover class	Sparse veg.	Water	Floating veg.	Total
Sparse veg.	515	8	0	523
Water	0	404645	1	404646
Floating veg.	0	9	9336	9345
Total	515	404662	9337	414514

Overall accuracy = 414496/414514 = (99.9957%); kappa coefficient = 0.9991

Table 16: 2019 Producer and user accuracy

Land cover class	Producer Accuracy (%)	User Accuracy (%)	Producer Accuracy (Pixels)	User Accuracy (Pixels)
Sparse veg.	100	98.47	515/515	515/523
Water	100	100	404645/404662	404645/404646
Floating veg.	99.99	99.90	9336/9337	9336/9345

4.2 Change detection classification results

Table 17: Change detection 2013 - 2014 in (%)

Land cover class	Sparse veg.	Water	Floating veg.	Row Total	Class Total
Sparse veg	3.821	5.204	2.751	100	100
Water	91.177	85.605	65.466	94.096	100
Floating veg	5.002	9.191	31.784	99.174	100
Class Total	100	100	100	0	0
Class Changes	96.179	14.395	68.216	0	0
Image Difference	12.458	0.254	79.913	0	0

Table 18: Change detection 2014 - 2015 in (%)

Land cover class	Water	Sparse veg.	Floating veg.	Row Total	Class Total
Water	97.812	99.144	82.568	99.317	100
Sparse vegetation	1.782	0.779	0.818	100	100
Floating veg	0.405	0.077	16.613	99.997	100
Class Total	100	100	100	0	0
Class Changes	2.188	99.221	83.387	0	0
Image Difference	13.634	-65.440	-79.842	0	0

Table 19: Change detection 2015 - 2016 in (%)

Land cover class	Sparse veg.	Floating veg.	Water	Row Total	Class Total
Sparse vegetation	0.927	0.032	0.779	100	100
Floating veg	1.247	81.914	0.552	99.999	100
Water	97.826	18.051	98.014	100	100
Class Total	100	100	100	0	0
Class Changes	99.073	18.086	1.986	0	0
Image Difference	-52.942	9.860	0.037	0	0

Table 20: Change detection 2016 - 2017 in (%)

Land cover class	Water	Floating veg.	Sparse veg.	Row Total	Class Total
Water	96.004	21.424	54.449	99.999	100
Floating veg	1.132	74.037	10.001	100	100
Sparse vegetation	2.864	4.539	35.550	100	100
Class Total	100	100	100	0	0
Class Changes	3.996	25.963	64.450	0	0
Image Difference	-3.081	27.892	308.647	0	0

Table 21: Change detection 2017 - 2018 in (%)

Land cover class	Floating veg.	Water	Sparse veg.	Row Total	Class Total
Floating veg	59.878	2.824	9.201	99.999	100
Water	31.812	95.977	82.039	100	100
Sparse vegetation	8.309	0.989	8.761	100	100
Class Total	100	100	100	0	0
Class Changes	40.122	4.023	91.239	0	0
Image Difference	65.372	-0.329	-54.382	0	0

Table 22: Change detection 2018 - 2019 in (%)

Land cover class	Floating veg.	Water	Sparse veg.	Row Total	Class Total
Floating veg	47.290	2.520	9.070	100	100
Water	52.280	95.648	90.726	100	100
Sparse vegetation	0.420	1.671	0.203	100	100
Class Total	100	100	100	0	0
Class Changes	52.710	4.352	99.797	0	0
Image Difference	1.254	-0.385	10.505	0	0

Table 23: Overall change detection 2013 - 2019 in (%)

Land cover class	Floating veg.	Water	Sparse veg.	Row Total	Class Total
Floating veg	59.313	2.074	24.301	87.027	100
Water	39.709	96.376	71.348	92.574	100
Sparse vegetation	0.978	1.550	4.351	90.351	100
Class Total	100	100	100	0	0
Class Changes	40.687	3.624	95.649	0	0
Image Difference	38.819	6.688	50.558	0	0

Table 24: Change of area for different vegetation

Type of vegetation	Area (Pixel count)							
	2013	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	Overall Inc./ Dec
Sparse veg.	161550	181676	83774	29547	120743	55080	60866	Increase
Floating veg.	209939	377708	72807	83645	106975	176907	179126	Decreased

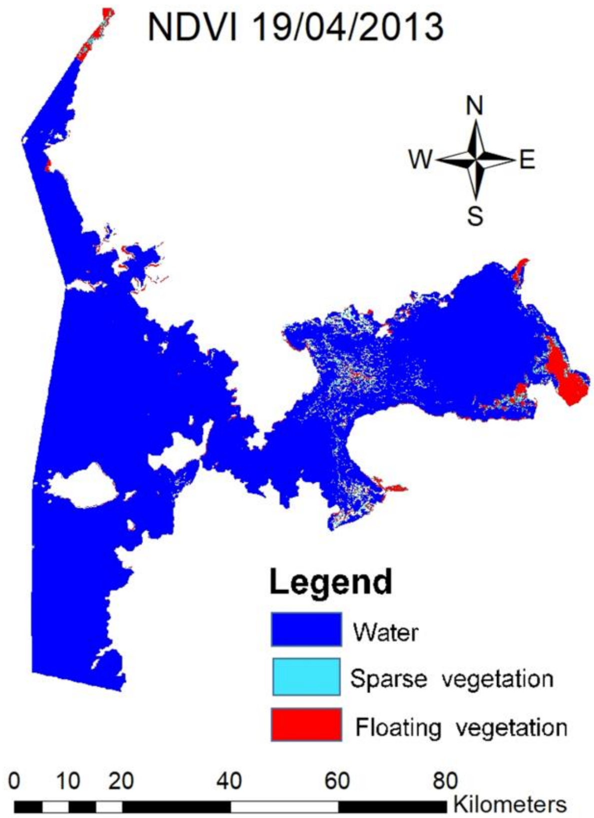
Table 25: Time series change in % area covered by Floating vegetation

Year of acquisition	Land cover class	Area (Pixel count)	% (Change)
2013	Floating vegetation	209939	(2013 – 2014) 79.91 (+ change)
2014	Floating vegetation	377708	
2014	Floating vegetation	377708	(2014 – 2015) -80.72 (- change)
2015	Floating vegetation	72807	
2015	Floating vegetation	72807	(2015 – 2016) 14.89 (+ change)
2016	Floating vegetation	83645	
2016	Floating vegetation	83645	(2016 – 2017) 27.89 (+ change)
2017	Floating vegetation	106975	
2017	Floating vegetation	106975	(2017 – 2018) 65.37 (+ change)
2018	Floating vegetation	176907	
2018	Floating vegetation	176907	(2018 – 2019) 1.254 (+ change)
2019	Floating vegetation	179126	

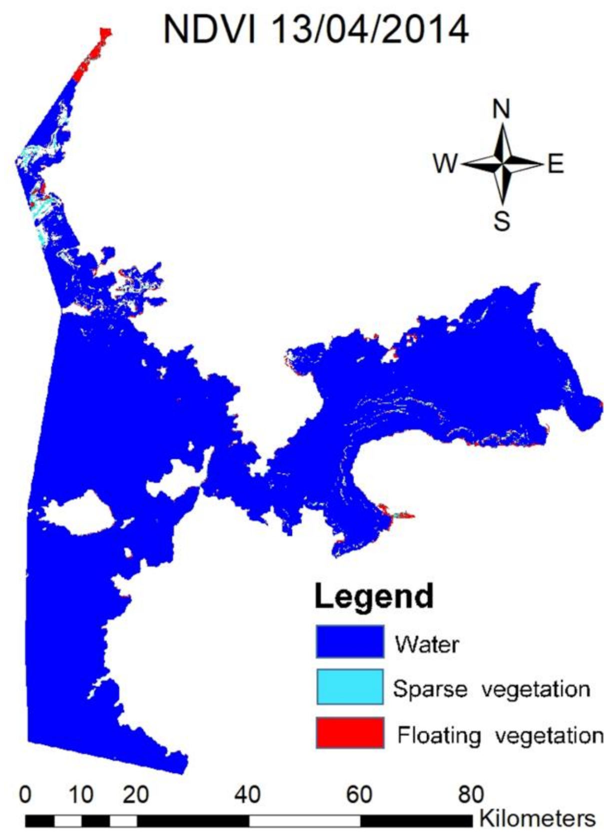
4.3 NDVI Classification results

In this study, NDVI was employed to help in determining where Water hyacinth flourishes more and in comparison to the results obtained in supervised classification. The analysis based on Landsat 8 OLI/TIRS dataset used in this study made it possible to highlight the trend of the floating vegetation referred to as water hyacinth within Lake Victoria basin from April 2013 to March 2019.

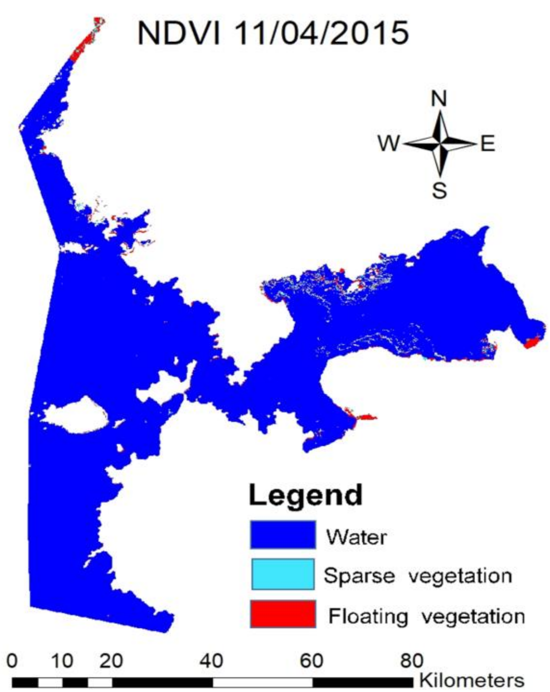
The results obtained from the NDVI calculations agreed with those obtained by supervised classification given in the section 4.1.1. It was observed in both cases that the percentage of area occupied by the Water hyacinth has been varying with the highest recorded in April 2014 at (9.9%) and the least in April 2015 at (1.9%) corresponding to 6811 Km^2 and 1307 Km^2 respectively. In particular, during the years 2014 – 2015 the phenomenon of the weeds proliferation seems almost absent which later picked up in 2018 - 2019. The sharp decrease between 2014 and 2015 could be attributed to prudent measures put in place by the Government following the alarming rate of Water hyacinth proliferation in 2014. These measures aimed at reducing dumping in rivers and lakes and controlling soil erosion from agricultural farms. During this period, a KES 8 million machine for the removal of Water hyacinth was introduced through a program initiated by the Kenya Maritime Authority (KMA), which hired the machine from the National Water Conservation and Pipeline Corporation. However, the process was inconsistent for the subsequent years thereby attracting new levels of Water hyacinth proliferation in the lake.



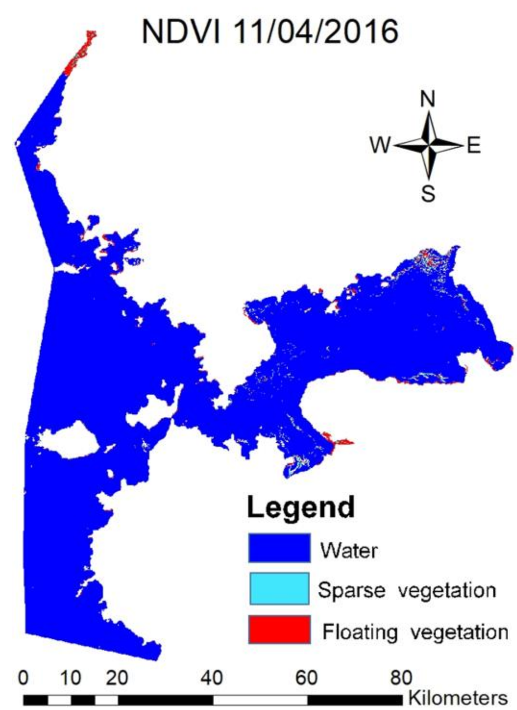
NDVI Classification Map 2013



NDVI Classification Map 2014

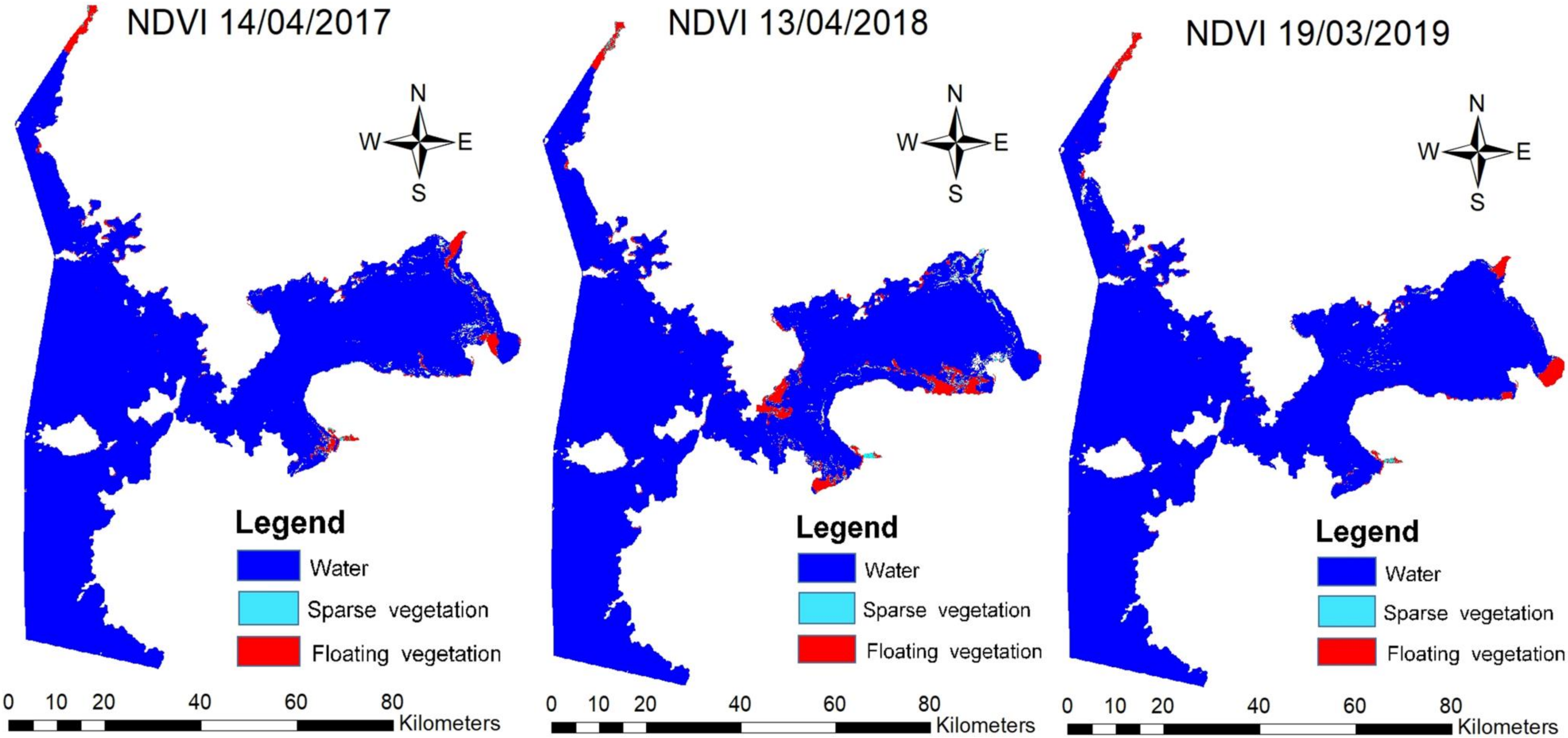


NDVI Classification Map 2015



NDVI Classification Map 2016

Figure 11: NDVI Classification map results 2013, 2014, 2015 & 2016



NDVI Classification Map 2017 **NDVI Classification Map 2018** **NDVI Classification Map 2019**

Figure 12: NDVI Classification map results 2017, 2018 & 2019

CHAPTER 5: CONCLUSION AND RECOMMENDATIONS

5.1 Research finding summary

The classification of the Kenyan part of Lake Victoria reveal that water weeds both floating (water hyacinth) and the sparse vegetation occupies a significant portion of the lake dominating the shores. The spread of these macrophytes is mainly on the Winam Gulf part of the lake due to its shallowness for much deposition as well as being the inlet from rivers Sondu - Miriu, Kisat, Nyamasaria, Nyando, Yalla, Kuja and Awach originating from fertile agricultural regions. These rivers brings with them eroded fertilizers from the agricultural forms during the rain seasons that directly influence the growth and flourishing of water weeds along the Gulf shores. Apart from the rivers, industrial pollutants through dumping are also on the spot as a source of high eutrophication in the lake.

In this study, classification of the Lake Victoria was done into three classes: water, sparse and floating vegetation (water hyacinth). The classes were achieved using maximum likelihood classification and the results compared by Normalized Difference Vegetation Index (NDVI) using ENVI 5.3 software.

The classification of the remotely sensed images of Lake Victoria Basin for the period between 2013 to 2019 indicate a drastic drop in both vegetation classes between 2013 and 2015 followed by gradual increase of floating vegetation from 1.9% (1307 Km^2) in 2015 to 4.7% (3233 Km^2) in 2019. The sharp drop in lake weeds between 2013 and 2015 could be as a result of mitigation measures that were launched in April 2013 by the Government to clean up Lake Victoria. In this exercise manual removal of water hyacinth was employed using locals around the lake. However due to lack of consistency in weed control and management, the evolution and encroachment of these aquatic weeds started increasing again from 2015. Contrary to the floating and sparse vegetation, the area covered by water remained relatively unchanged. Its slight change of about 3.9% (2683 Km^2) between 2013 and 2019 could be as a result of increased rainfall due to the climate change around the lake as well as sand harvest along the banks of the lake.

5.2 Conclusion

From the supervised classification and NDVI results obtained in this study, the distribution of water hyacinth is along the shores of the Lake Victoria. These shores are shallow and therefore much deposition of nutrients by sedimentation from Inlet Rivers and lake deposits occurs here. The deposited nutrients together with warm temperatures along these shores favours the growth of the water hyacinth. Winam Gulf and regions of the lake bordering Siaya County shows much proliferation of this weed as they are fed by rivers such as Sondu, Awach, Gucha, Yalla and Nzoia River. These rivers originate and pass through highly practiced agricultural and industrial areas thereby sweeping along with them nutrients into the lake.

During supervised classification, three classes that were considered included; open water, sparse vegetation and floating vegetation (water hyacinth). From the results obtained, the percentage of water hyacinth in comparison to other classes was 5.779% (2013), 9.864% (2014), 1.889% (2015), 2.184% (2016), 2.793% (2017), 4.628% (2018) and 4.693% (2019). The highest spread of water hyacinth was observed in 2014 followed by a drastic drop in 2015. Rapid decrease of water hyacinth in 2015 indicates clearly that adequate measures to eradicate the weed from the lake were put in place after an alarming growth rate of 2014 was recorded. However, the measures were not consistent for the subsequent years resulting to its continuous increase in the lake towards 2019.

Change detection analysis results indicates a maximum positive change (increase) in water hyacinth by 79.91% between 2013 – 2014 followed by a drastic decrease of -80.72% between 2014 and 2015. For the subsequent epochs, the change detection in water hyacinth showed a gradual increase. This could be as a result of inconsistent control measures that were employed in 2014.

Therefore from the general results analysis, it can be concluded that though the control and measures to eradicate water hyacinth from the Lake Victoria have been employed before, much needs to be done and if possible employ different methods or use a combination of available methods to achieve the best results. In addition frequent monitoring to assess the situation will be a key factor towards the weed control.

5.3 Recommendations

Since pollution from the inlet - rivers seems to be the major contributing factor to the growth of water hyacinth, this study recommends strict measures by the Government to those polluting rivers directly. This will help to ensure that effluents and sewerage dumped in the rivers are treated before being released into the rivers.

Water hyacinth managers have been relaying on manual methods such as hand picking whose results is not satisfactory due to it being slow and labour intensive. It is recommended that other methods such as mechanical that involve use of specialized machines as well as biological method through the introduction of weevils that feed on the weeds should be used. Though manual method gives direct employment to the locals, for it to be effective, this report recommends that more funding should be set aside for this project so that more workers are employed in the process. Employing more workers will enable the process of water hyacinth eradication faster and consistent.

Application of combined control methods such as mechanical alongside manual removal is also recommended as a measure to eradicate water hyacinth from Lake Victoria and other infected Kenyan water bodies. In Malaysia for example, in various sites water hyacinth has been successfully controlled through the combination of manual removal with biological control (Nai Kin, 1995, personal communication). If this is also applied in our country, water hyacinth will be managed effectively and within a short period of time.

The study also recommends that industries should adopt green technology to do away with industrial effluents that introduces chemical pollutants into the lake. This together with the pollutant and sewerage treatment before releasing into the rivers and lakes will have an effect of reducing and eradication of water hyacinth from the Lake Victoria.

Urbanization and land use around the area surrounding Lake Victoria have not been looked into in this study; I therefore recommend that further studies should be conducted to understand the effect of human settlement on pollution leading to Water hyacinth spread in the lake.

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