

**MAKERERE**



**UNIVERSITY**

**COLLEGE OF ENGINEERING DESIGN ART AND TECHNOLOGY**

**SCHOOL OF THE BUILT ENVIRONMENT**

**DEPARTMENT OF GEOMATICS AND LAND MANAGEMENT**

**LAND USE/LAND COVER CHANGES AND ITS RELATIONSHIP WITH MALARIA  
PREVALENCE IN LUWERO DISTRICT.**

**PROJECT REPORT**

**SEMESTER II 2020/2021**

**LSG 4103 LAND PROJECT**

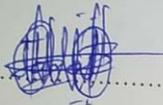
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**A FINAL YEAR PROJECT REPORT SUBMITTED FOR THE AWARD OF BACHELORS  
DEGREE IN LAND SURVEYING AND GEOMATICS**

**DECLARATION**

I **NANSUBUGA JANAT FHIRDAUS** hereby declare that the information presented in this report is originally my work and it has never been submitted to any other university or institution for the award of a bachelor's degree in Land Surveying and Geomatics.

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**APPROVAL**

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**SUPERVISOR**

## DEDICATION

I dedicate this report to my loving family especially my parents (Mr. and Mrs. Kyanyaka Ibrahim and Kyanyaka Hidayat) for their continuous support in giving me encouragement, enthusiasm and all other un-valuable assistance.

## ACKNOWLEDGEMENT

First of all, I would like to thank the Almighty God because it is for the faith I have in him and the mercy he has for me that I was able to complete this proposal successfully.

I would like to extend my sincere thanks to my Department Supervisor Mrs. Angwech Judith and Mr. Mugumya Vincent (Project Coordinator) for their guidance and extended thanks to the whole Geomatics Department for their continued support as I build my Surveying career.

Finally, I thank all my classmates and friends who have supported me during my coursework and studies at Makerere University.

## ABSTRACT

Malaria is among the top deadliest diseases in the world. Despite recent attempts in reducing malaria morbidity and mortality, it remains one of Uganda's deadliest diseases. Uganda has the third highest deaths from malaria in Africa and is ranked 5th amongst countries in the world with the highest malaria prevalence and Luwero district is among the hotspots for malaria in Uganda with 24% rates. This paper associates the dynamics of high malaria prevalence in Luwero district with five land use land cover; water, agriculture, vegetation, wetlands and built-up. Furthermore, the elevation and slope are key factors explaining malaria diffusion throughout the region. In this study, Landsat8 datasets of 2015 and 2020 were used to assess the spatial change in Luwero's land use land cover and the elevation and slope are key factors explaining malaria diffusion throughout the region. This was achieved by mapping land use/ cover categories in the study area using unsupervised ISODATA classification, performing post classification change detection overlying the change map with the elevation and slope factor maps and malaria spatial distribution and assessing the their relationship with malaria prevalence using GIS and Remote sensing techniques. Results from this study showed that, 29.4% of agriculture in Luwero district increased from 2015 to 2020. The prevalence showed that it was high and moderate which contributes to (85%) of the total area in Luwero due to the increase in agriculture. The paper identifies the effects of land use land cover types on malaria diffusion, providing policymakers with information for regional and local policies to control malaria and minimize its effects on Luwero district.

## LIST OF ABBREVIATIONS

**GIS-** Geographical Information System **MHO-**

Ministry of Health

**WHO-** World Health Organization

**UBOS-** Uganda Bureau of Statistics

**ITN-** Insecticide- Treated Net

**IRS-** Indoor Residual Spraying

**VHTs-** Village Health Teams

**LULC-** Land Use Land Cover

**TC-** Town Council

**PCC-** Post Classification Comparison

# TABLE OF CONTENTS

## Contents

DECLARATION .....	2
DEDICATION .....	3
ACKNOWLEDGEMENT .....	4
ABSTRACT .....	5
LIST OF ABBREVIATIONS .....	6
TABLE OF CONTENTS .....	7
LIST OF FIGURES .....	10
LIST OF TABLES .....	11
CHAPTER ONE: INTRODUCTION .....	12
1.1 Background .....	12
1.2 Problem Statement .....	13
1.3 JUSTIFICATION OF THE STUDY .....	14
1.4 Research Objectives .....	14
1.4.1 Main objective .....	14
1.4.2 Specific objectives .....	14
1.5 Description of the Study Area .....	14
CHAPTER TWO: LITERATURE REVIEW .....	16
2.1 Malaria .....	16
2.1.1 Background .....	16
2.1.2 Malaria Transmission .....	17
2.1.3 Malaria prevalence in Uganda .....	17
2.1.4 Factors that influence malaria transmission .....	18
2.1.5 Malaria Control Measures in Uganda .....	21
2.2 Land Use/ Land Cover Patterns Associated With Malaria Transmission .....	23
2.2.1 Agriculture .....	23
2.2.2 Settlement. ....	24
2.2.3 Brick making .....	24
2.2.4 Water and wetlands .....	24
2.2.5 Vegetation .....	24
2.3 Ecological changes and “exposure risk” .....	25

2.4 Previous Methods .....	25
2.4.1 Remote sensing and Malaria .....	25
2.4.2 Geographical Information System in Malaria Control .....	26
2.4.3 Household interviews .....	27
2.5 Change detection methods .....	27
2.5.1 Image differencing .....	28
2.5.2 Principal component analysis .....	28
2.5.3 Post-classification comparison .....	29
2.6 Spatial Modelling Framework for Disease Mapping .....	29
2.6.1 Overlay Analysis .....	29
2.6.2 Interpolation .....	29
2.8 Related Studies .....	29
<b>CHAPTER THREE: DATA AND METHODS .....</b>	<b>31</b>
3.1 Introduction .....	31
3.2 Data Acquisition .....	32
3.2.1 Software and materials used in the project .....	32
3.2.2 Data Processing .....	32
3.3.3 Preparation of Data layers .....	32
Image Processing .....	33
Image classification .....	33
3.3.3 Change Detection Assessment .....	34
3.4 Overlay Analysis .....	34
3.4.1 Malaria Hazard Analysis .....	34
3.4.2 Malaria Prevalence Analysis .....	35
<b>CHAPTER FOUR: RESULTS AND ANALYSIS .....</b>	<b>36</b>
4.1 Environmental Factors .....	36
4.1.1 Elevation Factor .....	36
4.1.2 Slope factor .....	37
4.1.3 LAND USE LAND COVER FACTOR .....	38
4.2 Malaria Hazard Analysis .....	41
Discussion of the results .....	42
4.3 Malaria distribution analysis .....	43
4.3 Malaria prevalence Analysis .....	43

Identification of Malaria Risk areas .....	43
Discussion of the results .....	44
CHAPTER FIVE: CONCLUSION AND RECOMMENDATION .....	46
5.1 CONCLUSION .....	46
5.2 RECOMMENDATIONS .....	47
REFERENCES .....	48

## LIST OF FIGURES

Figure 1: A map showing the administrative boundaries of Luwero district .....	15
Figure 2: Flow chart for the adopted methodology .....	31
Figure 3: Data types used and their details .....	32
Figure 4: Description of Land Cover categories .....	34
Figure 5: An image of the reclassified elevation layer of Luwero district .....	36
Figure 6: An image of the reclassified slope layer of Luwero district .....	37
Figure 7: LULC map of Luwero district in 2015 and 2020 .....	39
Figure 8: Pie-charts showing the proportion of each LULC of Luwero in 2015 and 2020 .....	39
Figure 9: The percentage change of each land cover class of Luwero district in 2015 and 2020 ..	40
Figure 10: A graph showing the change in each land use land cover of luwero district in 2015 and 2020 .....	40
Figure 11: Pie-charts showing percentage increase of water, wetlands and agriculture and THE LULC CHANGE MAP .....	41
Figure 12: A map showing the degree of hazard in Luwero district. ....	41
Figure 13: A map showing the malaria distribution change of Luwero district in (2015 -2020) ..	43
Figure 14: A map of malaria prevalence of Luwero district. ....	44
Figure 15: Area coverage of malaria prevalence of Luwero district. ....	44

## LIST OF TABLES

Table 1: Producer and user accuracy showing the probability that the classified pixels in each land cover represent the category on ground.....	38
Table 2: The area in sq. km occupied by each land cover class in 2015and 2020.....	39
Table 3: A table of land use land cover change matrix.....	40
Table 4: The area statistics of the hazard layer with the corresponding LULC.....	42

# CHAPTER ONE: INTRODUCTION

## 1.1 Background

Despite recent attempts in reducing malaria morbidity and mortality (Gething et al., 2011), malaria remains one of Uganda's deadliest diseases. According to ministry of health statistics, it is the leading cause of death, accounting for more than 27% of all deaths in Uganda (Wetaya, 2016). Uganda has the third highest malaria mortality rate in Africa and is ranked fifth among countries with the highest malaria prevalence, having reported up to 10,000,000 cases of malaria in 2018. Malaria not only takes lives, but it also costs money and time, particularly during care, when patients are unable to attend school or work and must incur the costs of buying costly malaria medicine. Malaria transmission is affected by climatic and environmental factors which include temperature, rainfall, relative humidity, and land use/cover type. Population density and poverty levels are the social and economic factors, as well as development factors and malaria prevention measures such as the use of insecticide-treated mosquito nets and the distribution of health facilities, indoor spraying, all play a significant role in malaria risk levels.

There is a strong link between land use/land cover and the spread of malaria worldwide (Paul et al., 2018). The development of water resources, deforestation, cultivation of wetlands, crop cover and land use for agriculture on highlands and increased urban farming expand the malaria habitat with mosquitoes which in turn boost the transmission of malaria in different places. According to various scholars, malaria is known as a rural disease and it has been discovered that urbanization reduces Anopheles mosquito breeding. However, poor environmental management and periurban agriculture, including fish ponds, provide favorable habitats for mosquitoes, thus increasing malaria transmission due to higher adult Anopheles densities and more malaria episodes than in non-agricultural locations.

Deforestation is a major risk factor for emerging and re-emerging diseases in rural areas. The wide range of human activity, such as agricultural, hydroelectric, trans-migration, construction on roads

and mining, drives deforestation. These processes modify the elements of local habitats, for instance microclimates, soil and water, and most importantly vectors for human illness such as mosquitoes and the local flora and animal ecology. Mosquitoes are highly susceptible to changes in the landscape. Vector anopheles and, in particular, larvae and adult survival, reproduction and vector capabilities are affected by deforestation and land transformations, resulting in prolonged seasonal malaria transmission. Because of the clearing of forest lands for agriculture, especially rice cultivation, and mining, anopheles mosquitoes may have a better chance of surviving. Reclamation of natural papyrus-covered wetlands that restrict the breeding of anopheles mosquito because of the papyrus and little oil in them, as well as extensive valley grown across East Africa, particularly in Uganda, were also associated with increased vector prevalence and malaria spread due to a rapid population and more food demand (Paul et al., 2018). Therefore, this study is designed to evaluate the effects of land use on malaria prevalence using the Geographical Information System (GIS) method in Luwero district.

## **1.2 Problem Statement**

Malaria is mainly a rural disease in Africa (Paul et al., 2018), and according to WHO estimates, over 400000 people die from malaria each year, with Africa accounting for 94% of these deaths.

According to the Ministry of Health's 2019/20 report, Uganda has 16 malaria deaths per day with 25000 cases and clinically diagnosed malaria accounting for 30-50 percent of outpatients, 15-30 percent of hospital admissions, and 20 percent of all hospital deaths. According to the annual health report, over 20000 people in Luwero district were diagnosed with malaria, and at least 40 people died during the financial year 2019/2020, accounting for 11% of all deaths in the district.

According to daily monitor, migrating of people from high prevalence to low prevalence areas, human activities, climate change, seasonality like rainy season have increased the malaria incidence. And also land use patterns in Luwero such as crop growing, cattle grazing, sand mining, (Wanyama, Kisame and Rwetsiba, 2017) all of which are ideal habitats for mosquitoes, thereby raising malaria transmission. This is due to the limited research and practical experience on how collaboration across the agriculture and health sectors, this is because most literature do not represent effect of land cover on the malaria yet land use/land cover changes establish new habitats or extension or reduction which leads to human presence near habitats yet most control

and preventive measures are related to reducing the number of contact of between mosquitoes and humans (Vanwambeke et al., 2007). Therefore, this research identifies the effects of land use land cover types on malaria diffusion and provide policy makers with information for regional and local policies to control malaria and minimize its effects in Luwero.

### **1.3 JUSTIFICATION OF THE STUDY**

According to UMA, Luwero's forests, woodland and bush land are cut down for the large scale agriculture and cultivation for especially pineapple and rice growing which are potential breeding sites for mosquitoes.

This study provides a better understanding of malaria exposure and transmission as a result of human activities and land use/ land cover at different scales which provides information and enhances the understanding and prediction of disease risk in order to aid Ministry Of Health and Government policymakers in their efforts to eradicate malaria and improve people's lives in the district.

### **1.4 Research Objectives**

The objectives of the study are as follows:

#### **1.4.1 Main objective**

To assess the land use/land cover changes from 2015 to 2020 and assess their relationship with malaria prevalence in Luwero district.

#### **1.4.2 Specific objectives**

1. To assess the change in land use / land cover from 2015 to 2020 in Luwero.
2. To determine which type of land cover has the most significant effect on malaria prevalence in Luwero.

## 1.5 Description of the Study Area

Luwero District is found in Central Uganda, bordered by Nakasongola District to the north, Kayunga District to the east, Mukono District to the southeast, Wakiso District to the south, and Nakaseke District to the west. Luwero district covers an area of approximately 2,217 square kilometers. It is divided into thirteen (13) administrative units Bombo town council , Luwero town council , Wobulenzi town council , and sub counties of Bamunanika, Kalagala, Kamira,

Kikyusa, Zirowe, Butuntumula, Katikamu, Luwero, Makulubita, and Nyimbwa (Profi, 2016).

The district is composed of 90 parishes and 594 villages (Wanyama, Kisame and Rwetsiba, 2017). Luwero district is considered to be part of the greater Kafu River Basin area. River Kafu is primarily a papyrus wetland, which forms a drainage sink for a large part of central Uganda. Water drains eastwards from this swamp into Lake Kyoga, and westwards via the Nkusi River into Lake Albert.

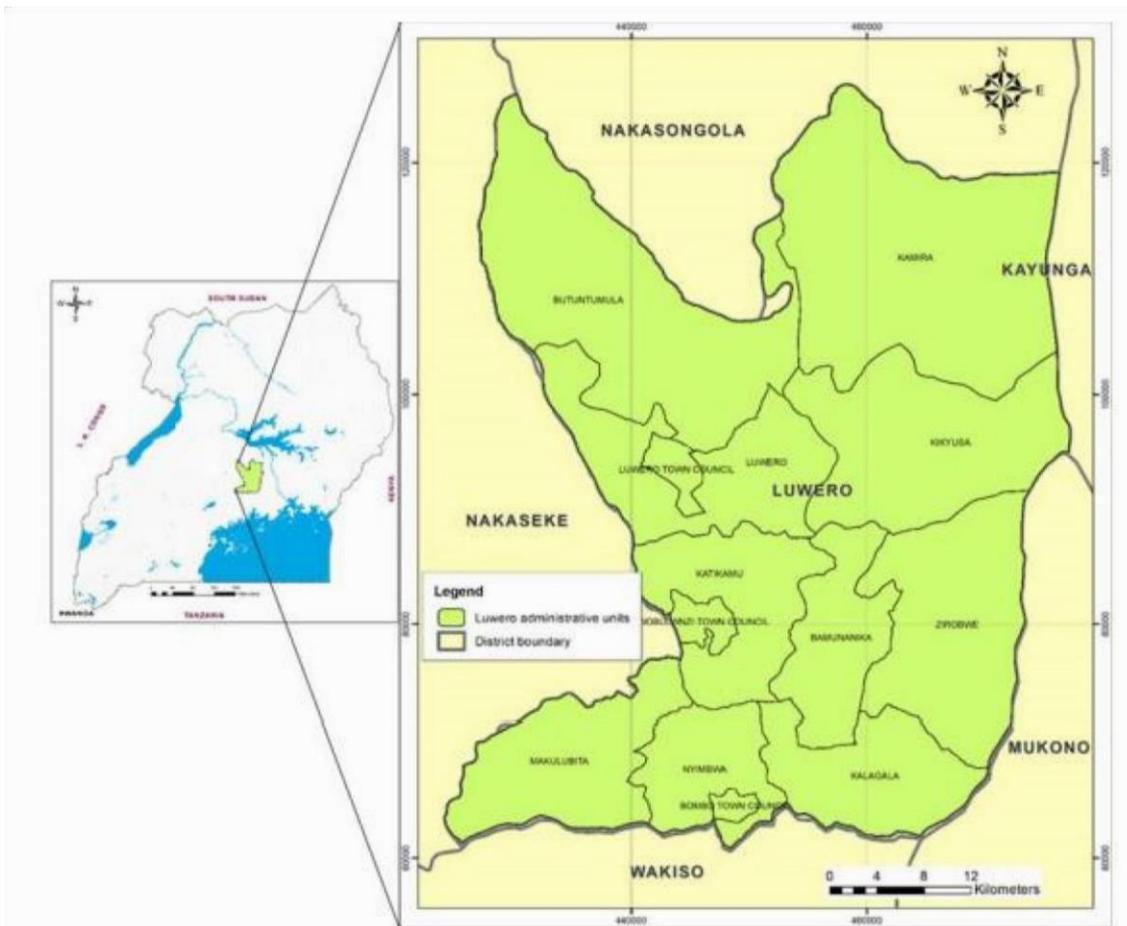


Figure 1: A map showing the administrative boundaries of Luwero district

## CHAPTER TWO: LITERATURE REVIEW

### 2.1 Malaria

#### 2.1.1 Background

Malaria is a deadly human disease caused by protozoan parasites of the plasmodium family, which is spread primarily through the bite of the female mosquito of the anopheles species and affects majority of the world's population especially those in Africa and Asia. (Abdulselam, 2020 and Mulefu et.al, 2016).

Despite a century of scientific advances in preventing, managing, and understanding the parasite and its mode of reproduction, malaria remains one of the world's most severe disease burdens. He also stated that malaria is endemic in over 95 percent of the country and is the leading cause of morbidity and mortality in Uganda, and that the country's baseline transmission potential has likely increased over the last twenty to forty years as a result of deforestation, road construction, and wetland cultivation (Wielgosz et.al, 2014). The WHO reports that modifiable environmental factors account for 30 to 53 percent of the global malaria burden (500,000 deaths). According to the Ministry of Health (MOH), malaria is the leading cause of morbidity and mortality in Uganda, accounting for approximately 8–13 million episodes per year, 30–50 percent of outpatient visits at health facilities, 35 percent of hospital admissions, 9–14 percent of hospital deaths (nearly half of which are in children under the age of five), and a large number of deaths occurring outside of health care settings (Tensaye, 2016). According to the Ministry of Health statistics, it is the leading cause of death in Uganda, accounting for more than 27 percent of all deaths (Wetaya, 2016).

Malaria is a parasitic disease that triggers fever, chills and a flu-like illness. Symptoms usually appear after a period of seven days or more after infection from a mosquito bite. Early diagnosis and treatment of malaria is key. If left untreated, the disease can lead to severe illness and death. There is no commercially available vaccine against malaria although a promising vaccine against *P. falciparum* is currently being evaluated in a large clinical trial in seven African countries. Luwero is among the hotspots for malaria in Uganda. According to Luwero District Health report for financial year 2019/20, not less than 221,910 and 40 people were diagnosed and died as a

result of malaria infections which accounts for 35.1% of all cases registered in health centers as well as

10.7% of total deaths respectively. Malaria killed at least 40 people in the most affected areas of the district which are Kikyusa and Kamira sub-counties and it constituted 11% of the total deaths across the district

### **2.1.2 Malaria Transmission**

The Anopheles mosquito is the parasite's definitive host in its lifecycle, where sexual reproduction between male and female gametes occurs, while the human theoretically acts as the intermediate host, where only asexual multiplication occurs (Tensaye, 2016). Anopheles gambiae s.l. and Anopheles funestus are the most common malaria vectors in Uganda, with A. gambiae s.l. being the dominant species in most locations. Only P. malariae, P. ovale, P. falciparum, and P. vivax infect humans out of the 30-40 Plasmodia vector types. Although all four malaria parasite species are present in Uganda, P. falciparum is responsible for the vast majority of cases (Jfdwolff, 2004). In sub-Saharan Africa, Uganda has the third highest number of P. falciparum infections and some of the highest recorded rates of malaria transmission in the world. Malaria transmission is stable and perennial in 90–95 percent of the country. In the rest of the country, particularly in the highlands, transmission is low and unstable, with the potential for epidemics (Kamareddine, 2012).

### **2.1.3 Malaria prevalence in Uganda**

Malaria kills about 90% of people in Sub-Saharan Africa today. This is because Plasmodium falciparum, the most harmful of the four malaria species, causes the majority of infections in Africa. It is the most common and difficult to manage in Africa. Malaria kills one million Africans per year, the majority of whom are children under the age of five (Tensaye, 2016).

After 2009, MIS reported a prevalence of 52%; five years later, the national prevalence had dropped to 30%. (ranging from 56 percent in the North Eastern sub-region to 6 percent in the Southwest and as low as 4 percent in Kampala). According to the 2016 national Demographic

Health Survey (DHS), malaria incidence has not decreased nationally. Some areas, such as the West Nile region, saw a significant decrease, falling from 51 percent to 25 percent, while several other regions saw increases. Malaria accounts for 20% to 34% of outpatient visits and 25% to

37% of hospital admissions in Uganda, according to data from the Health Management Information System (HMIS) in 2016. In 2016, an average of 60% of all recorded malaria cases were laboratory confirmed, with May having the highest rate at 90%. Hospital admissions have remained relatively unchanged over the last two years as compared to 2015 HMIS results, although laboratory confirmed cases have risen by five percentage points to 60 percent.

(Initiative, 2018).

#### **2.1.4 Factors that influence malaria transmission**

Because of the significant health and economic costs of malaria, there is still an increasing demand for tools that will aid in understanding the contributing elements (Nkurunziza et al., 2010). However, an unknown geographic distribution of mosquitos was identified to cause malaria, despite the fact that parasite eradication remains a tough scenario despite high resolution satellite photography and fieldwork (Tensaye, 2016). Malaria transmission is strongly linked to climatic, environmental, and socioeconomic factors, with climatic and environmental factors identifying malaria-risk areas and controlling mosquito maturity and parasite development, and socioeconomic variables determining a region's vulnerable population. Based on a review of the literature, past research, and interviews with malaria specialists, the following climatic, environmental, and socioeconomic (Eniyew, 2018) factors that have a significant impact on malaria incidence and prevalence were identified.

##### **2.1.4.1 Climatic factors**

In general, epidemiology studies on malaria in Africa have found a link between climate variables and malaria (Shem et al., n.d.). An link between climate variability and malaria epidemics has been discovered in seven East African highland locations in Ethiopia, Kenya, and Uganda, implying that climatic variability had a significant role in the outbreak of epidemics in the East African highlands (Nkurunziza et al., 2010). Interactions between maximum temperature, minimum temperature, and rainfall have a significant and favourable influence on malaria transmission. In Botswana, rainfall, temperature, and altitude were the most likely predictors of malaria prevalence (Craig et al., 2007).

## **1. Rainfall factor**

According to district-level data from 2015 to March 2017, Uganda still has two peaks in malaria transmission each year, coinciding with the two rainy seasons (Initiative, 2018). Matzarakis, Oguntoke, and Adeofun (2011) identified high-risk precipitation areas, indicating that precipitation is a key player in malaria occurrence and that increased precipitation provides more breeding sites for mosquitoes in the form of rainy water stagnation, but excess rain can also destroy breeding sites.

## **2. Temperature Factor**

Temperature can affect mosquito breeding because it affects the length of the immature stage in the life cycle. For example, malaria development is influenced because the parasite does not develop below 18 C and above 40 C. (Ferrao et al., 2018). As temperatures rise, the egg, larval, and pupil stages are shortened, increasing turnover. Temperature also affects the length of the saprogenic cycle of the parasite within the mosquito host, i.e. when temperatures rise, the saprogenic cycle is reduced (Wondim et al., 2017). (Eunice, 2018) suggested that rainfall is positively significant on malaria incidences whereas average temperature is not a significant predictor for malaria incidences based on results from Pearson correlation test in Luwero District.

However, Ferrao *et al.* (2018) mentioned that topography remains the single most important aspect for small regions, that defines large scale differences in malaria risk because climate variables change little over the limited range of latitude.

### **2.1.4.2 Environmental factors**

#### **1. Topographic (Elevation) Factor**

In general, topography has a significant impact on mosquito reproduction and, as a result, the number of malaria cases. Because elevation affects precipitation and temperature, it can be

utilised as a surrogate factor. Cooler temperatures come from higher topographies, limiting the parasite's reproduction rate (Shililu et al., 2003). According to Cohen et al. (2008), in their topography study, they produced wetness indices and household-level malaria risk in two villages in the western Kenyan highlands, indicating that *Plasmodium falciparum* transmission generally declines with rising topography. Malaria distribution and transmission vary by location in Ethiopia.

## **2. Slope Factor**

As indicated in Arega (2009), steeper slopes allow the fast movement of water and they have less chance to accumulate stagnant water. Hence, it is unlikely to attract mosquito. Relative to steeper slopes, gentler slopes are slopes where surface water movement is stagnant which creates favorable situation for mosquito breeding.

## **3. Distance Factor**

The most obvious factor influencing the distribution of mosquitoes is the distribution of breeding sites (Efe and Ojoh, 2013). Larval mosquitoes are usually highly aggregated in pools of waters with specific characteristics (Gimnig, Hightower and Hawley, 2007). A malaria mosquito prefers for breeding mainly water collections from rains. However, the mosquito breeds also in intermittent rivers and streams, around ponds, swampy and marshy areas, slowly running shallow irrigation waters and around shallow dams. Therefore the distance from breeding sites is based on

## **4. Land Use Land Cover**

The LULC has a direct impact on malaria burden due to its effects on breeding sites, adult mosquito survival rate, and dispersal (Martens & Hall, 2000). Malaria mosquitoes in Uganda prefer rainwater collecting for reproduction. The mosquito, on the other hand, breeds in irregular or broken rivers and streams, near ponds, swampy and marshy places, slowly running shallow irrigation waters, and near shallow dams. Furthermore, as mentioned by Malhotro and Srivastava (Don & Pandu, 1995), the quantity of water in irrigated areas as a

result of seepage, silting, and stagnation creates an excess of locations for malaria vector hatching. Land use land cover change could allow the establishment of new habitats or the extension or reduction of a vector's range, but could also modify the composition of the mosquito vector community, because vector species differ in their habitat preferences for the immature stages

### **2.1.4.3 Socio-Economic Factors**

#### **1. Population Density**

Historically, population movement has contributed to the spread of disease through interactions between infected and uninfected people. Population movement, on the other hand, can hasten or increase malaria transmission in other ways. As people move, they can increase their risk of contracting the disease by changing the environment and introducing new technology, such as deforestation and irrigation systems (Martens & Hall, 2000), which can create new places for mosquito larvae to develop and increase mosquito breeding sites; at the same time, workers may be exposed to more mosquitos. There is a positive correlation between the number of people and *Anopheles* mosquitoes living in a particular region, and the intensity in which the disease can be transmitted. When population densities are high, there is a greater likelihood malaria will be transmitted and vice versa (Eniyew, 2018).

### **2.1.5 Malaria Control Measures in Uganda**

Efforts to eradicate the burden of malaria by targeting the *Anopheles* vector, have intensified recently through the use of effective tools for malaria control, notably long-lasting insecticide treated nets (ITNs), indoor residual spraying (IRS) of insecticides, long lasting insecticidal material (LMs), treatment with artemisinin-based combination therapies (ACTs), intermittent preventive therapy (IPT) for high-risk groups, space spraying, introduction of the Village Health Team (VHT) concept in 2001 (Kimbugwe et al., 2014) and proper preventive measures. These efforts have been made possible by recent focused policy recommendations and increased support from governments and international organizations (Kamareddine, 2012).

#### **□ Insecticide-treated mosquito nets (ITNs)**

ITNs include long-lasting insecticidal nets (LLINs), where the insecticide lasts for up to 3 years, and nets conventionally treated, where the insecticide is active for up to 12 months. WHO

recommended that all health ministries and donor agencies scale up the distribution of ITNs, specifically to target populations of small children and pregnant women (WHO, 2007) since they are the population at risk. Long-lasting ITNs are the main preventive strategy used in Uganda. Since 2006, over 3 million ITNs have been distributed nationwide. With continued support from the President's Malaria Initiative (PMI) and the Global Fund for AIDS, Tuberculosis, and Malaria, the NMCP aimed to increase the number of households owning one or more ITNs to at least 85%, the number of households owning two or more ITNs to at least 60%, and the percentage of pregnant women and children under 5 who will have slept under an ITN the previous night to more than

85% (Yeka et al., 2012). There still exists a large gap both in terms of ownership and utilization.s

#### □ **Indoor residual spraying (IRS)**

Indoor residual spraying was the main strategy of the Global Malaria Eradication Campaign which resulted in the elimination of malaria from many countries and greatly reduced its burden in others (**WHO, 2015**). Inclusion of IRS in control programs was reinitiated in Uganda, after a gap of about 40 years, in 2006. The NMCP strategy for IRS, supported by PMI, has emphasized implementation in epidemic-prone areas, high transmission settings, and high-risk situations, such as camps for internally displaced persons or refugees (Yeka et al., 2012). A study in Uganda during 4–18 months following discontinuation of IRS, absolute malaria test positivity rate (TPR) values increased by an average of 3.29% per month.

- **Village Health Teams (VHTs)**

The Village Health Team (VHT) concept that serves as a community's initial point of contact for health care became part of Uganda's National Health Strategy in 2001. Mortality and morbidity rates in Uganda are among the highest globally ("Uganda Program Brochure," 2012) and in response to this crisis, the Uganda Ministry of Health (MoH) created this program to bring basic preventive care to rural villages. VHTs in Uganda provide the lowest level of care at the village level, classified as Health Center I (HC-1) and serve an average of 100 households of approximately 500 people. The VHTs provide a range of preventive health care services, and in some districts where there is support (Initiative, 2018), with members' selection done on a

popular vote and the team must be gender balanced with at least a third of women (Kimbugwe et al., 2014).

- **IPT for high-risk groups**

Intermittent preventive therapy (IPT) with SP is a full course of anti-malarial medicine that has shown to reduce clinical malaria, anemia, and mortality (Tizifa et al., 2018). It is aimed for the high-risk groups such the children below 5 years and pregnant mothers. The original policy for IPT with SP treatment once during the second and third trimesters for pregnant women was adopted in Uganda in 1998. IPT is administered as part of an integrated package of care through antenatal clinics, with directly observed treatment. Uganda has a high level of antenatal clinic attendance (95% of pregnant women according to the 2009 UMIS). However, according to the 2007 UBOS statistics, the 2006 UDHS indicated that only 37% of pregnant women received at least one dose and only 16% received two doses of SP, with coverage varying greatly in different parts of the country (Yeka et al., 2012).

## **2.2 Land Use/ Land Cover Patterns Associated With Malaria Transmission**

### **2.2.1 Agriculture**

Agriculture is the primary means by which rural populations manage and modify their environment which makes it an especially important strategic element of rural malaria control. The interactions between agricultural systems and malaria have been documented and studied extensively but the primary consideration is how agriculture can alter the local reproductive rate of malaria transmitting mosquitoes or reducing malaria transmission in rural populations. In the case of Uganda, cultivation of maize, rice, cotton, and a variety of tree crops have been identified as potentially impacting rural malaria transmission for varying reasons.

Maize is the most widely cultivated crop in Uganda and may contribute to vector reproduction as its pollen is a food source for the larvae of anopheles vectors in Africa.

Cotton by comparison has a robust history of interaction with malaria vectors based on the heavy agricultural pesticide-use associated with the crop which may lead to local insecticide resistance.

Rice is a crop of particular interest for malaria control due to the potential for interaction between irrigation systems and mosquito reproduction.

Tree-Crops may also play a role in anopheles reproduction. Many species of anopheles mosquitoes have been documented as adapting based on local agroforestry patterns. In some cases the *Anopheles gambiae* uses tree holes in specifically in acacia, avocado, and mango trees as breeding sites.

### **2.2.2 Settlement.**

Settlement places like homes tend to be surrounded by vegetation. Mosquitoes are known to use vegetation as resting places, which can be seen near homes in several communities. It is from such resting places that mosquitoes approach and enter houses, commonly in the evenings and at night, from where they transmit malaria. Consequently, maintaining vegetation near houses facilitates the presence of mosquitoes in an area because of availability of resting places. Harboring mosquitoes near houses also facilitates their entry because of the reduced distance they have to travel.

### **2.2.3 Brick making**

Brick making drains stagnating water in form of small and large pools of water around homesteads which cannot be easily eliminated. For the small pools they dry out quickly without rain but the larger mud pools hold water for a longer period of time and support stagnant water which are potential sites for mosquitoes breeding. These are mostly made during the dry season and normally for business purposes and own house construction (Paul et al., 2018). The brick making pits have also been found to increase the outbreak of malaria in Uganda.

### **2.2.4 Water and wetlands**

Water class (including deep water, shallow and shady water, wetlands and fishponds) is a predominant risk factor for malaria transmission because it can form vector-breeding sites. However, the deep water class remain a protective factor against malaria as it does not allow the formation of breeding sites for mosquitoes (Stefani et al., 2013)

### **2.2.5 Vegetation**

Mosquitoes are known to use vegetation as resting places. During the dry season, the resting sites can be sparse and the amount of available vegetation could affect mosquito survivorship and dispersal away from the home. Vegetation around a homestead is likely to be an important determinant of malaria transmission and may promote the abundance of adults and/or larvae of malaria vectors (Stefani et al., 2013).

## **2.3 Ecological changes and “exposure risk”**

The distribution of malaria is determined by climate and other geographic factors that influence the development of mosquitoes and Plasmodium at a given time, but it is also influenced by environmental alterations over time. Ecosystem changes resulting from natural phenomena or human interventions, on a local or global scale, can alter the ecological balance and context in which vectors and their parasites develop and transmit the disease (Patz et al., 2000). Patz & Olson, (2006) says that changes in temperature patterns, due to global climate change and in variation in local land use practices, may alter malaria risk. Some authors directly relate environmental alteration to cases of malaria. Adjusting for population, access to care and district size, a 4.3% increase in deforestation between 1997 and 2000 was associated with a 48% increase in malaria risk. Vittor et al., 2006 and Vittor et al., 2009 suggested that deforestation and other human environmental alteration favour the presence of both *An. darlingi* larvae and adults . However, Conn et al., 2002 and Moreno et al., 2007 suggested that human intervention could increase the presence of *An. marajoara* over *An. darlingi*: forest clearance and pollution may reducing the availability of larval sites for *An. darlingi* and increase habitats preferred by *An. marajoara*.

## **2.4 Previous Methods**

### **2.4.1 Remote sensing and Malaria**

Earth observation satellites permit to acquire wide ranging data concerning the continental surfaces of the Earth, with very different techniques (optical or radar imagery, radar altimetry, etc.). These data differ in their spatial, temporal, radiometric and spectral resolutions and can therefore document many environmental features at different spatial and temporal scales. The use of remote sensing (RS) to provide new insights for epidemiological studies was identified very early (Cline, 1970), as many diseases have been linked to environmental features. Herbreteau et

al. (2007) found that RS was often, and increasingly, used to study parasitic diseases including malaria. The challenge, when studying malaria, is to identify all the natural factors (such as seasonality, rainfall, temperature, humidity, surface water and vegetation) and anthropogenic elements (such as agriculture, irrigation, deforestation, urbanization and movements of populations) of the study area, and to link them with either the incidence of disease or the presence of vectors whilst also integrating temporal and spatial variations. This would then enable the identification of risk factors from the set of possible environmental parameters. Remote sensing (RS) and geographic information systems (GIS) have proved to be an innovative and important component in studies of public health and epidemiology and have been used for monitoring, surveillance and spatial modelling of diseases, provide examples of how earth observation satellites can be used in studies of ecology and prediction of malaria, and have contributed with examples for the mapping of malaria vectors, using mid-resolution RS imagery such as Landsat ETM or SPOT (De Oliveira et al., 2013).

#### **2.4.2 Geographical Information System in Malaria Control**

Recently, Geographical Information System (GIS) has emerged as a tool for the efficient storage, analysis, and presentation of geographical data and as an innovative and important component of many projects in public health and epidemiology (Ottawa et. al., 1995 and Salui, 2017). One of the most useful functions of GIS in epidemiology continues to be its utility in basic mapping. GIS may also involve more sophisticated spatial analysis of disease occurrence and contributing environmental factors (Salui, 2017). The application of remote sensing and GIS has been significantly developed over the past 25 years for ecological modeling with special emphasis on vectors and vector-borne diseases. These studies were conducted on the appreciation of remote sensing and GIS applications to the study of vectors' bio diversity, vector presence, vector abundance and the vector-borne diseases with respect to space and time.

GIS facilitates the integration of quantitative malaria determination and control data with data obtained from maps, satellite images, and aerial photos (Ottawa et. al., 1995).

GIS serve as an important platform for preparing, mapping and modeling various variables related to malaria for example elevation, wetland, distance from roads and river, urban areas and population density (Mulefu et. al., 2016). Remote Sensing also plays an important role by

providing environmental information such as timely satellite image, DEM and LULC data of the study area. Thus, researches show that GIS and remote sensing are important to create operational maps which could help the concerned bodies to identify hazard and risk areas for disease management. Risk maps are fundamental for estimating the scale of the risk, and hence the resources needed to combat malaria. GIS tools facilitate a systematic and comprehensive prevalence mapping in a more effective and scientific way by combining and spatially assessing multiple factors (Salui, 2017). This method is worthy especially, because it contributes lot to more informed decision and policy making process in terms of planning for intervention and controlling malaria (Eniyew, 2018). Hence, it will be effective if the results of this study will be incorporated into ongoing malaria eradication programs at national level in general and in the study area in particular by World Health Organization and the Ministry of Health.

### **2.4.3 Household interviews**

It involves use of structured questionnaires to the households, key informant interview, transect walks and direct field observations.

Household interviews involves selecting a sample of households using any sampling technique to represent the households in the study area.

- **The structured survey questionnaires;**

This covers various aspects related to types of land uses/cover and patterns related to malaria transmission, control methods employed by the inhabitants , information on household demographic characteristics, land use information including crop production and animal husbandry, household livelihood and anthropogenic activities associated with malaria transmission, including people's knowledge, perceptions, and behaviours in relation to malaria transmission and control.

- **Key informants interviews;**

Its focuses on the types of land cover / use and natural resources management practices in relation to malaria transmission. These include various district officials like medical officer, planning officer, lands officer, forest officer, education officer, community development officer, executive officer and water engineer, village leaders and village natural resources committees.

- **Field observations;**

This involve transect walks following in-depth discussions with key informants. These transect walks enable general observation of the land use patterns, vegetation types and distribution, farming methods and mosquito breeding sites.

## **2.5 Change detection methods**

Changes occurring on the earth's surface can be attributed to either natural or anthropogenic forces. Natural changes are related to both seasonal and annual variations in climatic conditions, and are often reflected by variations in natural land cover. The change detection procedures assume that a change in surface cover will produce a corresponding change in the reflectance of the study area. Change detection helps in finding the relationship between human interactions with environment in order to have a better understanding and decision making. Many change detection techniques have developed recently; the most commonly used are image differencing, principal component analysis and post-classification comparison.

### **2.5.1 Image differencing.**

Image differencing is an image processing technique used to determine changes between images. The difference between two images is calculated by finding the difference between each pixel in each image, and generating an image based on the result. For this technique to work, the two images must first be aligned so that corresponding points coincide, and their photometric values must be made compatible, either by careful calibration, or by post-processing. The complexity of the pre-processing needed before differencing varies with the type of image.

Image differencing is a method of subtracting the DN (Digital Number) value of one data with the other one of the same pixel for the same band which results in new image of images taken from two different time period and represents difference image (Karthik & Shiva Kumar, 2017).

### **2.5.2 Principal component analysis**

Principal component analysis (PCA) is a pixel based change detection method widely used for land cover change detection. It is computationally expensive compared to spectral index or image differencing methods but produces considerably more output information. Given a

multidimensional dataset, PCA will find a new set of uncorrelated axes or principal components (PCs) such that the first PC contains the majority of the variance contained in the data. PCA can be applied by computing the eigenvectors of the covariance or correlation matrix of the input data. An additional matrix of eigenvalues is produced where each entry describes the variance captured in the corresponding PC. PCA using the covariance matrix is referred to as unstandardized PCA whereas PCA computed with the correlation matrix is termed standardised PCA. Both standardised and unstandardized PCA are commonly applied through Singular Value Decomposition (SVD). This is an efficient and more robust method than eigenvalue decomposition and additionally produces a matrix of Singular Values (SVs), which are directly related to the eigenvectors (Sule, 2020).

### **2.5.3 Post-classification comparison**

The post classification approach is the comparative analysis of independently produced classifications for different dates. The post classification approach is used for detecting, monitoring and assessing land cover changes basing on the comparative analysis of independently produced classification images of the same area at different dates. It gives the size and distribution of changed areas (either negative or positive), but also the percentages of other land cover classes that share in the change in each land cover class individually (El-Hattab, 2016).

## **2.6 Spatial Modelling Framework for Disease Mapping**

### **2.6.1 Overlay Analysis**

Overlay analysis is the simplest form of spatial modelling, and consists of stacking different thematic maps on top of one another. Firstly, since each hazard or risk element is represented as a separate layer, it is possible to modify each element individually to re-assess the final risk layer. This eases evaluation of different adaptation strategies to determine how best to mitigate the risk faced in particular areas due to malaria outbreak. Secondly, by developing this GIS method it is possible not only to identify current areas where adaptation is most necessary to deal with the risks posed by malaria, but also possible to identify areas that are most at risk in the future.

### **2.6.2 Interpolation**

Interpolation is a process whereby known data points are used to infer values over a space between the points to create a continuous surface. For example, data from a network of pollution monitoring stations may be interpolated to estimate the most likely values between sample locations. There are several different types of interpolation, including kriging, inverse distance weighting (IDW), splining and Thiessen polygons (Bailey & Gatrell, 1995). Although such models are often used to predict likely values for exposure assessments, they can also form the basis of visualizing spatially continuous data.

## **2.8 Related Studies**

Several studies have been carried out on malaria incidences through employing of various models. For example: Musa *et al.* (2012), examined the relationship between malaria and environmental and socioeconomic variables in the Sudan using health production modified model. The regression results showed significant relationships between malaria and rainfall and water bodies. Other variables including Human Development Index, temperature, population density and percent of cultivated areas were not significant.

Eunice (2018), employed the Poisson and negative binomial regression models to model the climate variables that is; rainfall and temperature, and how they are associated with malaria incidences in Apac District. Negative binomial model provided a better fit as compared to the Poisson regression model as indicated by the residual plots and residual deviances due to over dispersion in the data. The result obtained suggested that rainfall was positively significant on monthly malaria incidences whereas average temperature was not a significant predictor for malaria incidences based on results from Pearson correlation test in Apac District. This study showed a significant association between monthly malaria incidence and climate variables that is rainfall and temperature.

(AREGA, 2009), employed the Pair wise Comparison method for weighting environmental and socio-economic factors which he used for mapping malaria hazard areas and then the malaria risk areas at Awassa and Wondongenet Woredas. The layers were combined by using weighted multi criteria evaluation. The basis for the calculation of the map was the risk computation model developed by Shook (1999) after which 68% of the total area is highly exposed to malaria hazard and more than 60% is under high risk of malaria.

## CHAPTER THREE: DATA AND METHODS

### 3.1 Introduction

The study is aimed at first identifying changes in the land use/cover and malaria prevalence and then the relationship. To detect the changes in land use/cover, land use/cover maps will be used depending on related previous works (Vanwambeke et al., 2007). To determine the relationship malaria and Land Use Land Cover parameters will be used (Barbieri et al., 2005).

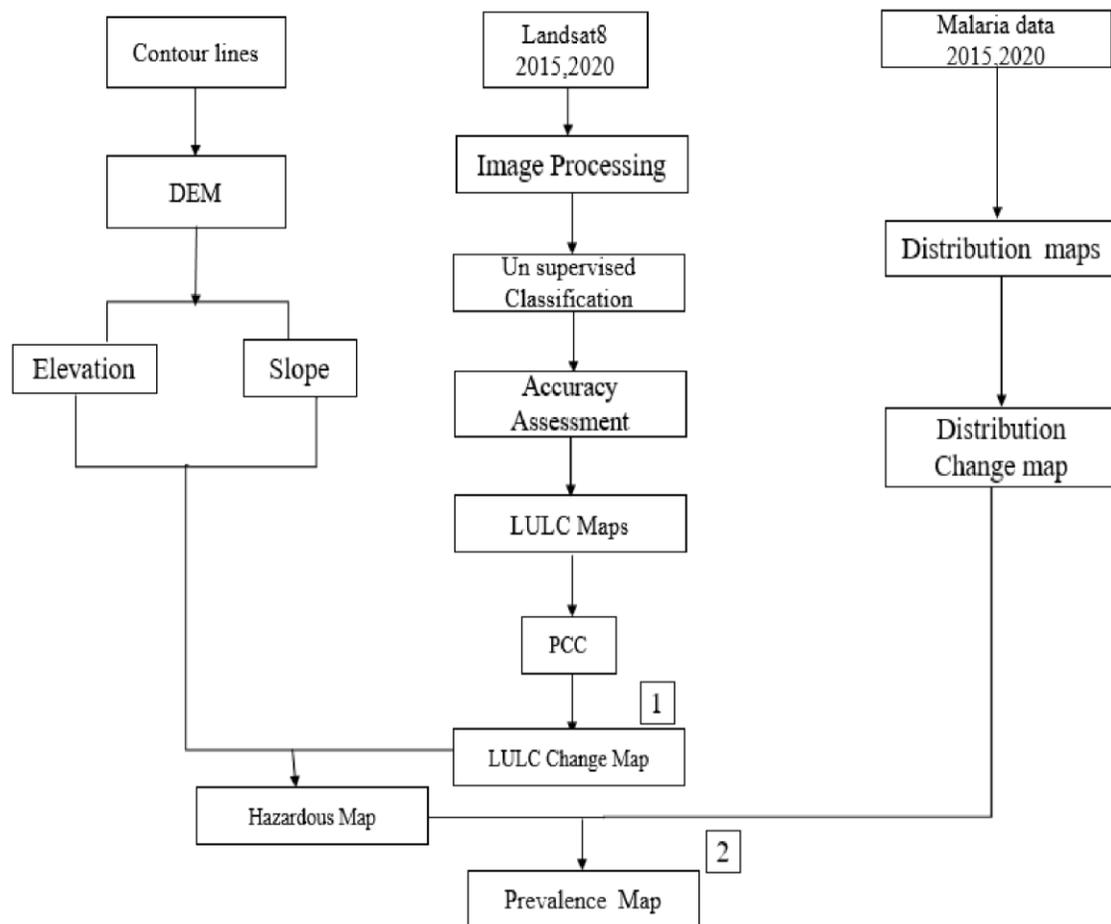


Figure 2: Flow chart for the adopted methodology

### 3.2 Data Acquisition

The data for this topic was classified into three sets namely; remotely sensed imagery, GIS data and epidemiological data.

No.	Types of data	Description	Spatial resolution	Year of acquisition	Format	Source of data
1	Land cover images	Land sat 8 imagery	30m	2015 and 2020	Raster	USGS
2	Contours data	Uganda_SRTM20 DEM	20m	2019	Vector	ASTER
3	Malaria	Malaria data	-	2015 - 2020	Excel	Luwero district
4	Administration boundaries	District, sub county and parish data	-	2019	vector	UBOS

Figure 3: Data types used and their details

### 3.2.1 Software and materials used in the project

The software types used for different types of activities in the process of generating **malaria risk zone** map include: Q GIS 3.10, ENVI classic and Microsoft excel 2013.

### 3.2.2 Data Processing

Malaria transmission is strongly associated with environmental conditions, which control mosquito maturity and parasite development (Musa *et al.*, 2012). This study focused on environmental factors such elevation, slope, distance from breeding sites (water), and LULC. To assess the relationship between land use and malaria of the study area using GIS and Remote Sensing was used.

### 3.3.3 Preparation of Data layers

QGIS and ENVI software were used for the data entry and processing of all the data. The generation of thematic layers involved the environmental factors which include; Elevation, Slope and Land Use/Land Cover factors. The elevation and slope layers were obtained by processing the SRTM 20 x 20-meter resolution Digital Elevation Model (DEM) obtained from the contour lines of Luwero district. It was added into Q GIS where the layers were generated. ENVI software was used to process (enhancement and classification) the Landsat 8 images of the study area into a .geotif, while other datasets were processed with the use of QGIS software. The administrative boundaries vector dataset of Luwero district were merged and dissolved with the .geotif image in QGIS to create the data set for Luwero district. The epidemiological data in csv format was integrated in Q GIS to create a shape file which was then merged with the administrative boundaries vector dataset of Luwero district to create shape file for the district which was expressed as thematic layer for malaria distribution. The layers were then converted to raster using Conversion Tools/Feature to Raster and classified into five classes from the layer properties, basing on the previous research. Each of the factors was expressed as a thematic layer using Q GIS.

## **Image Processing**

The Landsat TM images obtained were surface reflectance and did not require geometric, radiometric and atmospheric correction. The image bands (2, 3, 4, 5, 6 and 7) were added into ENVI which were merged in the order of 2, 3, 4, 5, 6 and 7 into composite images, using the *composite bands display*. The three composite images were mosaicked to form one single .tif image as shown below. Using the Luwero extent shape file, the mosaic was clipped to create an image of the study area.

## **Image classification**

### **Unsupervised classification**

This study unsupervised classification because of difficulty in the manual visual interpretation. Unsupervised classification using ISODATA Algorithm was performed on each of the images. ISODATA algorithm clusters pixels using minimum distance technique (Lillesand *et al.*, 2014). This technique generates clusters depending on the similar spectral characteristics inherent in images and then the user assigns classes to with help of some little knowledge of the study area and this is done by reclassification.

### **Reclassification and Assigning.**

Un supervised classification generates clusters depending on the similar spectral characteristics inherent in images and creates many classes which need to be grouped or reclassified into classes that best suit the study. This was done by exporting the classified image as .geotif from ENVI, then added to Q GIS as raster and assign and reclassify it using the Semi-Automatic Classification Plugin tool (SCP). This was reclassified to five class; water, wetlands, vegetation, agriculture and built-up. The results were used to do post classification reclassification and change detection.

<b>Land use /cover class</b>	<b>Description</b>
Built-up area	Includes industrial, commercial and residential areas. Also includes man-made structures such as roads & bare land around settlements
Agriculture	Cropland, cultivated wetland and pasture land
Wetland	wetlands
Vegetation	Tree cover and shrubs
Water	Ponds, dams

Figure 4: Description of Land Cover categories

### 3.3.3 Change Detection Assessment

Changes occurring on the earth's surface can be attributed to either natural or anthropogenic forces. Natural changes are related to both seasonal and annual variations in climatic conditions, and are often reflected by variations in natural land cover. Many change detection techniques have developed recently; the most commonly used are image differencing, principal component analysis and post-classification comparison (Lu et al., 2004). The post-classification change detection technique will be used in this study, because it does not only give the size and distribution of changed areas (either negative or positive), but it also gives the percentages of other land cover classes that share in the change in each land cover class individually (El-Hattab, 2016).

The change detection will be performed on the land use/cover maps using post classification comparison method to obtain the land use/cover changes maps (thematic layer), then also the changes in the thematic maps of the malaria distribution with done to create thematic layers.

## 3.4 Overlay Analysis

The thematic layers were overlaid to obtain the maps of interest.

### 3.4.1 Malaria Hazard Analysis

Hazard is the probability of occurrence of damaging natural phenomenon within specified period of time (Arega, 2009). For the purpose of identifying areas of malaria hazard, this study focused on, elevation factor, slope factor and LULC factor as the environmental factors of malaria incidence in the study area. The malaria incidence and transmission requires the environment

with lower elevation (higher temperature), abundance of wet lands and agriculture, occurrence of gentle slopes and availability of waters (Tensaye, 2016). The factor layers were classified, and overlaid by the stacking to produce a hazard layer of the study area.

### **3.4.2 Malaria Prevalence Analysis**

Mapping of malaria prevalence included hazard and malaria distribution change layers. The layers were overlaid to obtain the prevalence map. This was used to show areas of very high to very low prevalence in relation to land use /cover to see which LULC types most affects malaria.

## CHAPTER FOUR: RESULTS AND ANALYSIS

### 4.1 Environmental Factors

Malaria transmission is strongly associated with environmental conditions, which control mosquito maturity and parasite development. Based on literature search (AREGA, 2009), previous works, and interviews with malaria experts, the following environmental factors that greatly influence malaria incidence and prevalence were presented.

#### 4.1.1 Elevation Factor

The elevation layers illustrated below was generated from the DEM that was generated from the contour lines, classified, reclassified and assigned new values ranging from 1 to 5. These were categorized into very high, high, moderate, low and very low respectively basing on how favourable they are for mosquito breeding.

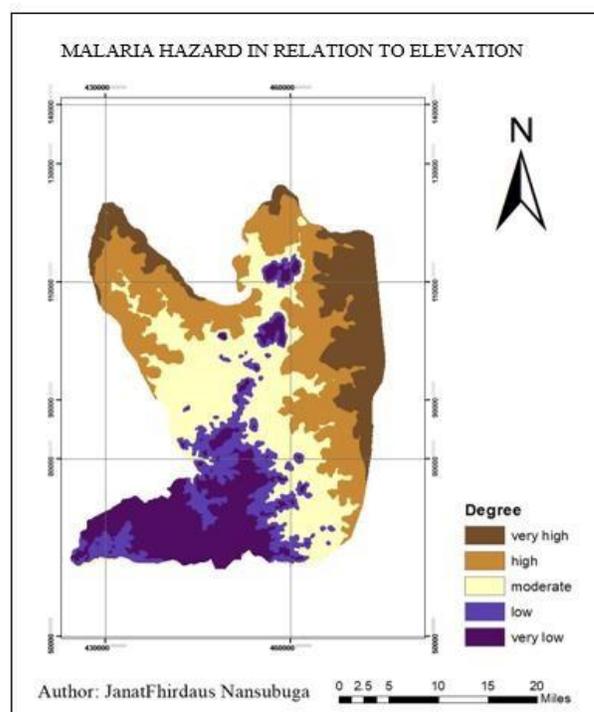


Figure 5: An image of the reclassified elevation layer of Luwero district

### Discussion of the results

Elevation generally has a great influence on mosquito replication and thus affects the rate of malaria cases. Very high elevations result in very cool temperatures, which limits the reproduction

rate of the parasite (Eniyew, 2018). And as stated by Bishop and Litch (2000), transmission does not occur at altitudes above 2,000m. Since Luwero's elevation ranges from 1025m a.s.l to 1,385m, it is prone to any malaria outbreak.

□ From the results, very low elevation with very high risks to malaria is observed to be covering the largest geographical area of the study area, while high and very high elevation areas are observed to be the small in the study area covering of the study area. This implies that the largest part of the study is favourable for mosquito breeding, which exposes many people in those areas to malaria outbreaks.

#### 4.1.2 Slope factor

The slope layer illustrated below was generated from the DEM, classified, reclassified and assigned new values ranging from 1 to 5. These were categorized into very high, high, moderate, low and very low respectively basing on how favourable they are to malaria prevalence.

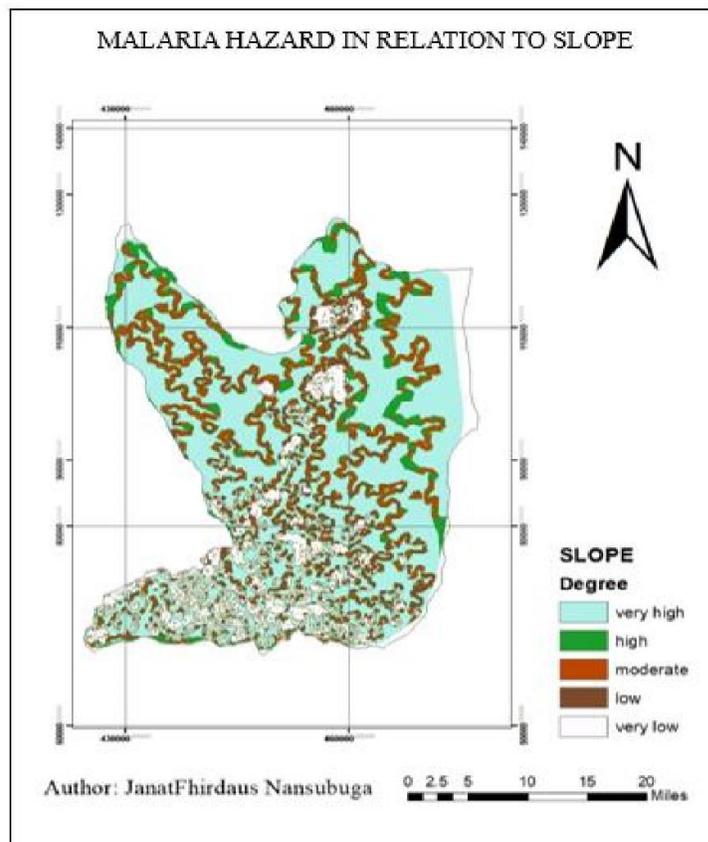


Figure 6: An image of the reclassified slope layer of Luwero district

## Discussion of the results

As indicated in AREGA (2009), steeper slopes allow the fast movement of water and they have less chance to accumulate stagnant water. Hence, it is unlikely to attract mosquito. Relative to steeper slopes, gentler slopes are slopes where surface water movement is stagnant creates favorable situation for mosquito breeding. Thus, relatively, gentler slopes are more favorable for malaria mosquitos breeding than steeper slopes due to their high capacity of accumulating stagnant water as heavy rainfall showers the area (Fig 6).

- Therefore, slope analysis result reveal that, the majority of the study area falls under the slope which gentler slopes covers 49.2% of the total study area. This implies that the study area is highly hazardous.

### 4.1.3 LAND USE LAND COVER FACTOR

#### Results of classification and accuracy assessment

The total area classified is 5847.93ha. Seven Land cover categories were classified namely: built up area, water, vegetation, agriculture, and wetland. The classification produced the most satisfactory classified maps and had the highest accuracy.

From the statistics in table and the pie chart in figure, water, wetlands and vegetation reduced and agriculture and built-up increased from 2015-2020. Figure 10 shows that wetlands dominate the Kamira sub county of the study area, where as agricultural areas are equally distributed but most in the Kamira and Butuntumula sub counties.

*Table 1: Producer and user accuracy showing the probability that the classified pixels in each land cover represent the category on ground.*

Class	2015 Accuracy (%)		2020 Accuracy (%)	
	User	Producer	User	Producer
Built up area	100	100	100	100
water	90	100	100	97.22
vegetation	89.86	98.41	86.5	91.11
Agriculture	82.76	76.67	95	97.62
Wetland	84.88	74.44	88.12	100
<b>Overall accuracy</b>	<b>90.98</b>		<b>89.35</b>	

*Table 2: The area in sq. km occupied by each land cover class in 2015 and 2020*

Land cover class	Total Area(sq. km) in 2015	Total Area(sq. km) in 2020
Built up area	263.82	366.01
water	62.90	25.56
vegetation	648.26	557.08
Agriculture	687.55	880.30
wetland	553.42	386.99

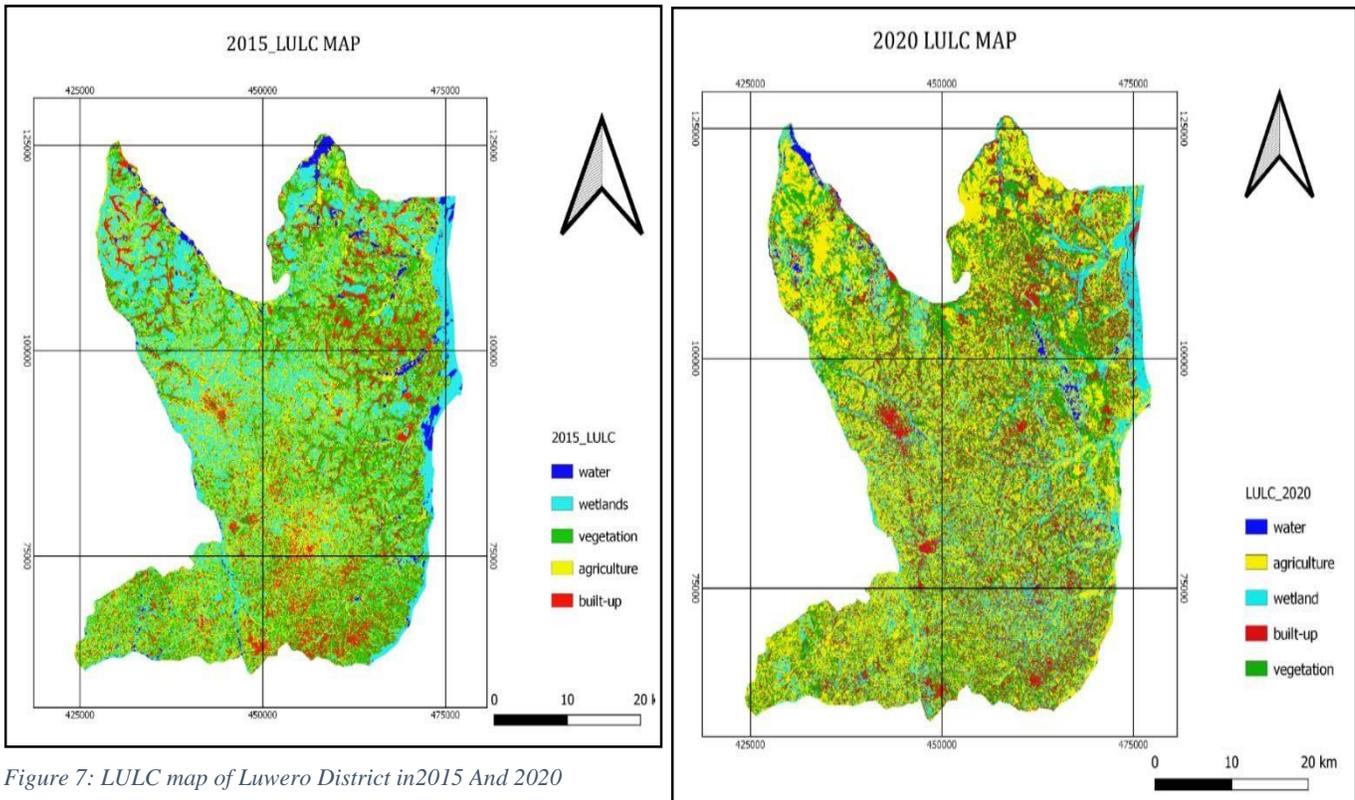


Figure 7: LULC map of Luwero District in 2015 And 2020

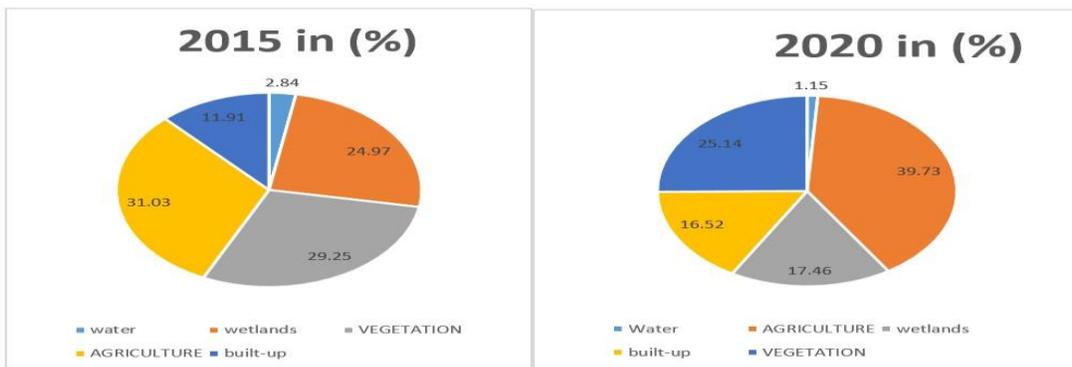


Figure 8: Pie-charts showing the proportion of each LULC of Luwero in 2015 and 2020

#### 4.1.3.1 Spatial-temporal analysis of land use and land cover using PCC

In table, it is evident that 59.4%, 30.1% and 16.17% of water, wetlands and vegetation respectively were lost with in a period of 5years (i.e. 2015 – 2020) and was due to increase in agriculture and built-up of 29.4% and 16.67% respectively.

CLASS	2015	2020	Percentage change (%)
Water	62.90	25.56	-59.4
AGRICULTURE	687.55	880.30	29.4
wetlands	553.42	386.99	-30.1
built-up	263.82	366.01	16.67
VEGETATION	648.26	557.08	-16.17

Figure 9: The percentage change of each land cover class of Luwero district in 2015 and 2020

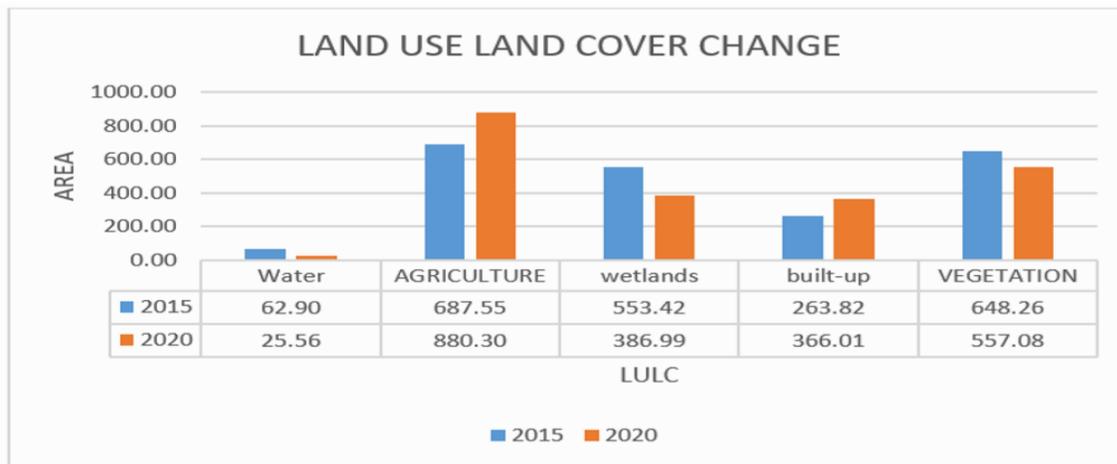
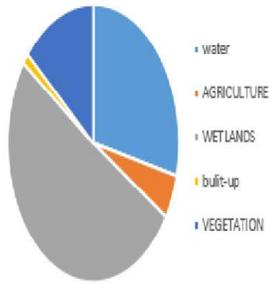


Figure 10: A graph showing the change in each land use land cover of luwero district in 2015 and 2020

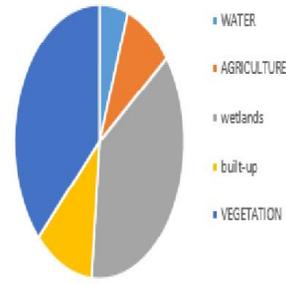
Table 3: A table of land use land cover change matrix

LAND USE LAND COVER CHANGE MATRIX [Sq. km]						
	2020					
2015	WATER	AGRICULTURE	WETLANDS	BUILT-UP	VEGETATION	Total
WATER	2.99	20.19	20.40	8.05	11.27	<b>62.90</b>
AGRICULTURE	7.29	289.89	122.93	98.82	168.62	<b>687.55</b>
WETLANDS	5.01	323.96	111.38	44.89	68.18	<b>553.42</b>
BUILT-UP	6.15	192.33	103.66	140.54	205.59	<b>648.26</b>
VEGETATION	4.11	53.94	28.62	73.71	103.43	<b>263.82</b>
<b>Total</b>	<b>25.56</b>	<b>880.30</b>	<b>386.99</b>	<b>366.01</b>	<b>557.08</b>	<b>3488.73</b>

2015-2020 PERCENTAGE CHANGE TO WETLANDS FROM



2015-2020 PERCENTAGE CHANGE TO WATER FROM



2015-2020 PERCENTAGE CHANGE TO AGRICULTURE FROM

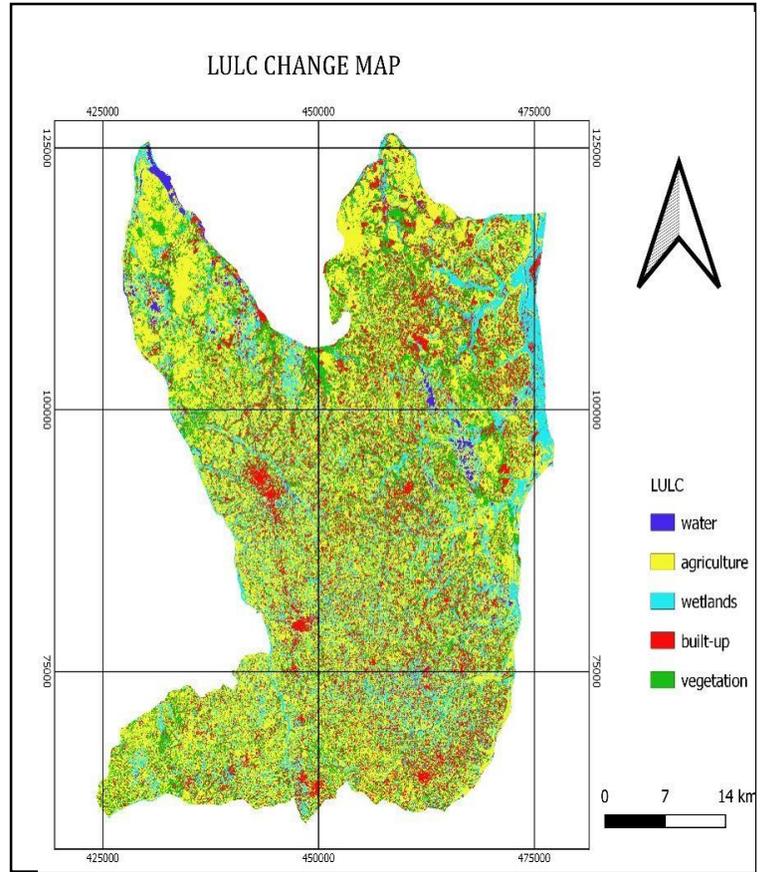
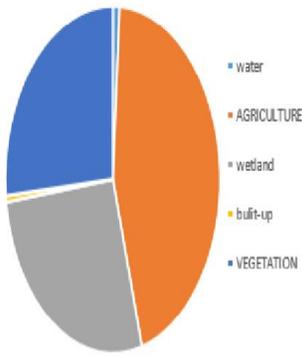
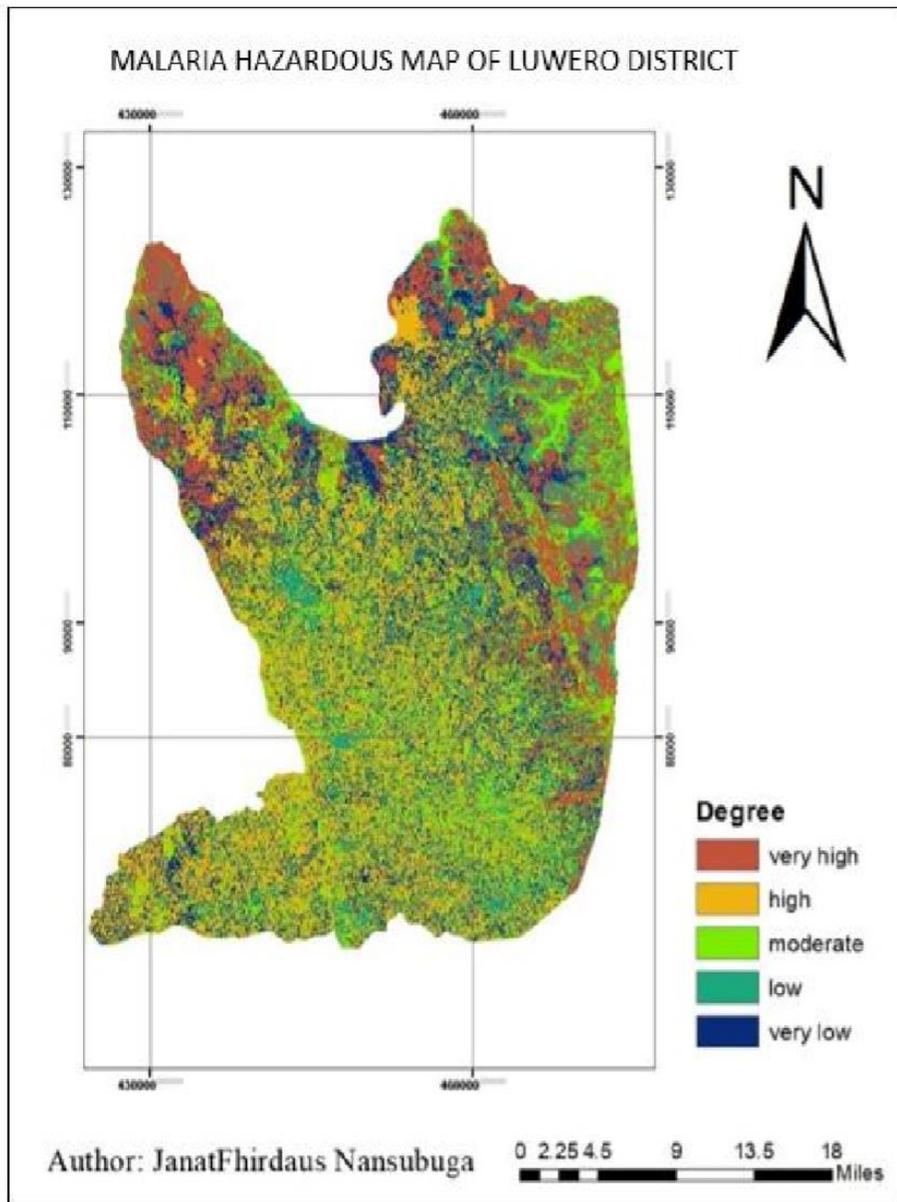


Figure 11: Pie-charts showing percentage increase of water, wetlands and agriculture and THE LULC CHANGE MAP

## 4.2 Malaria Hazard Analysis

Environmental factors such as elevation, slope, and LULC were considered as factors for malaria hazard areas in this study. The factor layers as for LULC it was change layer that sh were overlaid basing what has the most significant to generate the malaria hazard layer.



*Figure 12: A map showing the degree of hazard in Luwero district.*

Table 4: The area statistics of the hazard layer with the corresponding LULC

Hazard class	Area (km <sup>2</sup> )	Coverage (%)	LULC
Very high	156.56	10.2	Mostly in Water and agriculture
High	701.30	52.7	Agriculture
Moderate	356.99	23.2	Wetlands
Low	288.5	18.9	Built-up
Very low	110.7	7.2	vegetation

This table shows the hazard classes, the area and the coverage in percentage and the land use land cover classes that are found in the most hazardous areas.

### Discussion of the results

The malaria incidence and transmission requires the environment with lower elevation (higher temperature), abundance of wet lands and in agriculture areas, occurrence of gentle slopes and availability of water areas (Tensaye, 2016). From the above statistics of the malaria hazard layer;

- Areas with very low risks of malaria were the smallest 7.2% and those of low risk were the relatively small 18.7% while areas with moderate risks of malaria were the moderate in size with 23.2% and areas were found in wetland areas, increase in built-up areas and areas covered with vegetation (trees, bush, woodland) of the study area.
- Areas near water bodies and agricultural areas since they were at low elevation and gentle slope were identified to be very highly and highly more hazardous covering the largest 62.9% than the rest (figure 4-9).
- Therefore, the largest part of the study area is highly hazardous which was 62.9%. This show that except few areas, all others are under the exposure of malaria. The prevalence of such fact is mainly due to the excessive or increase in agriculture on gently sloping land and the irrigation practices in the study area.

### 4.3 Malaria distribution analysis

Malaria distribution map was analyzed by the malaria data of 2015 and 2020 which was joined with the Luwero sub county datasets to obtain the distribution maps of each year and change was obtained from the percentage to show the areas of high increase since the data showed an increase.

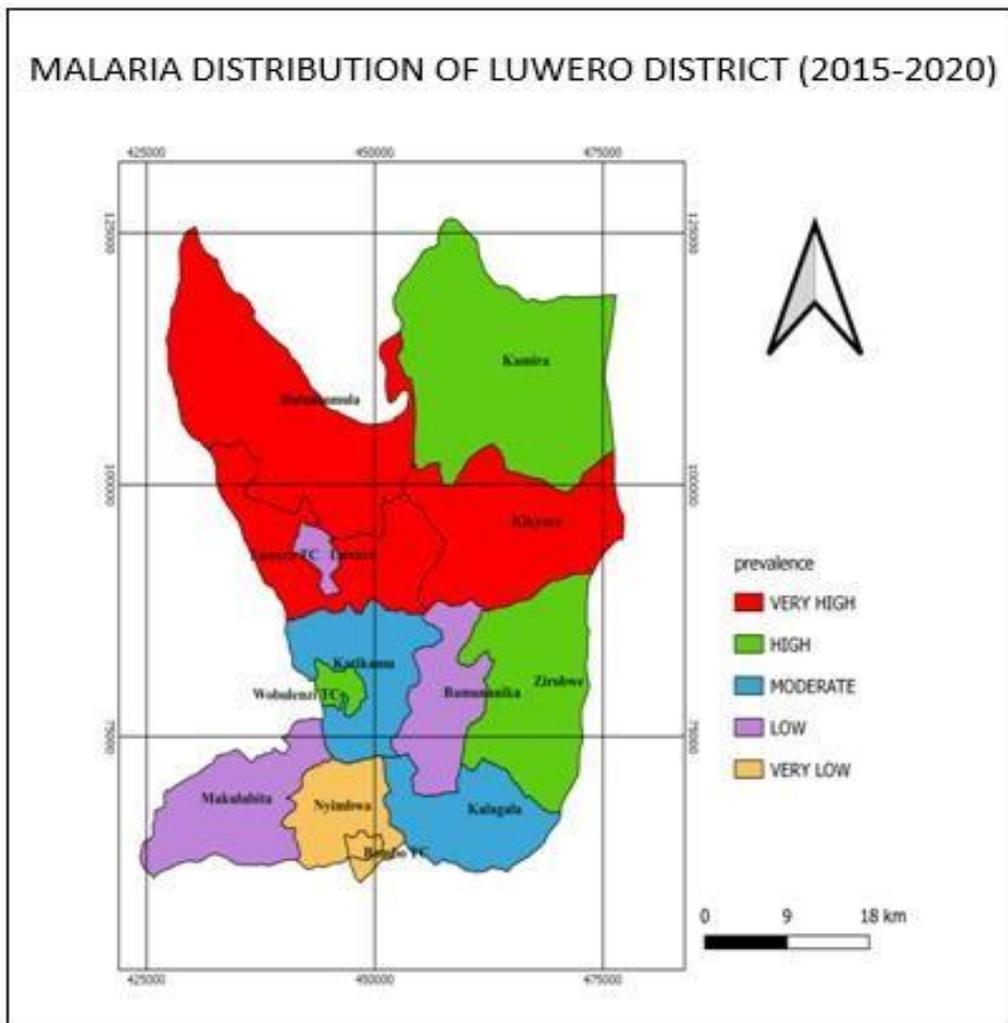


Figure 13: A map showing the malaria distribution change of Luwero district in (2015 -2020)

### Discussion of results

Areas of very high increase were found in Butuntumula, Kamira, Zirobwe and Wobulenzi town council sub counties and very low increase was found in Nyimbwa and Bombo town council sub counties. The rest fell in high, moderate and low increase.

### 4.3 Malaria prevalence Analysis

Malaria prevalence areas were analyzed basing not only on environmental factors (hazard factors) but also the distribution of malaria in Luwero using the malaria distribution change layer. The map of malaria prevalence areas was generated by overlaying the malaria hazard, and malaria distribution change layers.

#### Identification of Malaria Risk areas

The malaria prevalence map was generated using the malaria hazard, malaria distribution change layers which resulted as shown below.

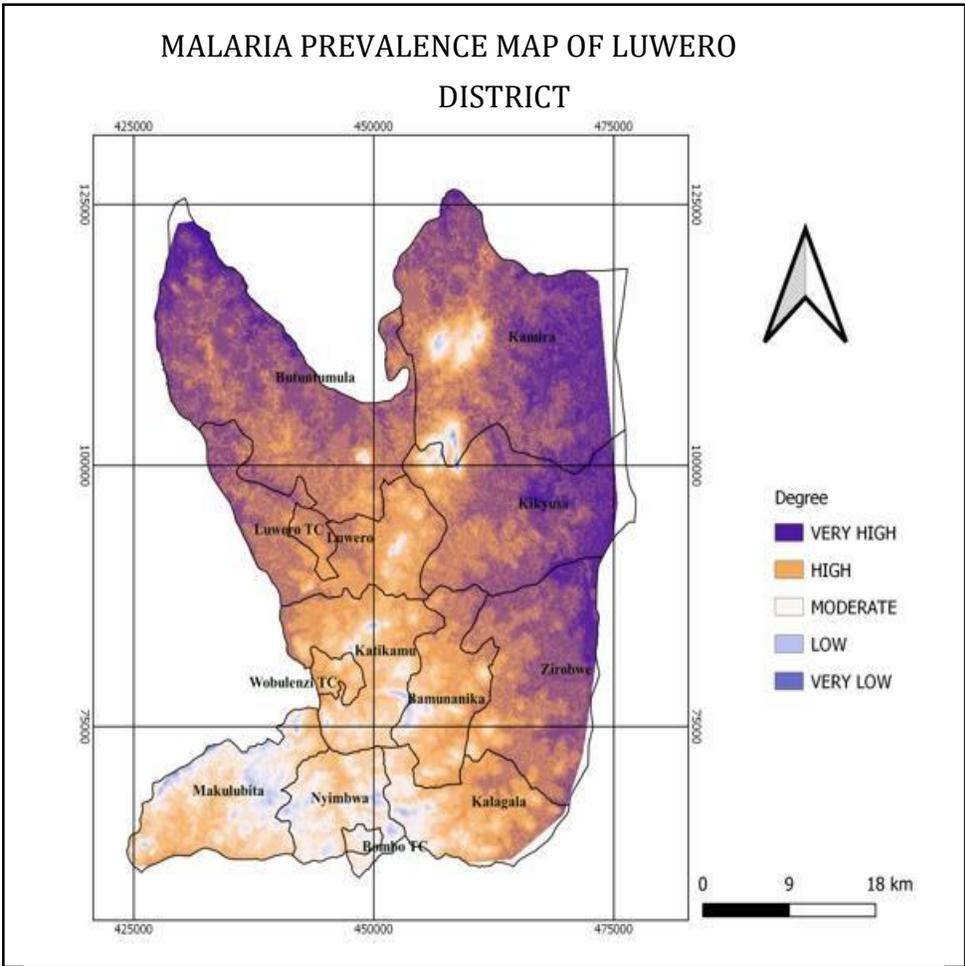


Figure 14 : A map of malaria prevalence of Luwero district.

Prevalence class	Area (km <sup>2</sup> )	Coverage (%)
Very high	488.8	36.4
High	823.5	49.4
Moderate	101.5	9.3
Low	63.1	5.5
Very low	5.7	0.4

Figure 15: Area coverage of malaria prevalence of Luwero district.

### Discussion of the results

In this study, for the purpose of identifying areas of malaria prevalence; malaria hazard and spatial distribution of malaria were used as input factors for malaria prevalence mapping.

- As a result, from the malaria prevalence map in *figure*, it is possible to conclude that the majority of the area (more than 80%) is have a high risk of malaria due to the high prevalence. The reason behind this seems due to the availability of favorable condition to the vector mosquito such as the gentleness of topography, presence of wetlands, grazing and the increasing agricultural practices in the study area. Moreover, the existence of the agroforestry (vegetation) might have provided more shelter and sites for resting for adult mosquitoes, which extends their longevity and density.
- Very highly prevalent areas are realized in Butuntumula, Kamira and Kikyusa sub counties and slightly in Luwero and Ziobwe. This may be due to increasing agriculture practices, the existence of wetlands and waters in mostly in Kikyusa in the study area. □ Highly prevalent areas are realized in Kalagala, Bamunanika, Wobulenzi TC and Katikamu sub counties. This may be due to increasing agriculture practices, the existence of wetlands and waters in mostly in Kikyusa in the study area.
- Moderate and low malaria prevalent areas were situated most in some parts of Makulubita, Nyimbwa and Bombo TC and very slightly in other areas. This is due to the increasing settlements that lead to a reduction in agriculture and wetlands and the high altitude and the steep slopes in these particular areas.
- Very low prevalent areas were identified only in a small parts of the study area at high elevation and steep slopes which is not favourable for mosquito breeding at all relative to the cold climatic condition.

## CHAPTER FIVE: CONCLUSION AND RECOMMENDATION

### 5.1 CONCLUSION

This study was aimed at analyzing and mapping the relationship between land use/land cover and malaria prevalence in Luwero district Central-Uganda using remote sensing and GIS. The relationship mapping considered only some of the environmental factors namely; slope, elevation, and LULC, which intensify mosquito breeding and spreading of malaria and malaria data of Luwero district.

From the land use land cover change map, it is observed that agriculture increased by 29.4%.

From the hazardous map, 62.9% of the study area has very highly and highly hazardous to malaria due to the increase of the land cover like water and intensive agriculture favorable for mosquito breeding and gentle slope. This is mostly in areas with less settlements in the Butuntumula and Kikyusa sub-counties.

From the prevalence map, very few malaria prevalence rates were identified to be in Nyimbwa and Bombo Town Council sub counties, occupying the smallest part of the study area due to the steepness and high elevation of the areas, the increase in settlement and less water and few areas occupied wetlands and agriculture which leads to less creation of breeding sites and less malaria distribution.

Similarly, the prevalence map was produced by overlaying the malaria hazard and the distribution layer. The results indicated that the majority of the area (more than 80%) is under very high and high prevalence to malaria. The reason behind this is about the availability of favorable environmental conditions to the vector mosquito such as the water bodies and gentleness of topography and the existence of suitable land uses and land covers for mosquito breeding such as presence of wetlands, grazing and high irrigation farming practices in the study area.

This concluded that an increase in agriculture leads to establishment of new and expansion of breeding sites leading to high malaria prevalence rates.

## **5.2 RECOMMENDATIONS**

It has been shown that GIS has potential to provide benchmarks for assessing the progress of control and indicate which geographical areas should be prioritized. So that it is worthy if the government, NGOs and other stakeholders use this malaria prevalence map to locate the areas in greatest need at the time of service to eradicate malaria.

It was observed that the agricultural and wetland areas have a high prevalence which are most located in Butuntumula, Luwero and Kikyusa sub counties, so more emphasis should be put in those areas to reduce the vulnerability and risk to the disease in these areas.

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