MALARIA RISK ASSESSMENT USING GEOGRAPHICAL INFORMATION SYSTEM AND REMOTE SENSING TECHNIQUES IN MECHA DISTRICT, WEST GOJJAM, ETHIOPIA

Dissertation submitted for Partial Fulfillment of the Requirements for the Award of the Degree of

Master of Science

In

Remote Sensing and Geographical Information Systems (GIS)

Addis Ababa University, Addis Ababa, Ethiopia

By

EMEBET DESSALEGNE

Under the guidance of

Dr. K. V. Suryabhagavan

Prof. M. Balakrishnan

School of Earth Sciences

College of Natural Sciences

Addis Ababa University, Addis Ababa

JUNE 2015

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ADDIS ABABA UNIVERSITY
SCHOOL OF GRADUATE STUDIES

Malaria Risk Assessment Using Geographical Information System and Remote Sensing Techniques in Mecha District, West Gojjam, Ethiopia

By

Emebet Dessalegne

College of Natural Sciences

School of Earth Sciences

Remote Sensing and GIS Stream

Approval By Board of Examiners

Dr. Seifu Kebede ______________________________

School head of Earth

Science

Dr. K.V. Suryabhagavan ______________________________

Advisor

Prof. M. Balakrishnan ______________________________

Advisor

Prof. Solomon Tadesse ______________________________

Examiner

Dr. Getachew Berhan ______________________________

Examiner

D E C L A R A T I O N

I hereby declare that the dissertation entitled "Malaria Risk Assessment Using Geographical Information System and Remote Sensing Techniques in Mecha District, West Gojjam, Ethiopia" has been carried out by me under the supervision of Dr. K. V. Suryabhagavan and Prof. M. Balakrishnan, School of Earth Sciences, Addis Ababa University, Addis Ababa during the year 2013-2015 as a part of Master of Science programme in Remote Sensing and GIS. I further declare that this work has not been submitted to any other University or Institution for the award of any degree or diploma.

Place: Addis Ababa

Date: June 2015

(Emebet Dessalegne)

C E R T I F I C A T E

This is certified that the dissertation entitled "**Malaria Risk Assessment Using Geographical Information System and Remote Sensing Techniques in Mecha District, West Gojjam, Ethiopia**" is a bonafied work carried out by Emebet Dessalegne under my and Prof. M. Balakrishnan guidance and supervision. This is the actual work done by Emebet Dessalegne for the partial fulfillment of the award of the Degree of Master of Science in Remote Sensing and GIS from Addis Ababa University. Addis Ababa.

Dr. K. V. Suryabhagavan
Department of Earth Sciences
Addis Ababa University
Addis Ababa

ABSTRACT

Malaria is a mosquito-borne parasitic disease that causes severe mortality and morbidity, particularly in Sub-Saharan Africa. It affects 3.5–5.0 billion people worldwide with environmental factors contributing for about 70–90% of the disease risk. Geographical information System (GIS) has emerged as the core of the spatial technology, which integrates a wide range of dataset available from different sources including Remote Sensing (RS) and Global Positioning System (GPS). In the present study, malaria risk map was carried out by statistically establishing the relationship of various parameters. To identify the statistical correlations between malaria cases and parameters the regression analysis and Normalized Difference Vegetation Index (NDVI) were applied. The study used weighted overlay technique of multi-criteria evaluation in ArcGIS environment to come up with the final risk map. The aim of the present study has to identify and categorize the malaria risk areas of Mecha District of Ethiopia. Eight factors viz., temperature, rainfall, altitude, distance from streams, distance from swamps and ponds, population density, health facilities and land-use/land-use were used to prepare Malaria-risk areas. To produce the final malaria-risk map, three components of malaria risk layers (malaria hazard, element at risk and vulnerability layer) were overlaid using multi-criteria decision-making technique, and further verified by ground truth and village-wise reports of the malaria cases. Four categories of malaria-risk ranging from very high to low were derived. Most of the study area was found to be in strong agreement with 97.99% high and moderate malaria risk in Mecha District. Highest significant correlation was found between rainfall, altitude and temperature and malaria incidence. Based on the output villages such as Merawi town, Amarit, Andinet, Inguty, Qurt Bahir, Tagel Wedefit, Adis Amba and Idget Behibret were identified with very high and high malaria risk areas and require immediate attention from health agencies as well as the local community for designing effective malaria control measures. Hence, it is suggested that GIS and RS tools can be applied for effective identification and mapping of malaria-risk levels, and this help to plan valuable measures to be taken in early warning, monitor, control and prevent malaria risk.

Key words: Geographic Information System, Malaria, Regression analysis, Remote sensing, Weighted overlay

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Table of Contents

List of Tables

List of Figures

ACRONYMS

AHP	Analytical Hierarchy Process
ASL	Above Sea Level
BOFED	Bureau of Finance and Economic Development
CR	Consistency Ratio
DEM	Digital Elevation Model
EIR	Entomological Inoculation Rate
ERDAS	Earth Resources Data Analysis System
FAO	Food and Agricultural Organization
GIS	Geographic Information System
GPS	Global Positioning System
GWR	Geographically Weighted Regression
MCDM	Multi Criteria Decision Making
MCE	Multi Criteria Evaluation
NMA	National Metrological Agency
NDVI	Normalized difference vegetation index
NIR	Near Infrared
RS	Remote Sensing
SNNPRS	Southern Nations Nationalities and Peoples Regional State
SRTM	Shuttle Radar Topography Mission
OLS	Ordinary Least Squares
OLI	Operational Land Imager
TM	Thematic Mapper
TOA	Top of Atmosphere
VIF	Variance Inflation Factor
WHO	World Health Organization

CHAPTER I

INTRODUCTION

1.1. Background of the study

Malaria has became a major health problem as it affects all age groups of the people in most part of the world, even though is more prevalent in the tropics. It is a serious vector-borne disease. It affects 3.5–5.0 billon people worldwide with environmental factors contributing for about 70–90% of the disease risk (Bautista *et al*., 2006). Around 300 to 500 million cases and more than two million deaths of malaria are reported each year, with more than 80% of these from sub-saharan Africa (Abdulhakim, 2013). Malaria is essentially an environmental disease, as the vectors require specific habitats with surface water for reproduction, and humidity for adult mosquitos to survive. The development rate of both the vector and parasite populations are influenced by climatic factors (Ashenafi, 2003).

Ethiopia is a predominantly a malaria-prone country like most other sub-saharan African countries. Approximately 4–5 million cases of malaria are reported annually in Ethiopia (Abdulhakim, 2013).

The severity of malaria is a function of the interaction between plasmodium, the parasite; the *Anopheles* mosquito, the vector; the human host and the environment (Zewdu, 2007). Vector abundance, duration of the extrinsic incubation period and survival rate of the vector, combined with the probability of the vector feeding of susceptible human host determine the risk of malaria infection, the stability of disease transmission, and seasonal patterns (Yihenew, 2007).

There are several factors associated with this disease and its control such as water bodies, rainfall, temperature, population, land-use/land-cover and health facilities (Palaniyandi, 2012). Understanding the causal factors is a prerequisite to design and implement appropriate malaria risk management. So as to mitigate the effect of this risk, effective malaria risk management methods are required. Spatial information on malaria distribution helps to prioritize protection measures.

1.2. Problem statement

Although successful eradication of malaria has been achieved in many countries, Malaria is still a major problem in many regions of the globe including Africa. The present research project is to study malaria problem in Mecha District, Ethiopia. The topography, rainfall, land-use/land-cover, irrigation practice and climatic conditions of this area have made it a malaria-risk District. Insufficient health facilities, the construction and implementation of Koga irrigation and perennial water bodies resulting from drainage canals also aggravate the problem in Mecha District (Zewdu, 2007). Currently, there is a serious malaria risk problem in the study area area but there is no any identified any to set early warning system.

To design and implement appropriate malaria control method in the study area, the malaria risk areas are to be identified. Malaria risk mapping using remotely sensed data and Geographic information system (GIS) has helped as it can be done in a short time scale with less labor and capital investigation. This method is intensive and effective in generating essential quantitative information on malaria (Gupta *et al*., 2008). It is also possible to identify distribution of malaria in the study area and categorize malaria-risk areas. Such investigations are not possible using conventional malaria assessment methods (Palaniyandi, 2012). Hence, this study has proposed to distinguish the spatial distribution of malaria and to identify malaria hotspot areas with the integration of GIS and RS techniques

1.3. Research objectives

1.3.1. General objectives

- The general objective of the present study was to identify malaria-prone areas in relation to malaria-risk factors for malaria control planning in Mecha District using GIS and Remote sensing techniques.

1.3.2. Specific objectives

- To generate different thematic maps of the study area showing malaria-risk factor.
- To characterize malaria-risk levels in relation to climatic and non-climatic factors in the study area.
- To develop a model based malaria-risk map of the study area.

1.4. Significance of the study

This study was aimed at using GIS and RS tools for identification of malaria-prone areas to identify malaria-risk areas to enable decision makers to use and ensure the scarce resources to the most high-risk areas to prevent or substantially reduce cost of prevention with efficient targeting of high malaria- risk areas. It is also expected to gather information about the District to help the community to control malaria using modern tools such as RS and GIS. Applying GIS and RS for visualizing and analyzing epidemiological data will provide valuable information for evaluation and monitoring of malaria purposes for the wider public.

1.5. Scope of the study

The scope of the study is spatially limited at Mecha District, which covers about 149,119 km^2. Malaria hazard map, element at risk map, vulnerability map and finally malaria-risk map are expected to be produced during this investigation.

1.6. Justification of the study

The main difficulty in controlling malaria transmission is lack of prior information on transmission of malaria in space and time. Therefore, there is a need for developing an effective and simple forecasting system of malaria transmission that could be incorporated in to decision-making systems for malaria control (Eveline *et al*., 2003). GIS and RS are increasingly used for the study of spatial and temporal patterns of vector borne disease. Such a system could be feasible and give adequate time for preparing for the prevention and control of transmission of the disease. In this technique, many factors associated with disease prevalence will be overlaid to identify malaria-risk areas.

1.7. Limitation of the study

The main limitation of the study was the unavailability of well documented relative humidity data and lack of kebelewise well documented malaria cases and other organized spatial malaria related data.

CHAPTER II

LITERATURE REVIEW

2.1. Malaria

Malaria is a vector-borne disease that can affect people of all ages. The vector *Anopheles* mosquitoes are influenced by environmental conditions. Insect vectors in particular are very sensitive to their environment, which in turn determines their presence and development. Consequently, climatic as well as landscape and land-cover factors greatly influence the spatial distribution of the vector and the diseases they transmit (Robert *et al*., 2003). Malaria is transmitted from one person to another by the bite of an infected female *Anopheles* mosquito, which feeds by blood sucking. About 20 different *Anopheles* species occur around the world. However, the following four species infect humans to cause malaria. *Plasmodium falciparum*, *P. vivax*, *P. malariae* and *P. ovale* . But, each of them differs in many aspects of their biology and geographic distribution. The most dominant human malaria parasites in geographical distribution are *P. falciparum* and *P.vivax*, which account for about 60% and 40% of the cases, respectively as Yihenew sighted in (Tulu, 1993).

2.2. Malaria burden

Malaria is a serious health problem in many of the developing countries, affecting between 300−500 million people annually, and the disease is a leading cause of human mortality in sub-saharan Africa (Kathleen, 2002). Malaria is increasing at an alarming rate in developing countries, where the transmission rates are higher (Robert *et al*., 2003). Africa accounts for more than 90% of the burden, where over 80% of malaria deaths occur (Wakgari *et al*., 2006). An estimated one million people in Africa die from malaria, every year.

2.2.1. Malaria in Ethiopia

Malaria is one of the main health problems in Ethiopia where it is increasing at an alarming rate. Ethiopians live at altitudes ranging from 100 m below sea level to 4220 m above sea level. The topography of the country made a fertile ground for the sustenance of the epidemic. More than 50 million (60%) of the population living in areas below 2000 m asl in Ethiopia are at risk of malaria (Abdulhakim, 2013).

2.2.2. Malaria in the Amhara Region

In 2002, widespread outbreak of malaria occurred in the Amhara and Southern Nations Nationalities and Peoples Regional State of Ethiopia (SNNPRS) (Aster, 2010). Amhara had about 5.1 million households at risk of the seasonal malaria assault and periodic epidemics. Some of the fastest growing towns in malaria-prone areas of the country include Adama, Awassa, Bahir Dar, Arba Minch, Dire Dawa, Kombolcha, Jijiga, Zeway, Gutin and Metema (Wakgari, 2006).

2.2.3. Malaria in the present study area

Malaria is a major health problem in the present study area (Mecha District of Ethiopia). As shown in Figure l, large numbers of people are affected by malaria, every year. Malaria transmission rate was high during the years 2003, 2004, 2005, 2006, 2010 and 2012, and low in 2002 and 2008. As shown in figure 2 malaria transmission rate fluctuate within the season, from September to December and March to May malaria transmission rate is high. The highest malaria transmission rates were in May, June, and November, and the lowest malaria transmission was in the months of August, February and March. The average malaria causes in each of the month were above 3000, this indicates that the malaria transmission in the study area is very high.

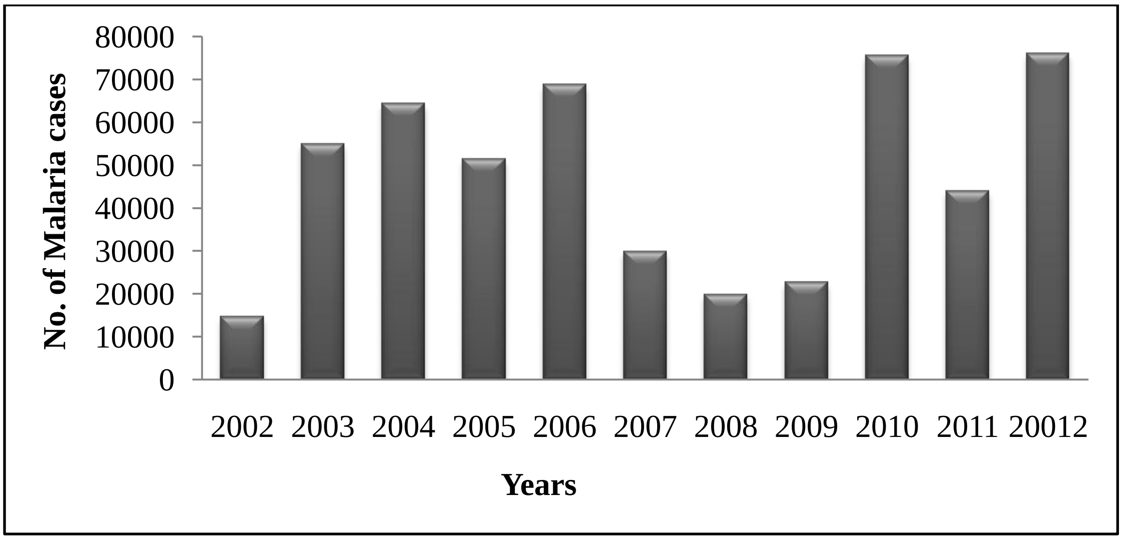

Figure 1: Average malaria cases reported in Mecha District (2002−2012)

(Source: Merawi health center)

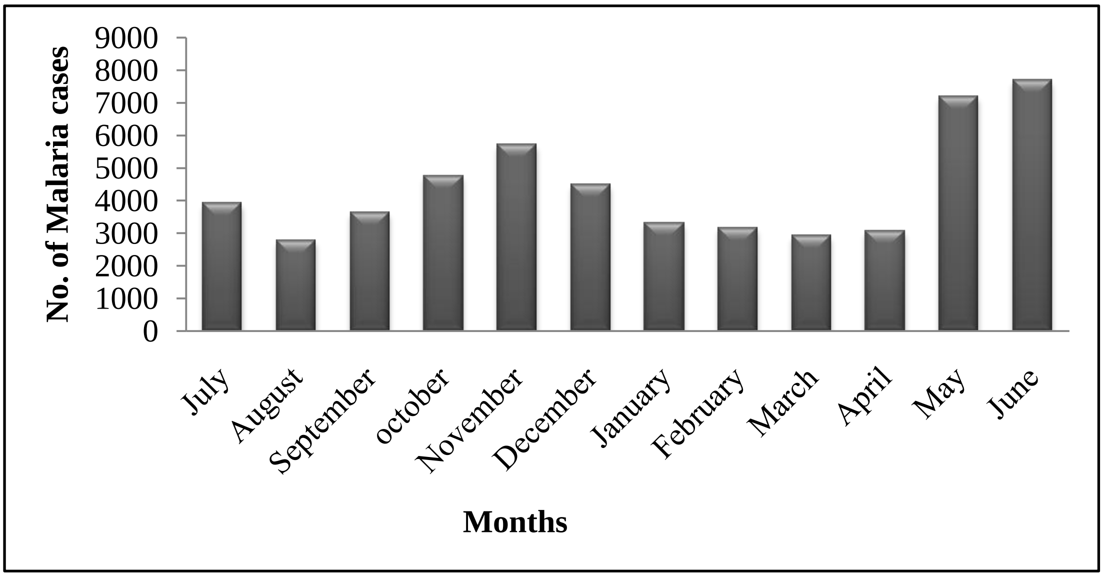

Figure 2: Average malaria cases in Mecha District per month (2002–2012)

(Source: Merawi health center).

2.3. Factors influencing malaria incidence

Although malaria is transmitted exclusively by *Anopheles* mosquitoes, Several factors determine both the importance of the species as a vector of malaria and the options for control. Understanding the malaria incidence factor is vital to assess the malaria risk. Factors influencing malaria incidence include rainfall, water bodies, slope, temperature, population, land-use/land-cover, altitude and irrigation. The causes explaining the spread of malaria in the world include climate changes, health service breakdown and population (Cintia and Evlyn, 2004).

Climate is one of the several important factors influencing the incidence and spread of malaria. Other important considerations include human related issues such as deforestation, agricultural developments, hydrological projects and urbanization (Ceccato *et al*., 2005). Climate affects the distribution of malaria. The three main climatic factors that directly affect malaria transmission are temperature, rainfall, and relative humidity. Several non-climatic factors, including health care, slope, elevation, population, development projects (irrigation) and water bodies can also affect the pattern of malaria transmission and the severity of the problem (Yihenew, 2007).

2.3.1. Climatic factors

2.3.1.1. Temperature

Temperature has a direct effect on the longevity of the mosquitoes. The spread of malaria requires conditions that are favorable for the survival of mosquito, for which a range of 18–26^{o}C is considered as suitable for mosquitoes for survival. A change of every 1^{o}C in temperature can change a mosquito's life span by more than a week. The temperature of 20–30°C and humidity > 60% are optimal for *Anopheles* to survive long enough to acquire and transmit the *Plasmodium* parasite (Devi and Jauhari, 2006). When the temperature decreases, the number of days necessary to complete the development increases for a given *Plasmodium* species. *Plasmodium vivax* and *P.falciparum* have the shortest development cycles, and are therefore more common than *P.ovale* and *P.malariae*. The time needed for the parasite to complete its development in the mosquito decreases to less than 10 days as temperature increases from 21°C to 27°C. The maximum temperature for the parasite development is 40°C. According to Devi and Jauhari (2006), below 15°C, the life cycle of *P.falciparum* in the mosquito body is limited (Devi and Jauhari, 2006).

Temperature would modify the growth of vectors, affect vector population dynamics and alter the rate at which they come into contact with human. Finally, a shift in temperature regime can alter the length of the transmission season (Yazoume *et al*., 2008). A study conducted in Dehradun, India showed that temperature was a critical variable in malaria epidemiology. At 26ºC the extrinsic incubation period of malaria was 9-10 days, whereas at 20−22ºC it was 15−20 days (Devi and Jauhari, 2006).

2.3.1.2. Rainfall

Rainfall has an impact on mosquito breeding. The case of malaria incidence is also related with rainfall. Mosquitoes require water for its life cycle to complete, as water is required for laying egg and development of larva, pupa, and adult (Jeefoo, *et al.*, 2009). Increased rain may increase larval habitat and vector population size by creating new habitat, but excess rain can eliminate habitat by flooding, and low rainfall can create habitat by causing rivers to dry into pools (Githeko *et al*., 2000).

2.3.1.3. Humidity sensitivity

Humidity can greatly influence transmission of vector-borne diseases such as malaria. Mosquitoes can desiccate easily and their survival decreases under dry conditions.

Humidity has been found to be one of the critical determinants in malaria disease models (Patz *et al*., 2005). The optimum average relative humidity is 60% at the temperature of 25^{o}C to 30^{o}C for malaria transmission. Temperature and relative humidity conditions increase the longevity and density of mosquitoes and thus initiate malaria transmission, if the parasite load exists in the community (Yazoume *et al*., 2008). Higher humidity makes the vector livelonger.

2.3.2. Non-climatic factors

2.3.2.1. Irrigation

Irrigation creates an ideal habitat for mass-production of mosquitoes (Stephen, 2006). Irrigation structures would offer ideal habitats for anopheline mosquitoes, which are vectors of malaria. Agricultural development, particularly with the use of irrigation, creates breeding sites for mosquitoes, leading to increased malaria transmission. According to Yihenew Alemu (2007), overall irrigated areas had significantly higher malaria infection prevalence rate as compared to non-irregated sites. The annual parasite index increased from 0.01 in 1961 to 37.9 in 1976, following the construction of Mahi-Kadana irrigation project in India (Asenso *et al*., 2011). Irrigated areas increase the malaria incidence by 22.7% and 16% during dry and rainy seasons respectively (Yihenew Alemu, 2007). For the non-irregated areas, the rainy and the dry season, malaria infection prevalence was 19.6% and 11.5%, respectively (Yihenew Alemu, 2007).

2.3.2.2. Altitude

Altitude and temperature are closely related in most parts of the world. Lowlands are warm (comfortable for malaria transmission), whereas highlands are too cold for malaria parasites and vectors to develop. Transmission usually occurs at altitude <2000 m asl, but occur up to 2400 m (Patz *et al*., 2005). Areas higher than 2,500 m asl altitude has a mean annual temperature of 10–15^{o}C which is considered free of local malaria transmission, the midland area, ranging in altitude from 1,500–2,500 m with a mean annual temperature between 15–20^{o}C has diverse malaria transmission patterns and in the hot lowland zone of areas below 1,500 m asl where the mean annual temperature range in between 20 to 25^{o}C, malaria transmission is endemic (Meron, 2010).

2.3.2.3. Slope

Slope is another dominant factor for mosquito breeding as it is used as a crucial factor for water stagnates. Slope is a topographic parameter associated with mosquito larval habitat formation, which is the measurement of the rate-change of the land per unit distance, affecting the stability of the aquatic habitat. According to Madeleine *et al*. (1999), gentle slope is more suitable to stage water easily, but steeper slope is not comfortable to stage water. The steeper slope values are related to lesser malaria hazard whereas gentle slopes are susceptible for malaria incidence
(Madeleine *et al*., 1999).

2.3.2.4. Population

Major environmental transformations like deforestation, and new construction what else, take place during resettlement, enhancing the proliferation of mosquito breeding sites, and resulting in major malaria outbreaks. Population movements and migration also make malaria problem worse in the areas from where the migrants came. Temporary migrant workers often bring the parasites back to the malaria-free highlands and local transmission can be readily established as many of these communities could support vector breeding (Aster, 2010). Human factors in Ethiopia contributing to the spread of malaria include population growth and movements, urbanization, water development schemes and agricultural development. Unregulated urbanization and increase in human population result in the increase of malaria prevalence (Martens, 1995). Ecological disturbances due to human actions such as deforestation and establishment of new settlement in previously unsettled areas allow breeding of mosquitoes.

2.3.2.5. Land-use/land-cover

The malaria risk factor, the influence of LULC such as bare land and dry vegetation; rain-fed farm land and water body; forest and bush land and irrigated farm land show risk levels low, medium, high, and very high, respectively (Dambach *et al.*, 2009). A study in the Amazon region has revealed that almost half the malaria-risk is estimated to occur among people living in forested areas (Oliveira *et al*, 2013). Another study conducted in Cameroon showed that agricultural water resource development, deforestation, wetland and land-use changes for agricultural purposes were all expanding habitats for malaria transmission mosquitoes (Levins and Yasuoka, 2007). LU/LC types can be classified into suitable mosquito habitant using the Normalized difference vegetation index (NDVI) values. Normalized difference vegetation index (NDVI) values indicate annual changes in vegetation activity and the extent cover reflecting climatic conditions temperature, rainfall as well as water conditions (Jun and Xing-Peng, 2006). Therefore, they are used to estimate the type of vegetation and mosquito's habitant. The habitants of vector mosquitoes differ according to the vegetation and the nature of the local environment. The malaria risk area will expand along with climatic changes, especially changes in ecosystems due to global warming (Ceccato *et al*., 2005). The larger the NDVI (above 3.5+) value indicates the higher the vegetation activity level and the area is thought to be covered entirely by forest, greenery or other vegetation (Richard and Poccard, 1998). Rainfall is the dominant factor for the growth of vegetations and a main reason that NDVI can be expected to be associated with transmission of malaria diseases hence rainfall is one of the most important determinants of mosquitoes breeding. This indicates that NDVI is highly correlated with both rainfall and Anopheles mosquitoes (Jun and Xing-Peng, 2006).

2.3.2.6. Health stations

Prevention of malaria can lead to a reduction in the number of patients in health facilities. The provision of free or low-cost nets at health facilities may also be an advantage to pregnant women and mothers to use preventive service (Erin *et al*., 2014). Minimum time required to arrive at the nearby health facilities is considered as less malaria vulnerable area. A study conducted in 2008–2009 in Ethiopia showed that 36% of the 70000 malaria deaths were due to out of reach of the health service facility. Out of an estimated nine million malaria cases annually, only 4–5 million will be treated in a health facility. The remainder will often get no medical support (Meron, 2010). Therefore, the absence or presences of health facilities have a direct effect on malaria treatment. Communities near the health stations will have an awareness to prevent the malaria transmission before the emergence of the disease, when the health institutions are available, the community is treated as soon as they are affected by the disease.

2.3.2.7. Water bodies

Water body is a typical place for mosquito breeding. Streams and swamps are crucial factors for malaria breading as breeding of mosquito is related to different water sources. Slow moving water is more comfortable to lay eggs and complete the life cycle of mosquitoes. Moving water is not conductive for malaria breeding as it destroys coition life stage of mosquitoes (eg. eggs, larva), during movement with pressure. Such type of water body is common in different parts of the present study area. This is one of the resource for expanding malaria transmission at an alarming rate. Mosquitoes flight ranges usually up to 2 km, but can be fly up to 5 km depending upon the species. As the flight range of mosquitoes is limited, the abundance of mosquitoes can be found around water bodies. A study conducted in Gambia indicated that total malaria transmission was 42% higher in wet season than in the rest of the year (Wiseman *et al*., 2006). Mosquito populations are higher during the wet season, when water is easily available for breeding than during the dry season (Omukunda *et al*, 2013).

2.4. Modeling spatial relationships using regression analysis

A model is a simplified and manageable representation of reality. Spatial statistical modeling are estimated quantities (parameters) that are intended to quantify the true underlying magnitudes in a map and their uncertainty (Kleinschmidt *et al*., 2001). There are different methods to validate the model performance/fit. Regression analysis allows to model, examine, and explore spatial relationships, and can help explain the factors behind observed spatial patterns (Oliveira *et al*., 2013). OLS is the best known of all regression techniques. It is also the proper starting point for all spatial regression analyses. It provides a global model of the variable or process that are trying to understand or predict (Ehlkes *et al*., 2014). Geographically Weighted Regression (GWR) is another type of spatial regression techniques that provides a local model of the variable or process that is trying to understand/predict. According to Kleinschmidt *et al.*, (2001), model can be impair in different reasons as model validation is very important to understand its performance. Strong multi-collinearity can impair the model and produce erroneous effects. The measure of the degree of multi-collinearity is the variance inflation factor (VIF) (Ehlkes *et al*., 2014).

2.5. Role of GIS and RS in malaria risk mapping

Geographic information system is an organized collection of computer hardware, software, geographical data, and personnel designed to efficiently capture, store, update, manipulate, analyze and display all forms of geographically referenced data. This system is capable of handling both spatial data and attribute data about such features. Geographic information system has emerged as the core of spatial

technology, which integrates wide range of datasets available from different sources including RS and GPS (Dambach *et al.*, 2009). Malaria is affected in areas of different climatic biological and physical factors such as elevation, slope, rainfall, temperature, LULC, distance from streams, swamps and ponds, distance from health stations, which are difficult to quantify in traditional methods. However, GIS has great potential as it has the capacity to generate and integrate different types of spatial and aspatial datasets at different scales in a more accurate time and cost effective way. Global position system data in a GIS assisted in preparing base map, mapping breeding habitats and analysis of areas of high disease prevalence
(Saxena *et al*., 2009).

Remote sensing is the science of acquiring information about the Earth's surface without actually being in contact with it. Remote sensing is applicable in a wide range of fields. Land-use/land- cover mapping, geologic and soil mapping, agricultural applications, forestry applications, rangeland applications, water resource applications, water pollution detection, flood damage estimation, urban and regional planning, wetland mapping, wildlife ecology application, archaeological applications, environmental assessment, and land-use suitability evaluation are some of the major areas where remote sensing has direct application (Sabins, 1997).

Remote sensing data in GIS have been used widely for identification, characterization, monitoring, surveillance of breeding habitats and mapping of malaria risk (Saxena *et al*., 2009). Mapping international, regional and local distribution of malaria is motivated by integration of GIS and RS to manage and demonstrate malaria-prone areas. Generally, the integration of GIS, RS and GPS technologies helped in identification of high malaria-prone areas, characterization of the factors of malaria prevalence and transmission and monitoring and surveillance of breeding habitats and mapping of malaria risk areas (Saxena *et al*., 2009).

CHAPTER III

MATERIALS AND METHODS

3.1. Description of the study area

Mecha District lies within 11° 8'−11°39' N latitude and 36°59' 51''−37° 20' E longitude covering a total area of 149,119 km^2 (Fig 3), located in the West Gojjam Zone in the Amhara Region, Ethiopia. It is about 35 km from Bahir Dar, the capital town of Amhara Regional State of Ethiopia. It has 44 villages including three town administrative villages.

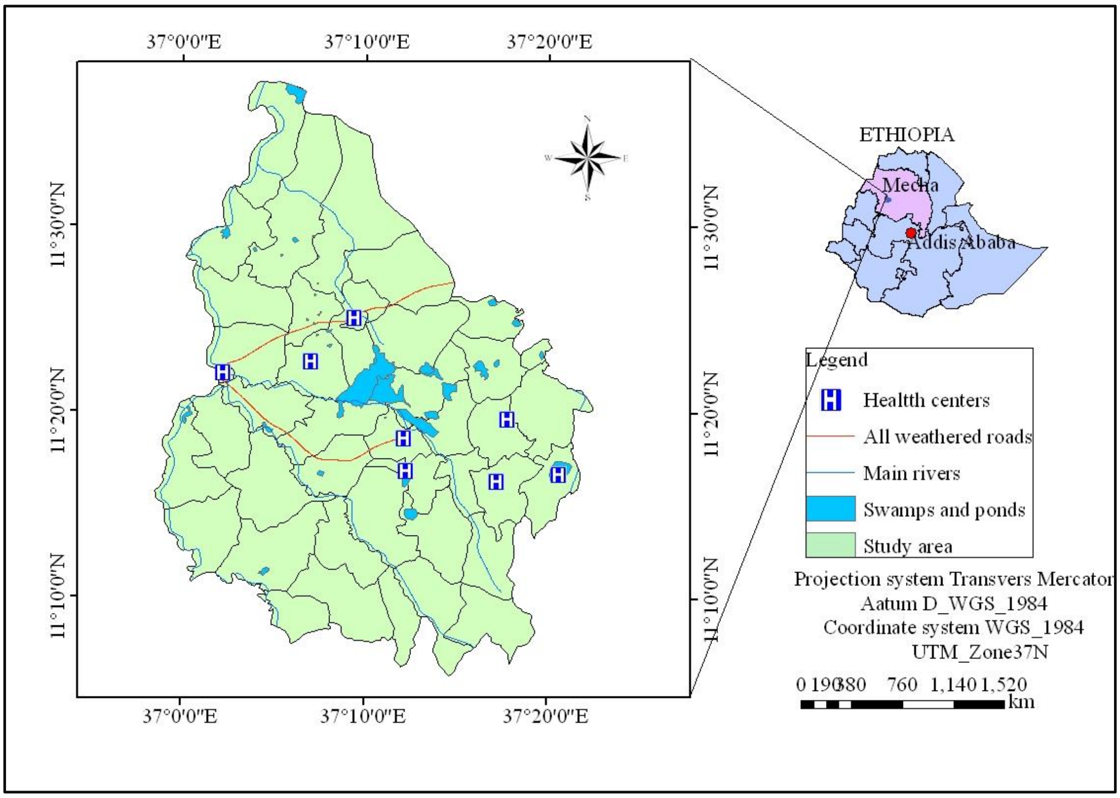

Figure 3: Location map of the study area

3.1.1 Topography and Slope of the study area

Mecha District is situated at an altitude range of 1720 m−2800 m asl. The area is characterized by flat lying topography with some hill terrain. Mecha District has a gentle slope relative to the surrounding Districts. The area characterized as fragile and mountain is very limited. The slope of the study area ranges from 0 to 57%. The majority of the area falls under 10% slope, which is a gentle slope. The elevation and slope of the study area are shown in Figure 4 and Figure 5, respectively.

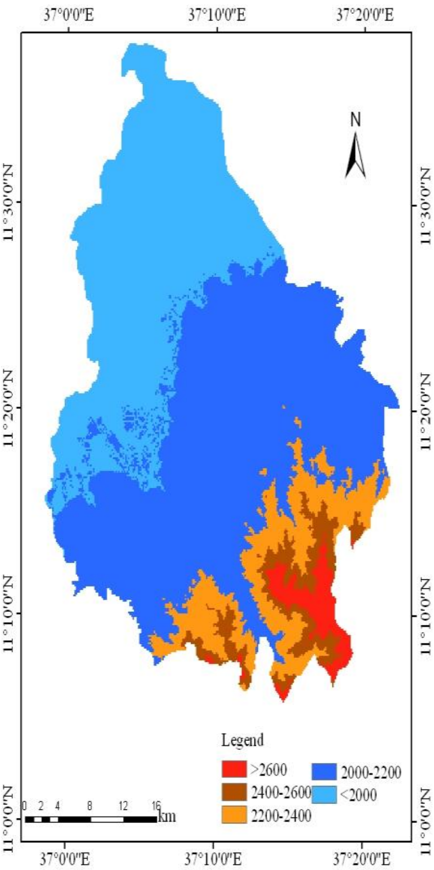

Figure 5: Elevation map

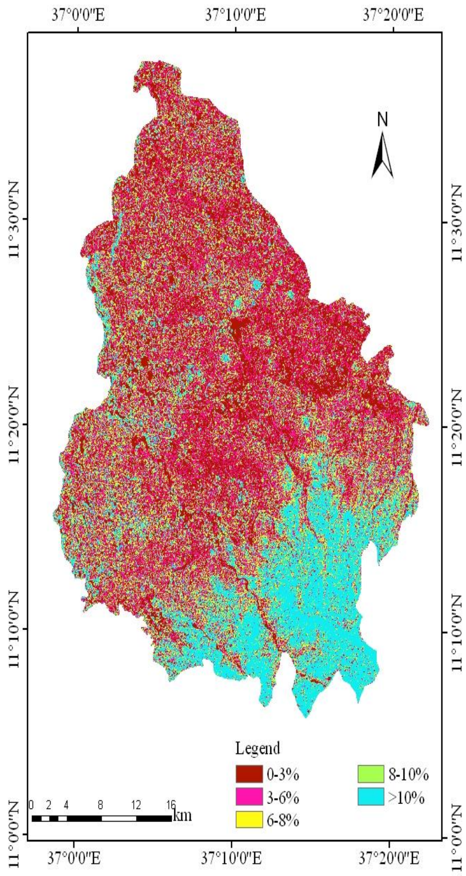

Figure 5: Slope map

3.1.2 Population

Based on the Information Bureau of Finance Economics and Development (BOFED) of Amhara Regional state, Mecha District has an estimated total population of 370,033 of whom 189,537 are female and 180496 are male. Among thus 333,441 are inhabitants, and 36592 are urban. Figure 6 shows the population density of the study area.

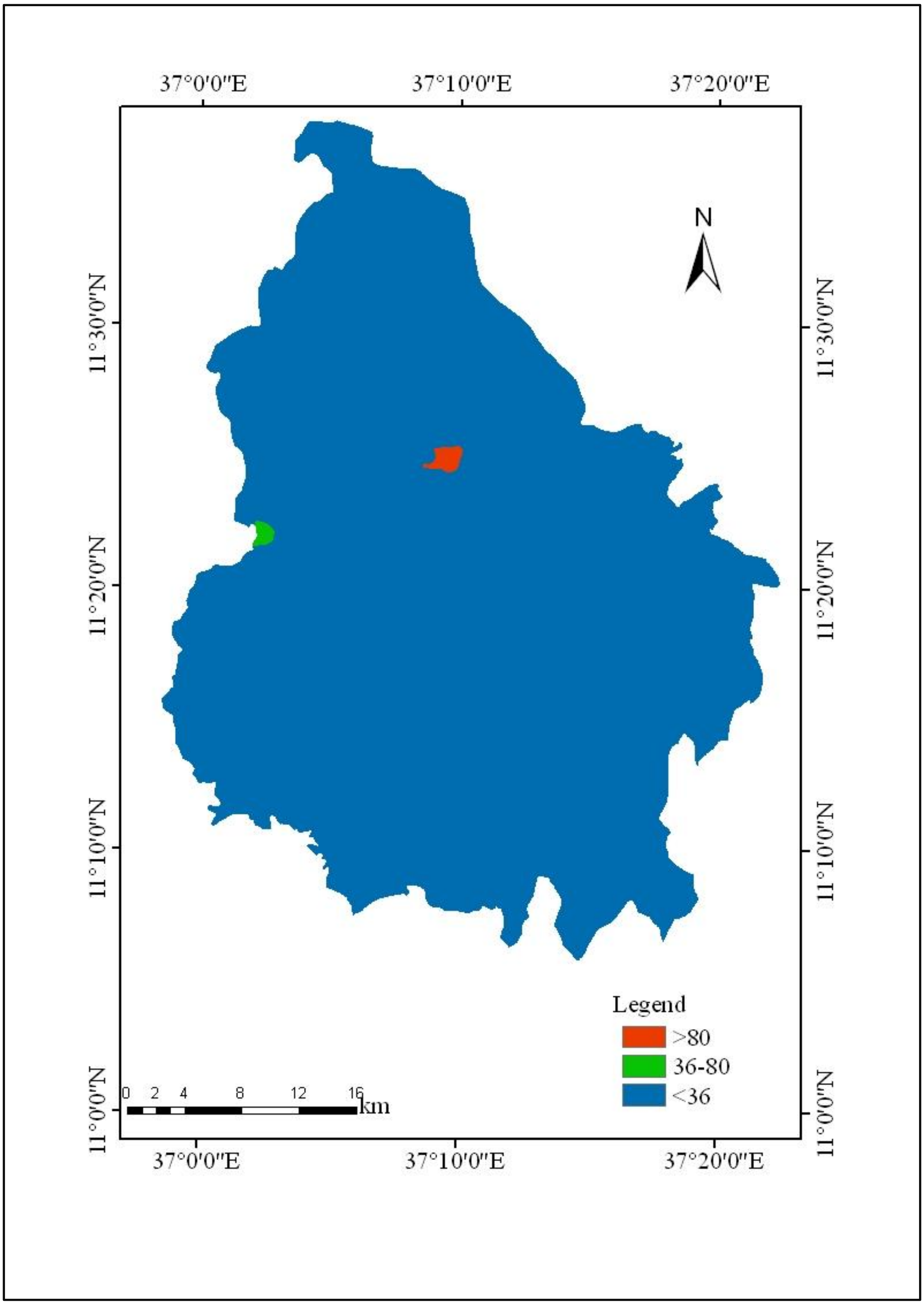

Figure 6: Population density of the study area

3.1.3 Temperature and Rainfall

Mecha District has different climatic variables in different seasons. The rainfall pattern of the study area varies from 1000 mm (mean minimum) to 2000 mm (mean maximum) in a year. The temperature varies from 16°C to 27°C. Table 1 shows the average temperature and rainfall respectively, of Merawi station for 10 years (2002–2012). The maximum average rainfall were recorded in July, August and June and minimum average rainfall were recorded in February, January and December, respectively. The maximum average temperature were recorded in April, May and March and minimum average temperature were recorded in November, December and January, respectively (Table 1).

Table 1: Monthly average temperature and rainfall at Merawi station (2002–2012)

Months	Jan.	Feb.	Mar.	Apr.	May	Jun.	Jul.	Aug.	sep.	Oct.	Nov.	Dec.
temperature(°C)	18.9	19.8	21.5	22.7	21.7	20.7	20.1	20.5	20.7	19.7	15.5	17.4
Rainfall(mm)	2.8	2.0	29.6	60.9	175.6	358.5	418.9	388.2	238	100.2	35.3	10.3

3.1.4 Soil

According to FAO, (1998) soil classification of Amhara Region, Mecha District has different types of soils. Main soil types include chromic luvisols, lithic leptosols, eutric vertisols and humic nitosols.

3.1.5 Land-use/land-cover

The main land-use of the District is dominated by agriculture of small holding farmers. Prominent farming activities are teff, maize, wheat, potato, sweet potato and sugarcane. Farmlands covered large proportion of the land-use/land-cover types. The rural economy of the people in the District is based on agriculture. Other source of economy is livestock.

3.2. Materials and methods

3.2.1. Materials

Various softwares and hardwares, materials and equipment were used to collect, process and analyze and present the final output using the image and other raw obtained from different sources. The following Table 2 shows the softwares, hardwares and their purpose used in the present study.

Table 2: Hardwares and Softwares

Materials	Purpose
ERDAS Imagine 9.2	Image processing, image classification, accuracy assessment etc.
ArcGIS 10.2	Developing factors, overlay analysis and final output map generation
IDRISI	Multi criteria evaluation(MCE)
Microsoft Excel	To write different numerical data
Microsoft Word	To write and put documents
Garmin GPS	To collect field data such as health facilities and training samples
Topographic map	To extract contour, swamps and ponds and for field survey purpose
Camera	To take photos during field work

3.2.2. Methodology

To compute the final model based malaria risk map of the study area, identification and selection of the major factors that can contributing for malaria breeding is very essential. These nine factors were selected by consulting experts to describe the factors and include LU/LC, streams, population, elevation, temperature, rainfall, ponds and swamps, slope and health station facilities. To identify the statistical correlations between malaria cases and climatic and some non-climatic parameters regression analysis was applied and NDVI value calculation was applied to identify the relationship between LU/LC types and malaria cases.

3.2.2.1. Regression Analysis

Regression equation is the mathematical formula applied to the explanatory variables in order to best predict the dependent variable that is trying to model. Regression analysis contains components *viz.* dependent variable, independent variable coefficients residuals etc. A general mathematical equation for regression analysis is:

$$\boldsymbol{Y = \beta 0 + \beta 1x1 + \beta 2x2 \ldots . \beta nxn + \varepsilon} \text{ .... } \mathbf{eq.\ 1}$$

Where, y is dependent variable, x1, x2…xn are independent variables, β0, β1, β2… βn are coefficients and ε is error term (residual) (Yihenew, 2007).

In this study, Global Weighted Regression (GWR) and Ordinary Least Square (OLS) were carried out to assess the spatial relationship between the parameters and the malaria cases and to validate the model performance. The dependent variable was malaria cases and the independent variables were temperature, rainfall, population density, slope, elevation, distance from swamps and ponds and distance from streams. The independent variable that has greater than 7.5 VIF (strong multi-collinearity) were cut off to overlay. Elevation variable (8.7) and slope variable (10.7) in regression model as shown in Table 7 associated with large VIF values indicating that both of these variables are telling the same story. Therefore, one of them should be removed from the model since slope was removed. To valid the spatial autocorrelation of the values associated with the geographic features in the study area, the Moran's I. was carried out. Moran's I tool measures spatial autocorrelation based on both feature locations and feature values simultaneously. It evaluates whether the pattern expressed is clustered, dispersed, or random (Oliveira *et al*, 2013). The Moran's index statistic for spatial autocorrelation is given:

$$\boldsymbol{I = \frac{n}{So}\frac{\sum_{i=1}^{n}\sum_{j=1}^{n} wij\ ZiZj}{\sum_{i=1}^{n} Zi^{2}}} \quad \text{.................... eq. 2}$$

Where, Zi= the deviation of an attribute for feature i from its mean

Wij= is the spatial weight between i and j, n= total number of features and

So= is the aggregates of all the spatial weights (Oliveira et al, 2013

And Ehlkes *et al*., 2014).

3.2.2.2. Image processing

To produce LU/LC map of the study area, landsate TM image of row 052 and path 170 of month January and year 2015 were acquired. Image processing starting from image pre-processing (Geometric and Radiometric correction), NDVI value calculation, layer stacking (band 2–7), image enhancement, image classification to the final accuracy assessment were done in ERDAS Imagine software. Radiometric correction is one of the pre-processing for creating high-quality satellite data. To correct the satellite image radiometrically, Operational Land Imager (OLI) band data was converted to TOA planetary reflectance using reflectance rescaling coefficients provided in the product metadata file. The following equation is used to convert DN values to TOA reflectance:

$$\boldsymbol{\rho\lambda' = M\rho Qcal + A\rho} \text{..eq. 3}$$

Where, ρλ'= TOA planetary reflectance, without correction for solar angle.

Mρ is Band-specific multiplicative rescaling factor from metadata (reflectance_mult_band_x,), Aρ is Band-specific additive rescaling factor from metadata (reflectance_add_band_x,), Qcal is Quantized and calibrated standard product pixel values (DN) reflectance multi & add bands.

Note: that ρλ' does not contain the sun angle correction. Hence, the image again converted into TOA reflectance with a correlation for the sun angle.

$$\rho\lambda = \frac{\rho\lambda'}{cos(\theta sz)} = \frac{\rho\lambda'}{sin(\theta SE)} \text{.......................... eq. 4}$$

ρλ = TOA planetary reflectance, θSE is Local sun elevation angle, θSZ is Local solar zenith angle; θSZ = 90° - θSE

To infer the relationship between the mosquito habitant and the LU/LC Normalized Difference Vegetation Index (NDVI) values was calculated. Normalized Difference Vegetation Index is an empirical formula designed to produce quantitative measures related to vegetation properties and are computed as:

$$\text{NDVI} = \frac{\text{NIR}-\text{Red}}{\text{NIR}+\text{Red}} \text{..............eq. 5}$$

Where: NIR is the reflectance measured in the near infrared channel (expressed in %); Red is the reflectance measured in the red channel (expressed in %). The higher the NDVI value is the denser or healthier the green vegetation (Jun and Xing-Peng, 2006).

After preparing each parameters the three layers ware developed from different parameters as follows:

Hazard map was assessed by combining the suitability of environmental condition for malaria transmission based on climatic and non-climatic factors. All factor parameters compatible to hazard analysis were generated before weighted overlay. The five parameters *viz*. metrological (rainfall and temperature), distance from ponds and swamps, altitude and distance from streams layers were selected. Generating malaria hazard map requires estimating weight factor for each individual hazard parameters. First, each hazard parameter was ranked according to their importance for mosquitoes breeding and transmission. Then the weighting values were assigned for each parameter. AHP is the process of weighting each factor using IDRISI software to ensure the consistency weighting. A pair-wise comparison is used to evaluate the relative influence of the factors. Which is done by applying a scale using 9-point rating scale ranging from 1 (equal importance) to 9 (strongly more important) and reciprocal values. By using this comparison matrix subjectivity is minimized (Saaty, 1977). The process is repeated till the desired value of CR is reached < 0.10 (Jacek, 2006, João et al., 2012, Suman et al., 2011). The more the CR is approaching to zero the comparison is more accurate. After assigning weight according to their importance for each hazard parameter, the hazard map was computed by overlaying the five selected hazard parameter factors.

$$\mathbf{CR = \frac{CI}{RI}} \text{.................}\mathbf{6}$$

Where, CI= consistency index

RI= is the average of the resulting consistency index depending on the order of matrix.

$$CI = \frac{\lambda_{\max}^{-n}}{n-1} \quad \text{............}\mathbf{7}$$

λ_{max}^{-n} = is the principal Eigen value of the matrix

n= is the order of matrix

Vulnerability map was generated from distance from health facilities map and population density map. The two layers were overlaid with 54% weight to population density map and 46% to health facilities map. Assign the weight was given by consulting Health experts, previous works and based on the regression result coefficients. The element at risk map was computed by reclassifying the land-use/land-cover of the study area. The land-use/land-cover type was ranked based on importance from the most importance to least importance and element at risk map was computed by reclassifying land-use/land-cover types of the study area by consulting the experts and based on NDVI values.

In this study, the malaria risk expressed as the product of malaria hazard map, vulnerability map and element at risk map using Shook model. To produce the malaria risk map, the influence factor were assigned for the three components of malaria risk layers (malaria hazard, element at risk and vulnerability layer) and overlaid. The methodological flowcharts are presented in Figures 7 and 8.

$\mathbf{R = H * E * V}$ Where; **R**= Malaria risk map, **H**= malaria hazard map**…. eq. 8**

V= vulnerability map **E**= malaria element risk map

Element at risk (E) includes economic activities, infrastructures, buildings, public service, irrigation activities and related activities at risk in a given area.

Hazard (H) is the probability of occurrence of a potential damaging natural phenomenon within a specified period of time and within a given area

Vulnerability (V) is the exposure of a given element or set of elements at risk resulting from the occurrence of a damaging phenomenon of a given magnitude

Risk is the expected degree of lose due to a particular natural phenomenon (Abdulhakim, 2013 and shook, 1997).

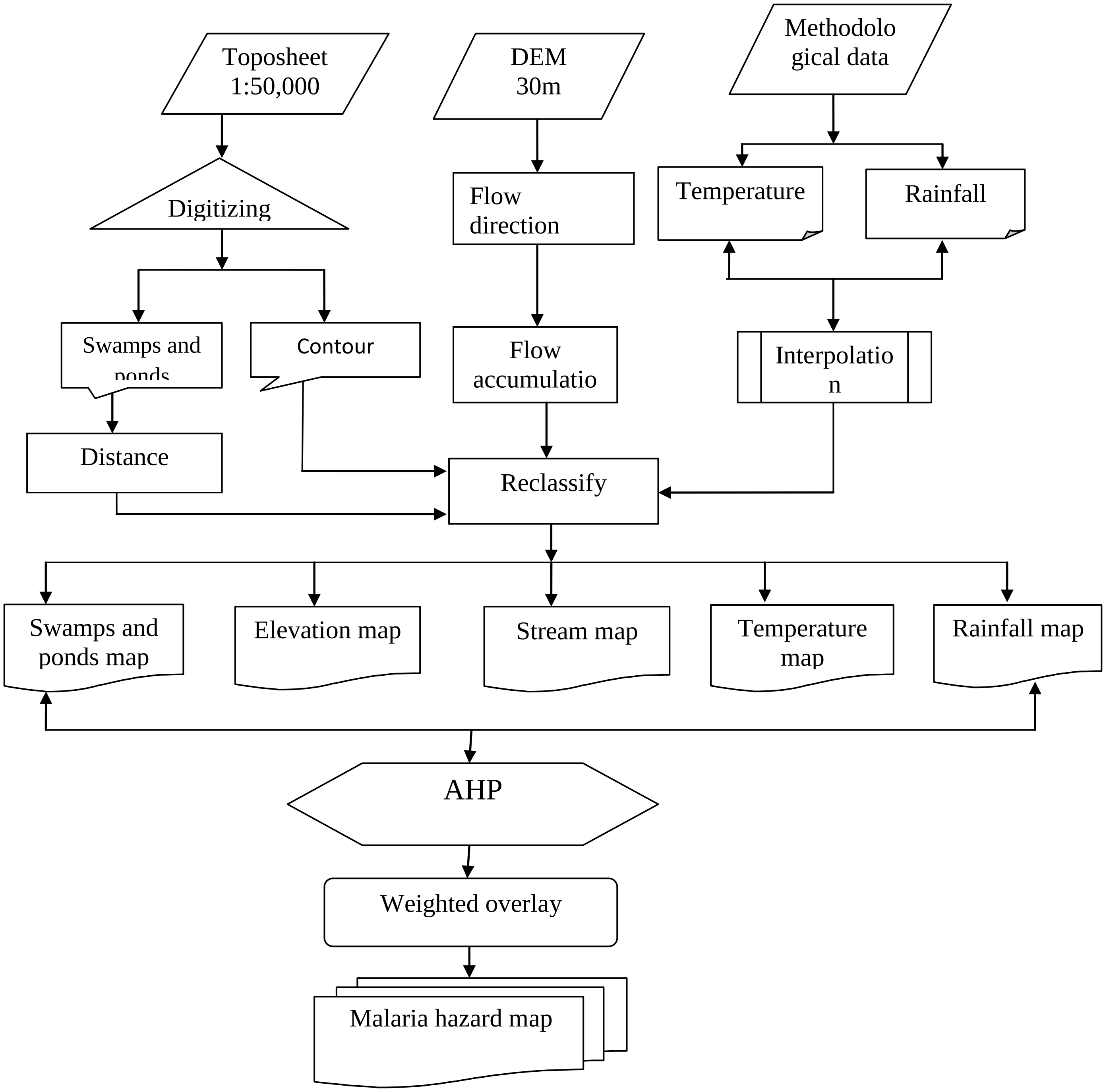

Figure 7: Malaria hazard flowchart

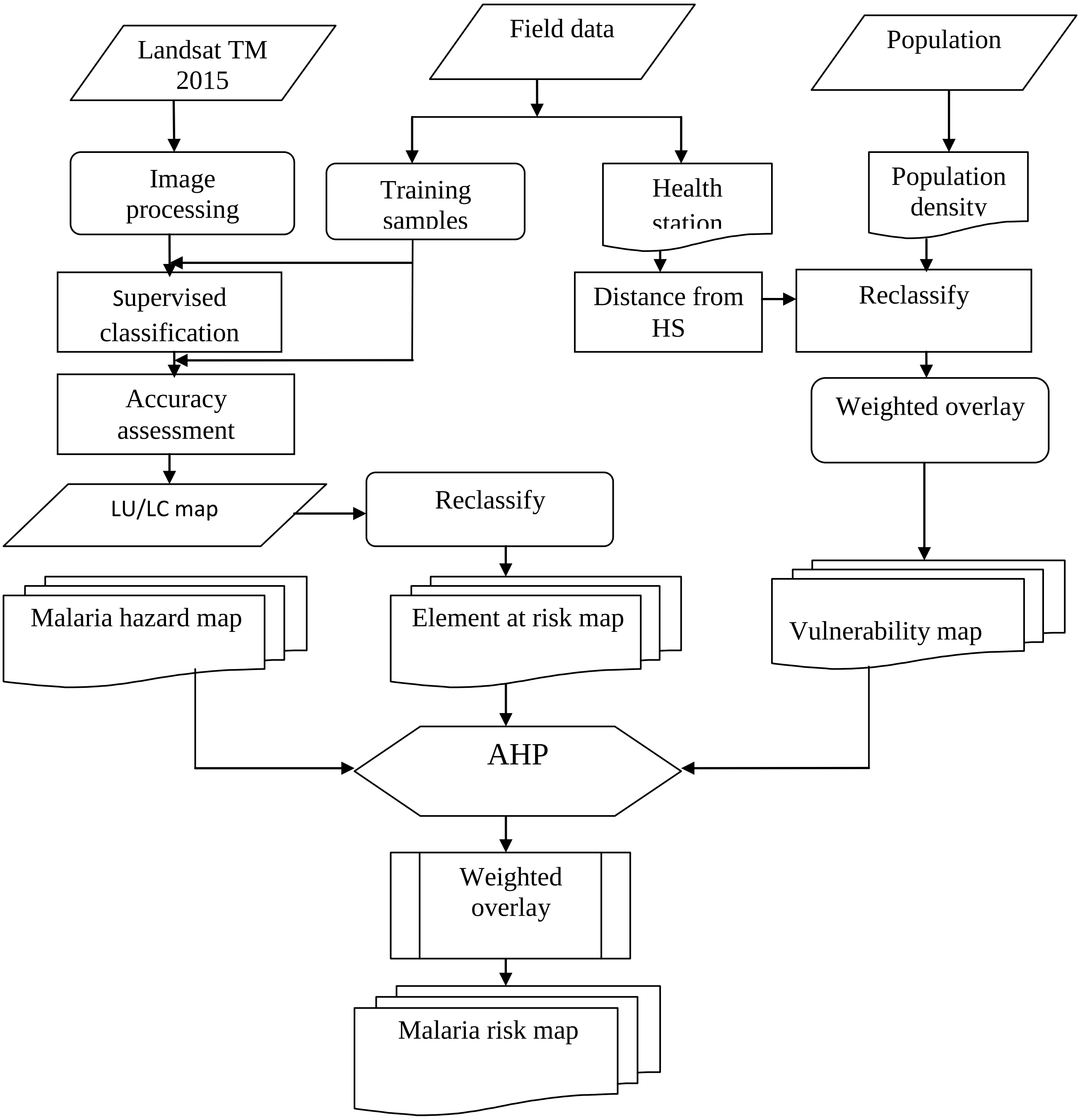

Figure 8: Malaria-risk flowchart

3.3. Data analysis

3.3.1. Factor development

Swamps and ponds: In the present study, swamps and ponds were taken as malaria risk factors. Most of the villages of the study area have ponds, which are used for agricultural purpose during the winter season. This non-moveable water creates suitable conditions for mosquito to lay eggs and complete life cycle. Swamps formed after heavy rainy season and after few months dry. This type of stagnant water is also suitable for malaria transmission as like as ponds. This influences the particular area with increased mosquito breeding and malaria prevalence. In this study, swamps and ponds were extracted from topographic map of the study area and field observations. In order to see the effect of swamps and ponds on malaria prevalence, distance from swamps and ponds were calculated within the study area using the ArcGIS 10.2 tool. This was classified into classes with a distance of 0–0.5 km, 0.5–2 km, 2–3.5 km, 3.5–5 km and >5 km and these were associated with malaria risk levels of very high, high, moderate, low and very low, respectively as shown in Figure 9.

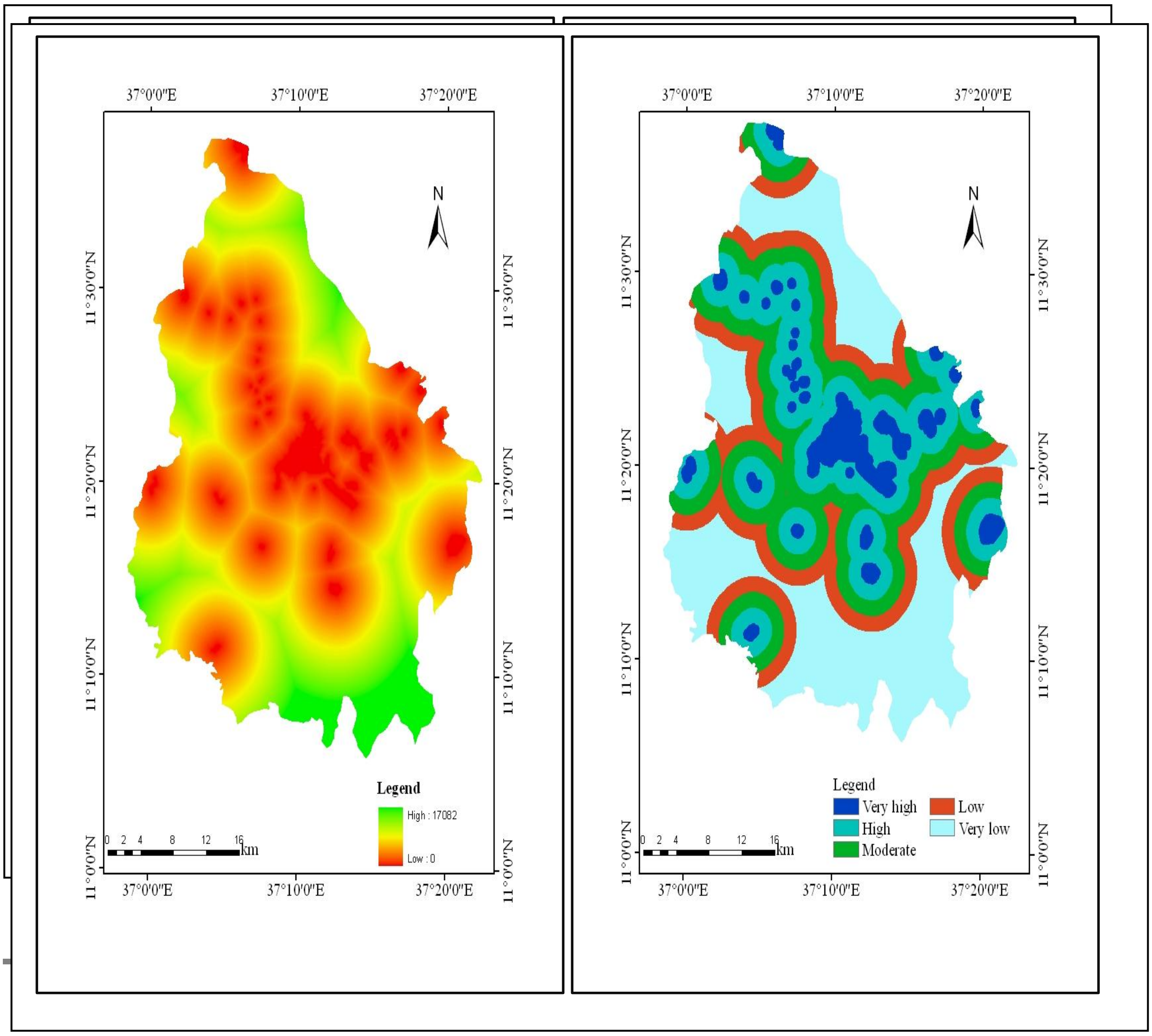

Figure 9: Distance from swamps and ponds

Population density: In the present study area, population movement is common; the movement is from highland to lowland areas for work opportunities temporarily. As the people move from highland to lowland, they increase the malaria transmission rate. Irrigation schemes are another human related activity in the study area. Koga irrigation project covers a wide area of the study area. It has 11 irrigation sites within the study area, which covers around 7250 km^2. As a result of such human activities, mosquito breeding is common in Mecha District. The human population data were collected from BOFED. The maximum population density of the study area is 125 people per km^2, and classified into < 36, 36–80, >80 and these were associated with malaria risk levels of low, moderate and high, respectively as described in Figure 10.

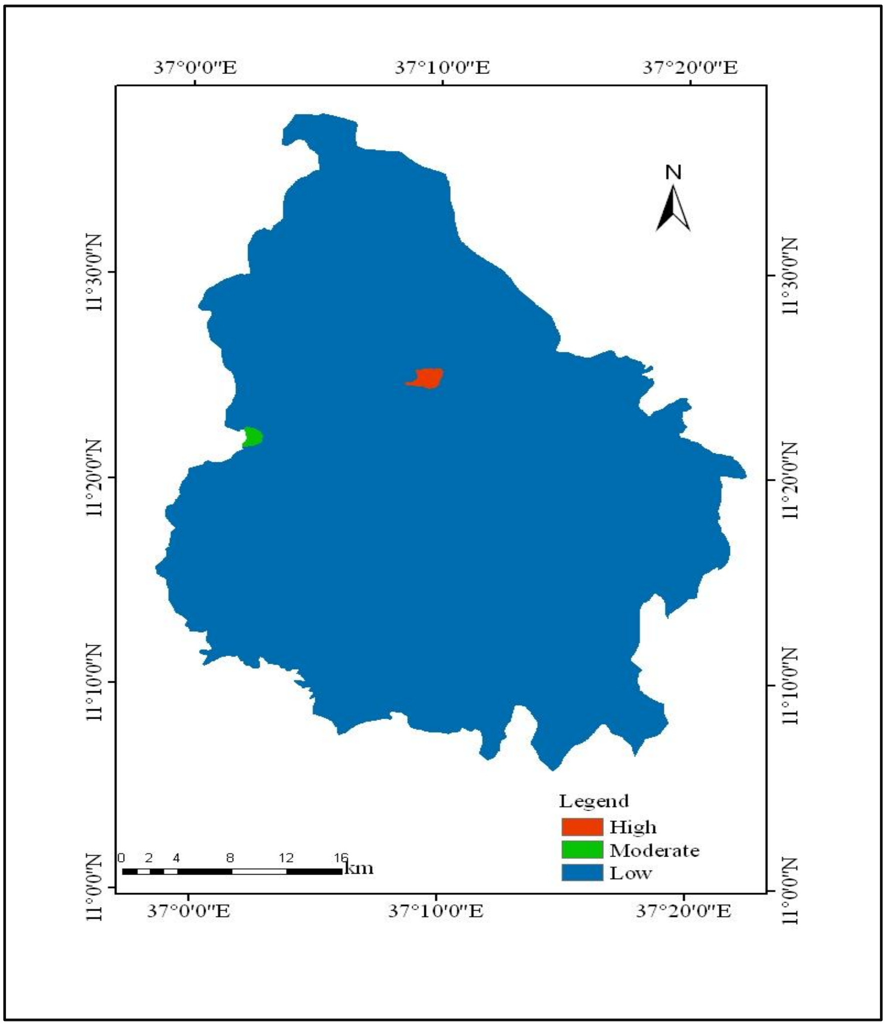

Figure 10: Population density for malaria prevalence

Rainfall and Temperature: The data were collected from the national metrological agency (NMA) for 10 years data, and the shape file of the selected metrological stations were generated from field survey data by using GPS point data (x,y coordinate). It includes 10 stations including the surrounding District metrological stations, only two of them found in the study District. Temperature and rainfall layers were interpolated by using kriking interpolation method and reclassified according to the importance of malaria transmission. The temperature was classified as <15, 15–17, 17–19, 19–21 and > 21 and these were associated with malaria risk levels of very

low, low, moderate, high and very high, respectively. Rainfall was classified as 98–100 mm, 100–103 mm, 103–105 mm, 107–108 mm and >108 mm and these were associated with malaria risk levels of very low, low, moderate, high and very high, respectively, as shown in Figure 11 and 12.

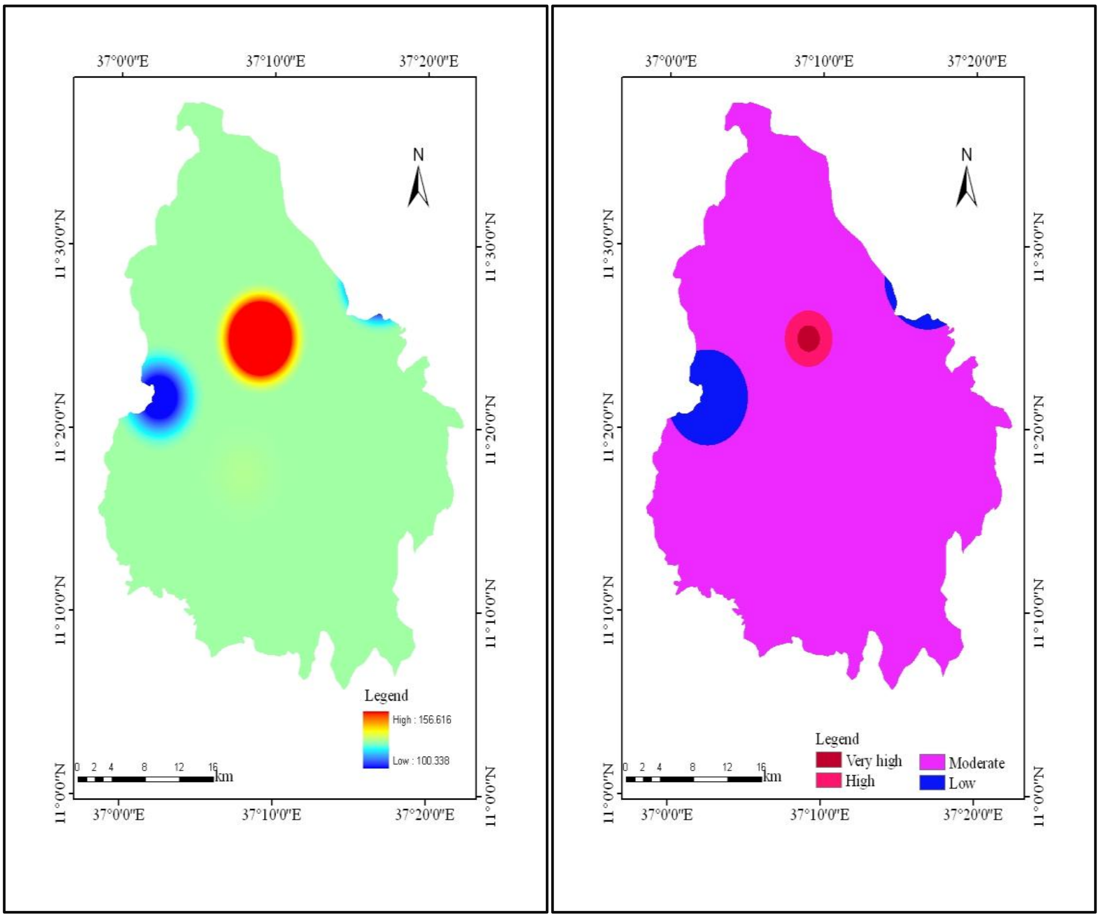

Figure11 a: Interpolated rainfall

Figure11 b: Classified rainfall

Figure 11: Rainfall factor for malaria prevalence

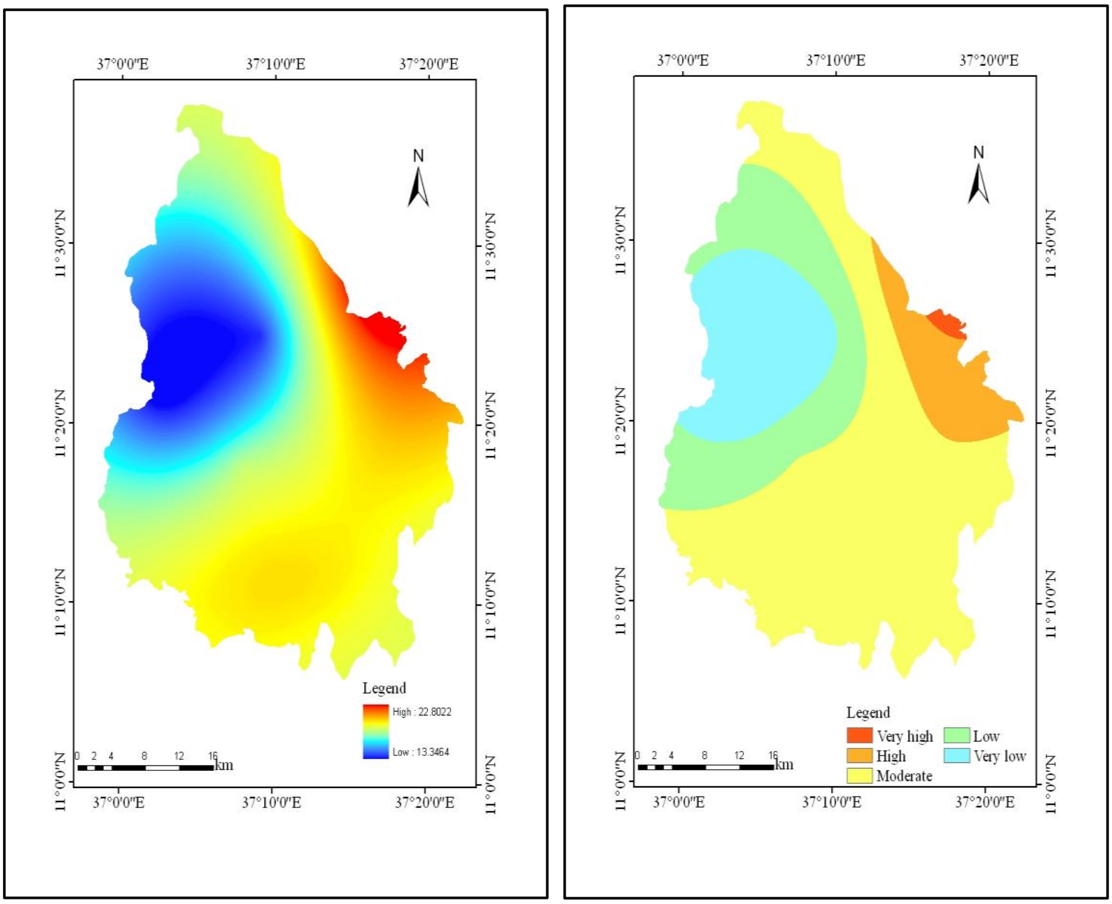

Figure 12 a: Interpolated temperature

Figure 12 b: Classified temperature

Figure 12: Temperature and malaria prevalence

Slope factor: The slope for the study area was extracted from the 30 m SRTM DEM the study area. The slope of the study area was classified as 0–3%, 3–6%, 6–8%, 8–10% and >10% and these were associated with malaria risk levels of very high, high, moderate, low and very low respectively as shown in Figure 13.

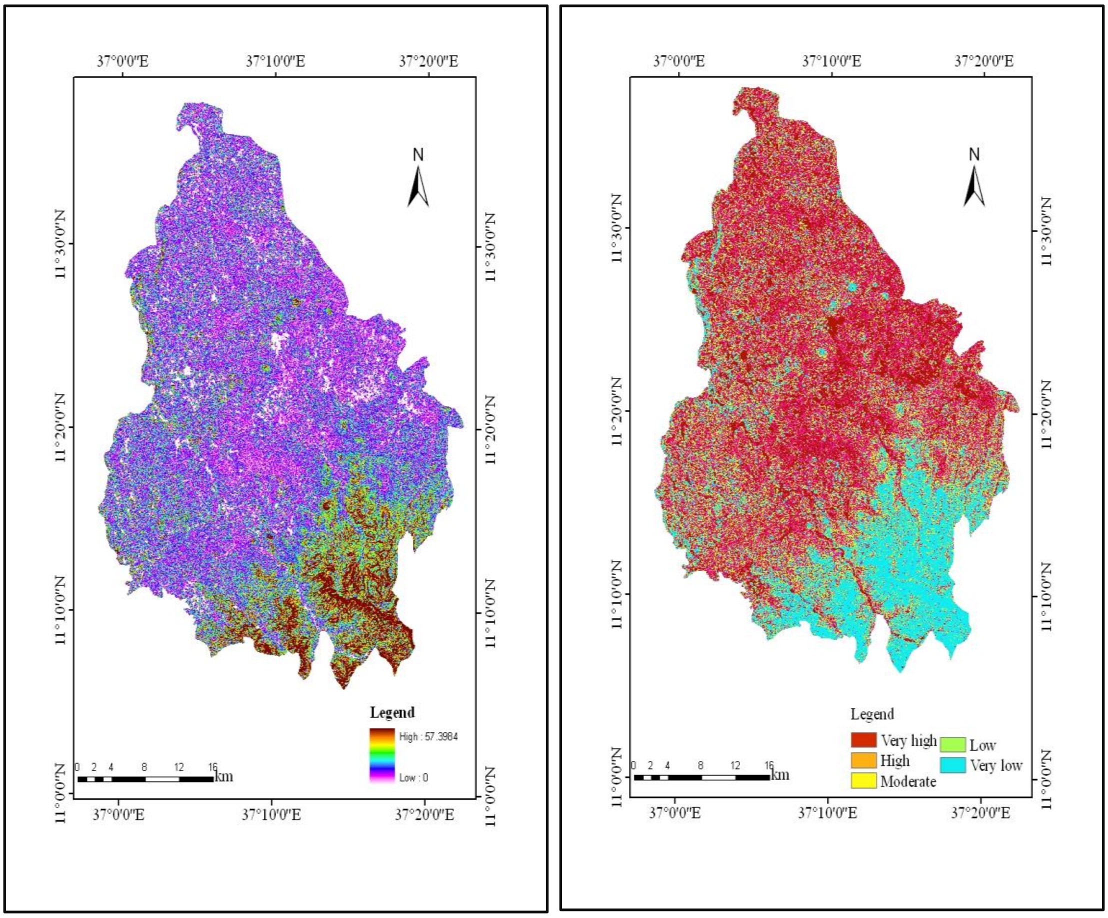

Figure13 a: Slope before classified

Figure13 b: Slope after classified

Figure 13: Slope and malaria prevalence

Stream factor: The streams for the study area were generated from the 30 m DEM of the study area by using ArcGIS 10.2 /spatial analyst tool/hydrology extension. After extracting the main streams based on their stream order, distance from streams was calculated from the streams within the study area using the ArcGIS 10.3 spatial analyst tool. This was classified into classes with a distance of <500 m, 500–2000 m, 2000–3500 m, 3500–5000 m and >5000 m and these were associated with malaria risk levels of very high, high, moderate, low and very low, respectively as shown in Figure 14.

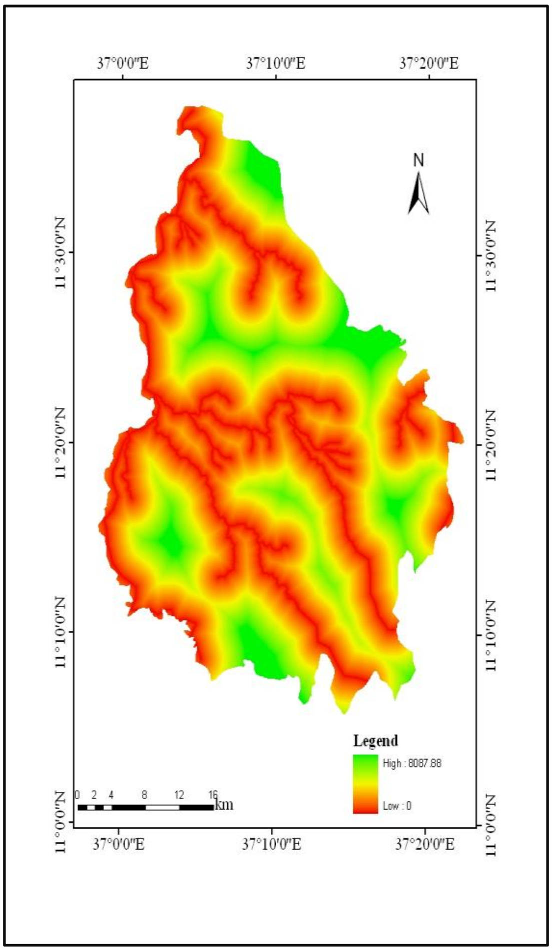

Figure 14 a: Before classification

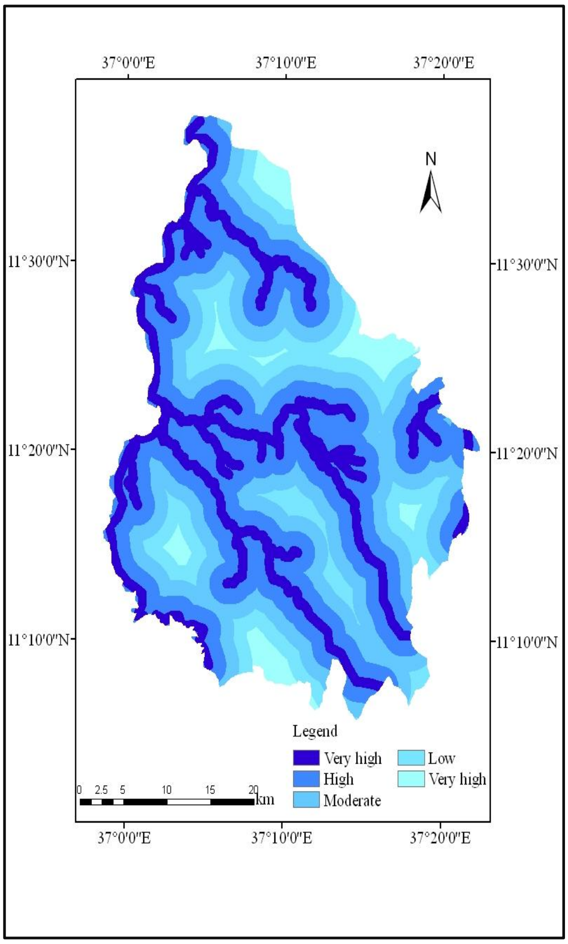

Figure 14 b: After classification

Figure 14: Distance from streams and malaria prevalence

Health institutions factor: In Mecha District, health facilities are insufficient. Most of the health posts are not functional to give its expected service. There is no any hospital in the District and the community cannot be treated with a short period of time at low cost. In this study, the health stations were collected during field data collection as point data and converted into shapefile using ArcGIS 10.2. After converting into shape file distance from health facilities was calculated within the study area using the ArcGIS 10.2 spatial analyst tool. This was reclassified into classes with a distance of 0–5 km, 5–10 km, 10–15 km, 15–20 km and >20 km and these were associated with malaria risk levels of very low, low, moderate, high and very high, respectively as shown in Figure 15.

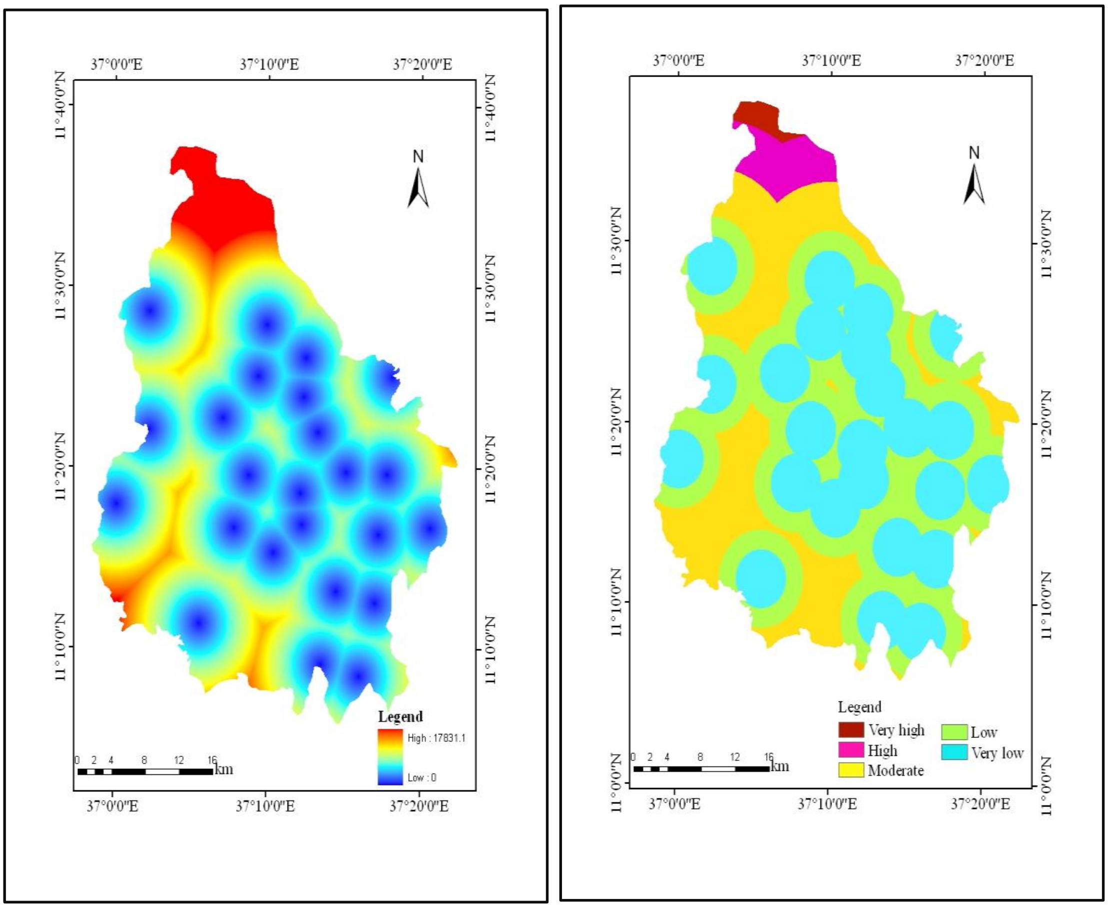

Figure 15 a: before classification

Figure 15 b: After classification

Figure 15: Distance from hea1lth facilities and malaria

Altitude: The altitude of the study area were generated from the topographic map of the study area. The topographic map of the study area is prepared by Ethiopian Mapping Agency with 1:50,000 scale. From this topographic map, the contour were extracted by digitizing in the ArcGIS 10.2 environment. The layer was reclassified in to five classes based on the importance of malaria prevalence. Based on this classification very high, high, moderate, low and very low, malaria risk levels were given to altitude ranges of <2000 m, 2000–2200 m, 2200–2400 m, 2400–2600 m and > 2600 m, respectively shown in Figure 16.

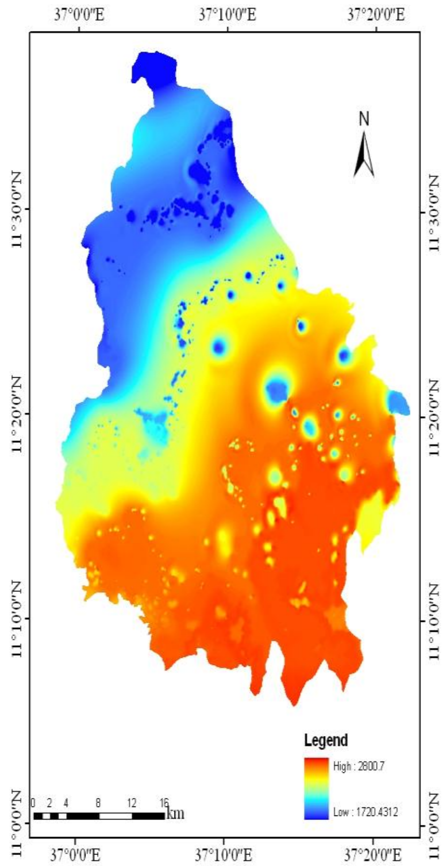

Figure 16 a: Before reclassified

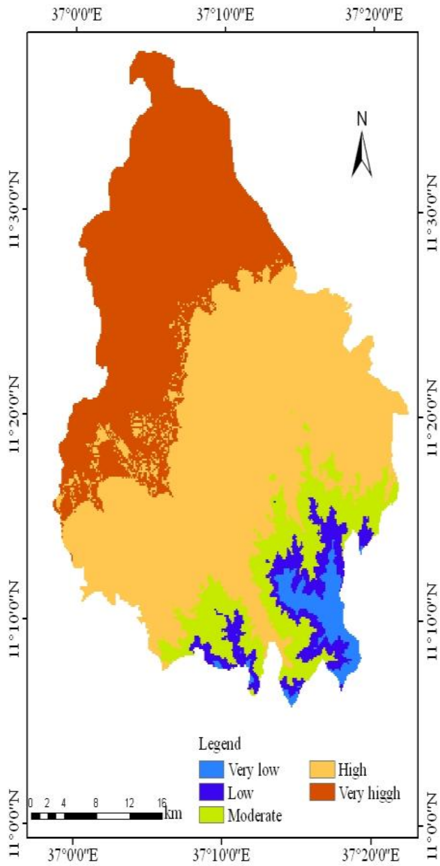

Figure 16 b: After reclassified

Figure 16: Altitude extent for malaria prevalence

Land-use/land-cover: Land-use/land-cover is another factor for mosquitoes breeding. Different land-use/land-cover types have different effect on the prevalence of malaria incidence. The land-use/land-cover was used as element at risk factor to identify the malaria-prone area. The training samples, collected from field survey were used to train training algorithm to carried out supervised classification. Maximum likelihood procedures were used for supervised classification of land cover data. This method gave more accurate results than other classification methods such as Decision Tree-, Minimum Distance- or KMeans (Oliveira *et al.*, 2013). Classification During the period of ground survey, a total of 280 GPS points were collected from all LU/LC types in the study area. The image was classified into main land-use/land-cover types as water bodies, irrigation area, settlement, farmland, wet land, plantation, grassland, shrub and bush land and bare land.

Accuracy assessment is essentially a measure of how many ground truth pixels were classified correctly. To perform quantitative classification accuracy assessment, it is necessary to compare two sources of information: first, the remote sensing derived classification data and second, the reference test information data obtained from field observation (Lillesand, M. and Kiefer, R.W. 2004). From the error matrix, the total accuracy of the classification was assessed using the kappa index. In this study, accuracy assessment was performed for supervised classification to ensure its accuracy relative to the ground truth points. The accuracy assessment resulted as follows in Table 3 and Table 4.

Table 3: Accuracy error matrix

Class name	Pl	Gl	Set	Wl	Ir	Far	Shrub	Wb	Bl
Plantation	5	0	0	0	0	0	0	0	0
Grass land	0	7	0	0	0	0	0	0	0
Settlement	0	0	3	0	0	2	0	1	0
Wetland	0	0	0	5	0	0	0	0	0
Irrigation	0	0	1	0	4	0	0	0	0
Farm land	0	2	0	0	0	6	0	0	0
Shrub land	0	0	0	0	0	0	5	0	0
Water body	0	0	0	0	0	0	0	6	0
Bare land	0	0	0	0	0	0	0	0	5
Total	5	9	4	5	4	8	5	7	5

Keys Pl= plantation, Shrub= shrub land, Gl= grass land, Wb= water body

Bl= bare land, Wl= wet land, Far= farm land and Ir= irrigation

Table 4: Summary of accuracy error matrix

Class name	Reference total	Classified total	Number corrected	Producers accuracy	Users accuracy	Kappa
Bare land	5	5	5	100.00%	100.00%	1
Plantation	5	5	5	100.00%	100.00%	1
Grassland	9	8	8	83.33%	100.00%	1
Settlement	4	5	3	75.00%	60.00%	0.5652
Wetland	6	5	5	83.33%	100.00%	1
Irrigation	4	5	4	100.00%	80.00%	0,7826
Farmland	8	8	7	80.00%	80.00%	0.7778

Shrub lands	5	5	5	100.00%	100.00%	1
Water body	7	7	7	100.00%	100.00%	1
Total	53	53	49			

Overall classification accuracy = 92.00%

Overall kappa statistics = 0.91%

The result shows the overall classification accuracy was 92% and overall kappa accuracy was 0.91%. Producer accuracy ranges from 75% to 100% and user accuracy ranges from 60% to 100%. Finally, the LU/LC reclassified in to five main groups which shows very high, high, moderate, low and very low malaria risk elements by consulting the malaria experts and regression analysis results. .

Overall accuracy and kappa index are both measure of overall accuracy of classification

Over all accuracy = (Total Number of pixels correctly classified)/ (Total number of pixels)

Producer accuracy is the total number of correct pixels in a category divided by the total number of pixels of that category as derived from the reference data (column total). This statistics indicates the probability of a reference pixel being correctly classified and is a measure of omission error.

User accuracy is a measure indicating the probability that the pixel is class A given that the classifier has labeled as belonging to the class

The Kappa factor is given by the formula:

Kappa = $\mathbf{Kappa} = (\mathbf{Po} + \mathbf{Pe})/(\mathbf{1} - \mathbf{Pe})$ ………. Eq. 9

Where: Po = is the proportion of correctly classified cases

Pe = is the proportion of correctly classified cases expected by chance (Lillesand, M. and Kiefer, R.W. 2004).

The following Figure 17 show the land-use/land cover type of the study area.

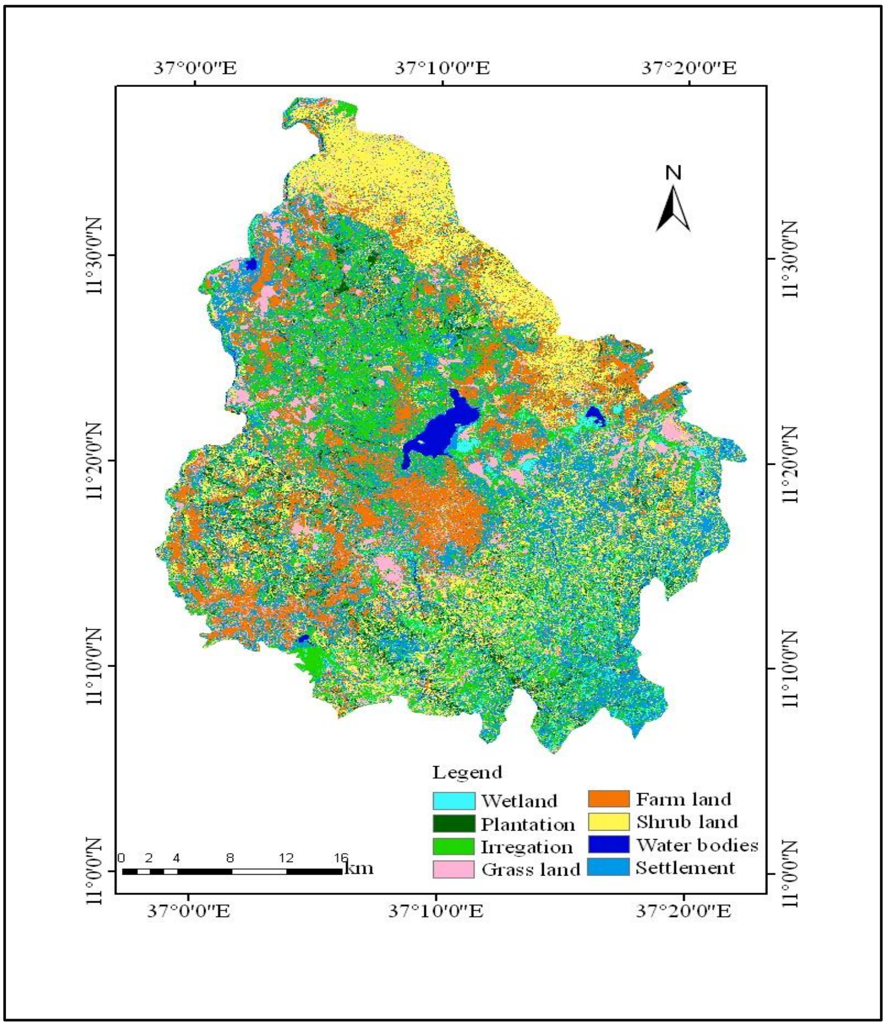

Figure 17: Land-use/land-cover map

CHAPTER IV

RESULTS

4.1. The relationship between malaria vs rainfall

In this study, rainfall was taken as the main climatic factor for the prevalence of malaria. As shown in Tables 11 and 12 rainfall has 44% influence factor for malaria hazard. The average rainfall of the study area varies from the lowest 2.056 mm to the highest 418.97 mm per month. The maximum rainfall was recorded in the months of June, July and August and the minimum was recorded in February, January and December. The highest number of malaria cases recorded was in the months of May, June, October and November and the lowest in the months of August, March and April. Generally, there is a positive relationship between malaria cases and rainfall in the months December to February and May to July, but the relationship was negative in the months of August to November, when the rainfall was high and less, respectively in the study area. Figure 18 shows the average rainfall and average malaria cases recorded in Mecha (2002–2012).

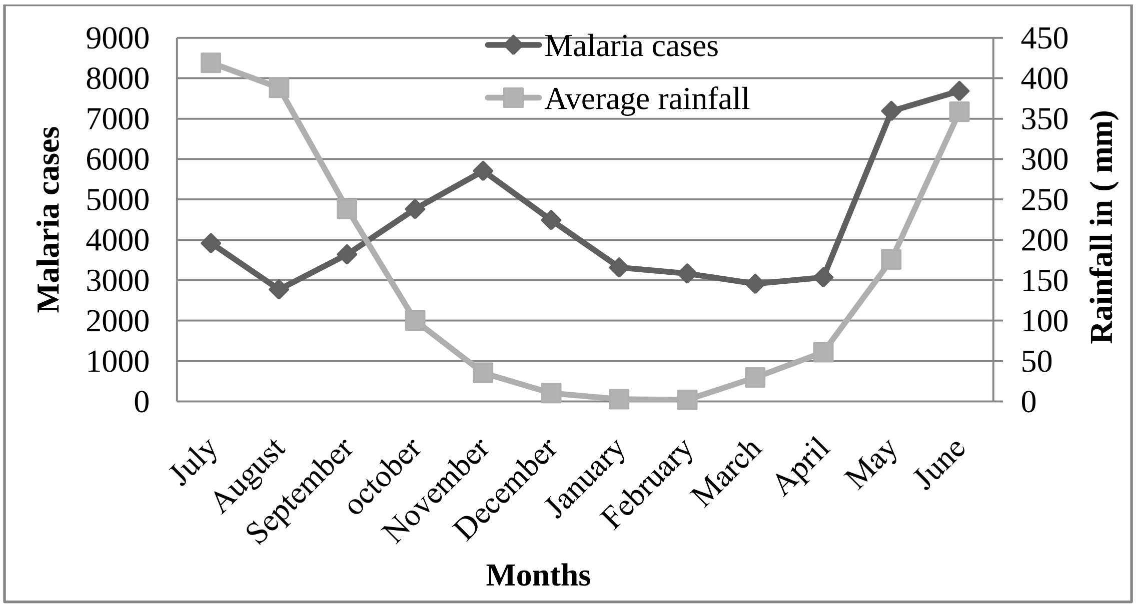

Figure 18: Malaria *vs* rainfall relationship in the study area (2002−2012).

4.2. Malaria cases vs Temperature

The present study revealed both negative and positive relationships between monthly incidence of malaria and temperature. There is a negative relationship during the months December to April and August, when the study area had the minimum and maximum temperature, respectively. This revealed that the increase in temperatures does not actually mean an increase in the malaria transmission risk if this is accompanied by a decrease or increase in rainfall. Although temperatures favour parasite development, the lack of water prevents mosquitoes breeding and vector development. The following Figure 19 shows the relationship between monthly malaria incidences with

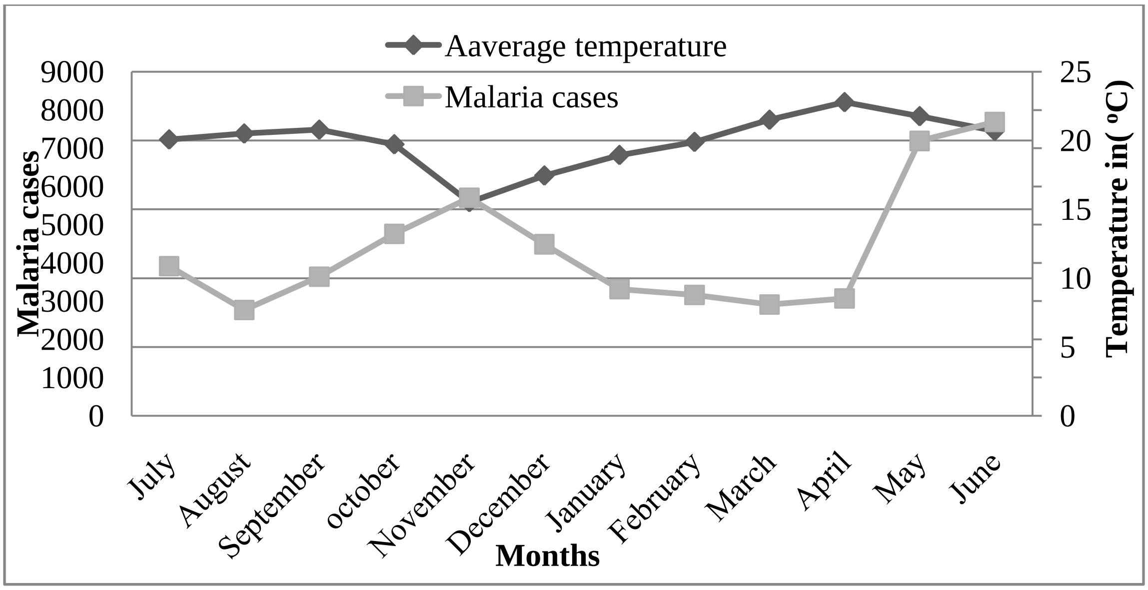

Figure 19: Malaria *vs* temperature relationship in the study area (2002−2012)

Table 5: Malaria cases and rainfall and temperature in Mecha District (2002–2012).

Months	**July**	**Aug.**	**Sep.**	**Oct.**	**Nov.**	**Dec.**	**Jan.**	**Feb.**	**Mar.**	**Apr.**	**May**	**Jun.**
Malaria case	39164	2770	3638	4760	5705	4487	3313	3162	2909	3070	7188	7683
Rainfall	418.9	388.3	238.2	100.3	35.4	10.4	2.9	2.06	29.7	60.9	175.6	358.5
Temp.	20.07	20.5	20.78	19.72	15.52	17.45	18.94	19.89	22.5	23.78	22.76	20.69

4.3. Regression Analysis for model validation

As shown in Table 6 rainfall, temperature and population density have strong positive relationship with malaria cases and altitude and slope have strong negative relationship. This indicates that these factors were the main parameters for malaria prevalence in the study area relative to others. The results obtained from the regression analysis shown in Table 7 and 8.

Table 6: Result of regression analysis

Variable	Coefficient	T-stat	Probability	Robust-t	Robust-p	R^2 (%)	VIF
Intercept	-75035357	-4.741755	0.000041*	-7.994938	0.000000*		
Pop. density	+69.1356	4.03773	0.000319*	6.851215	0.000000*	85.54	2.0
Health station D.	-0.031	-4.051082	0.007826*	-1.130710	0.000000*	19.6	1.7
Slope	-11.04497	-0.129678	0.897635	-0.191535	0.849318	16.68	10.7
Temperature	+115.4472	0.526501	0.526501	0.615132	0.542817	51.04	2.4
Rainfall	+752.86	4.76618	0.000039*	7.638637	0.000000*	64.02	1.9
Elevation	-114.44	-2.059156	0.488905	-0.848799	0.402299	17.04	8.7
Swamp D.	-0.04183	-4.839475	0.009351*	-0.746534	0.000014*	59.00	2.2
Stream D.	-0.08026	-0.587415	0.561046	-0.774150	0.444525	12.71	1.4

* An asterisk next to a number indicates a statistically significant p-value ($p < 0.01$).

The AIC, multiple R^2 and adjusted R^2 for this model was 657.72329, 0.8052 and 0.7566, respectively. Multiple R-Squared and Adjusted R-Squared are both statistics derived from the regression equation to quantify model performance. In this model, R^2 is 80.5299% that means this model explains 80.53% of the variation in the dependent variable (malaria cases).

Coefficients are values, that represent the strength and type of relationship the explanatory variable has to the dependent variable. When the relationship is positive, the sign for the associated coefficient is also positive (+) and negative relationships have negative (-) signs. As shown in Table 7, When the relationship is a strong one, the coefficient is large such as rainfall, temperature, altitude, elevation and population density. Weak relationships are associated with coefficients near zero such as distance from swamps and ponds and distance from streams. As shown in the Table 7 rainfall, population density and temperature had strong positive correlation with the independent variable. Altitude and slope had strong negative relationship with malaria cases. The results that shows the relationship were shown in Tables 6 and 7.

A regression analysis computed a p-value, for the coefficients associated with each independent variable. P-value was used to reject the null hypothesis for statistical test to valid the importance of explanatory variables to the present model. The regression analysis computed small p-values that indicate the explanatory variables were important to the model with a value different from zero (the coefficient was not zero).

As shown in Table 8 some explanatory variables were shown both negative and positive significant. The explanatory variable that showed negative and positive significance includes slope, distance from streams, distance from streams and swamps, and temperature. This indicates that all this variables were not statistically significant (P>0.01). However, population density, distance from health stations, rainfall and distance from swamps and ponds were (statistically) significant (P<0.01). The following Table 8 shows the significance values in percent for each explanatory variable.

Table 7: Results of explanatory regression analysis

Variables	**Variable significance (%)**	
	Negative	**Positive**
Population density	0.00	100
Slope	75.44	24.56
Altitude	85.44	14.56
Distance health stations	100	0.00
Distance from streams	60.18	39.82
Distance from swamps & ponds	100	0.00
Rainfall	0.00	100
Temperature	21.58	78.42

Moran's index tool calculates the Moran's Index value, Z score and p-value evaluating the significance of index. In the present model a p-value is small (0.000015), hence the null hypothesis was rejected that means there is spatial autocorrelation between the values associated with the geographic features in the study area. Moran's index value was 0.357501, this indicates that spatial features and their associated data values tend to be clustered (positive spatial autocorrelation) as it is greater than zero. The tool returns a Z score of 3.429816 this indicates that 3.429816 standard deviations were away from the mean. The following Table 8 shows the summary of Moran's Index calculations.

Table 8: Results of spatial autocorrelation

Variables	Values
Moran's Index	0.357501
Z-score	3.429816
P-value	0.000015

4.4. Identifying areas of malaria hazard

As shown in Table 9 and 10 the AHP revealed that rainfall, altitude, streams, temperature and swamps and ponds were the predictors of the malaria presence with percentage influence of 44%, 38%, 4%, 7% and 7% respectively. Rainfall and altitude were the dominant factors for the existence of malaria as hazard as compared with other selected malaria hazard factors and streams showed the least percentage influence as AHP pair-wise comparison revealed.

Table 9: Principal Eigenvector of the pair-wise comparison matrix

Factor	Weight
Altitude	0.3761
Rainfall	0.4455
Streams	0.039
Swamps and ponds	0.0694
Temperature	0.07

Consistency ratio (CR) is 0.02.

The consistency ratio for the Eigenvector of weights is within an acceptable range with the value 0.02. The following Table 10 shows the weight, rank and degree of vulnerability of each selected parameter to identify malaria hazard area to the study area.

Table 20: Characteristic of factors in relation to Malaria hazard area identification

Factors	Weight	Class	Rank	Degree of vulnerability
Rainfall	44	98–100 mm 100–103 mm 103–105 mm 105–108 mm >108 mm	5 4 3 2 1	Very low Low Moderate High Very high
Altitude	38	<2000 m 2000–2200 m 2200–2400 m 2400–2600 m >2600 m	1 2 3 4 5	Very high High Moderate Low Very low
Distance from Swamps and ponds	7	0–500 m 500–2000 m 2000–3500 m 3500–5000 m >5000 m	1 2 3 4 5	Very high High Moderate Low Very low
Distance from Streams	4	0–500 m 500–2000 m 2000–3500 m 3500–5000 m >5000 m	1 2 3 4 5	Very high High Moderate Low Very low
Temperature	7	<15^{o}C 15–17^{o}C 17–19^{o}C 19–21^{o}C >21^{o}C	5 4 3 2 1	Very low Low Moderate High Very high

The following map (Figure 20) shows the malaria hazard map of the study area. The malaria hazard map of level of malaria vulnerability illustrates 46.77 km^{2} (0.31%) very high, 64504.51 km^{2} (43.25%) high, 76446.74 km^{2} (51.26%) moderate and 8122.58 km^{2} (5.44%) low. This reveals most of the study areas were subjected to high and moderate malaria hazard area. The following Figure 20 shows the malaria hazard vulnerability of the study area.

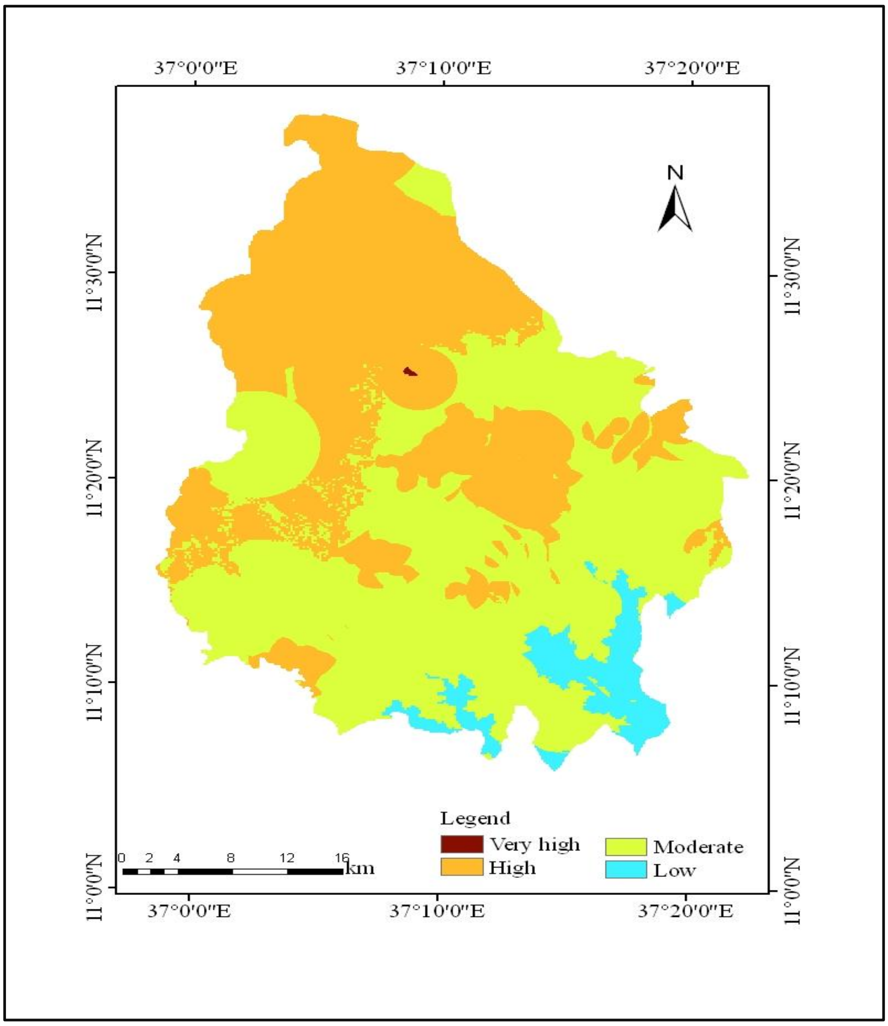

Figure 20: Malaria hazard map of the study area

4.5. Malaria vulnerability

The following map (Figure 21) shows the malaria vulnerability of the study area. The result, illustrates, 1878.04 km^2 (1.26%) moderate, 39794.21 km^2 (26.68%), low and 107446.73 km^2 (72%) very low level of malaria vulnerability. This indicates the majority of the study area is under very low malaria vulnerable relatively.

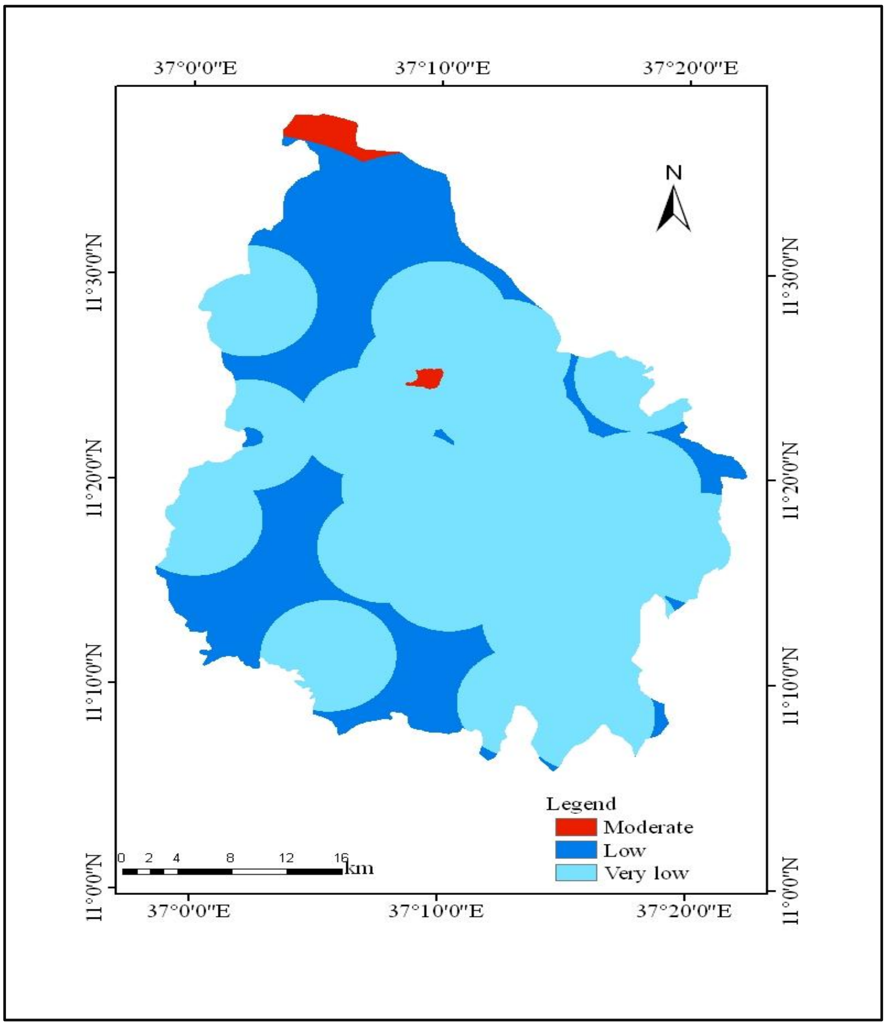

Figure 21: Malaria vulnerability

4.6. Element at risk map of malaria

Figure 22 shows the element at risk vulnerability level that was developed from different LU/LC types. The results of NDVI values was ranges from -0.266708–0.569553 as shown in figure 22 b. The lowest (negative) NDVI values indicate the water bodies. The highest NDVI values indicate plantation and bush lands The following Table 11 shows the results of NDVI value for each LU/LC types revealed from the study.

Table 11: NDVI values for each land-use/land-cover types

Variables	NDVI
Irrigation	0.143
Water bodies	-0.075
Farm land	0.144
Plantation	0.245
Grass land	0.178
Bare land	0.148
Wet lands	0.103
Settlement	0.114
Bush and shrub lands	0.188

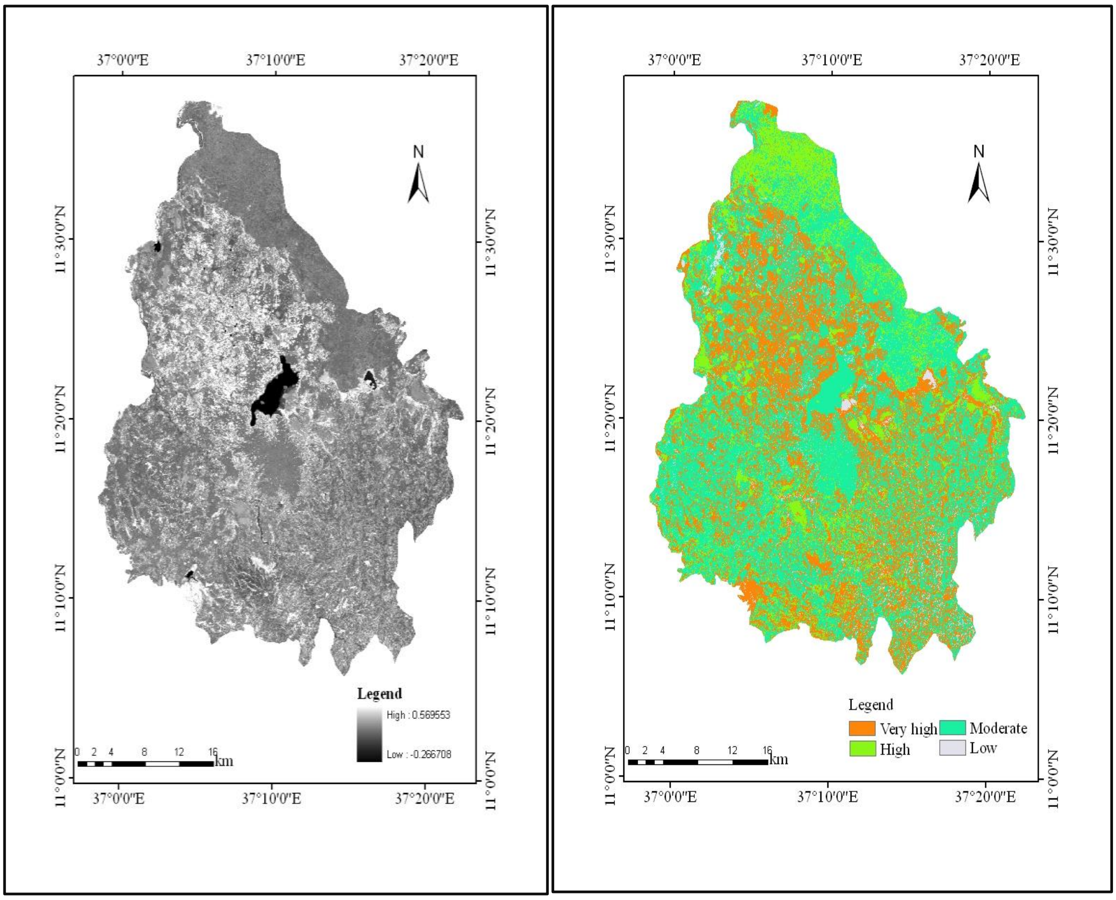

Figure 22 a: NDVI value map

Figure 22 b: Reclassified LU/LC

Figure 22: Element at risk map of malaria

The element at risk map (Figure 22) illustrates that 48523.66 km^2 (32.54%) very high, 21365.29 km^2 (14.32%) high, 75556.48 km^2 (50.66%) moderate and 3673.56 km^2 (2.46%) low level of malaria vulnerability.

4.7. Identifying malaria risk area

As shown in the Table 12 the study was revealed malaria hazard, element at risk and malaria vulnerability had respectively a 63%, 31% and 6% weight of influence for the existence of malaria disease, (Table 12). Malaria hazard layer was the dominant factor for the final malaria risk map. The following Table 12 shows the importance of three layers for final risk map.

Table 32: Characteristic of factors in relation to Malaria risk area identification

Factors	Weight	Rank	Degree of Vulnerability
Hazard map	63	1 2 3 4	Very high High Moderate Low
Element at risk map	31	1 2 2 4	Very high High Moderate Low
Vulnerability map	6	2 3 4	Moderate Low Very low

The final risk map was described as very high, high, moderate and low level of malaria risk. Malaria risk map of Mecha District illustrated that there is no any area, which is free from malaria risk. The result shows that 33.59 km^2 (0.23%) is very high, 69305.82 km^2 (46.47%) is high, 76830.96 km^2 (51.52%) is moderate and 2948.61 km^2 (1.97%) is low risk areas for malaria. The majority of the study area is subject to high and moderate risk of malaria and there is no area in the study area free from malaria risk. The following Figure 23 shows the malaria risk map of the study area.

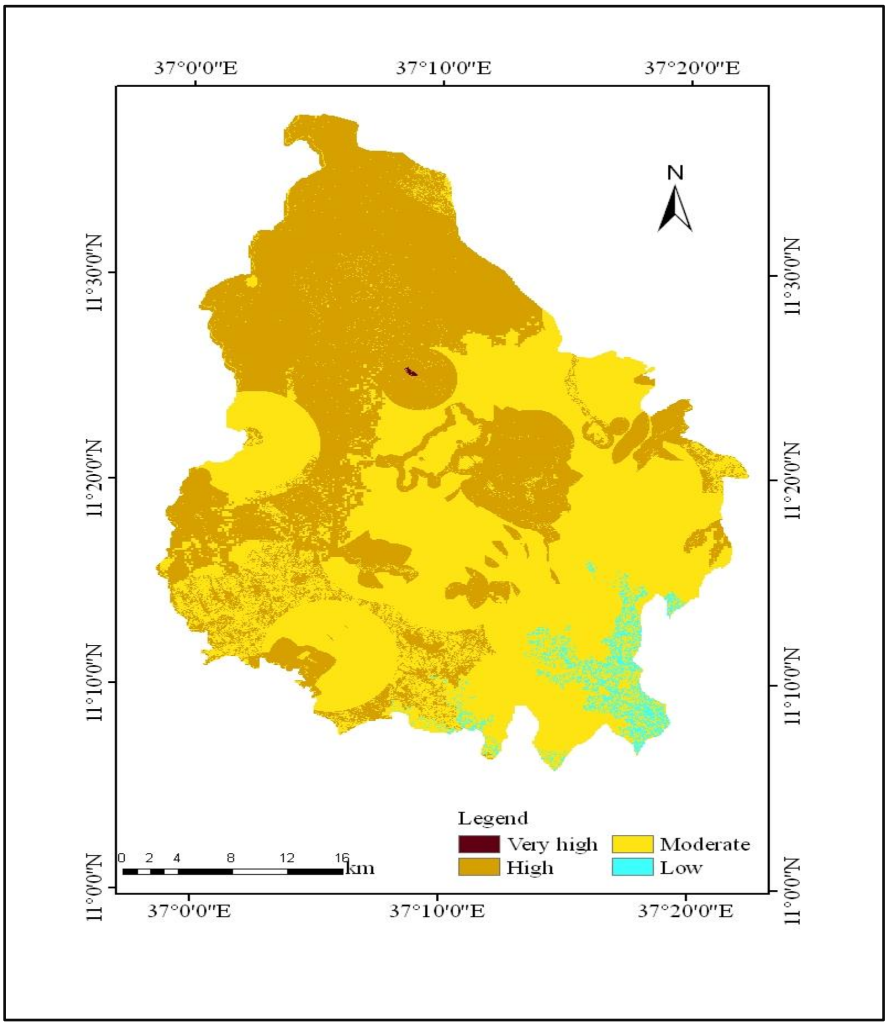

Figure 23: Malaria risk map of the study area

The final model based risk map revealed that all selected parameters *viz.* rainfall, altitude, temperature, slope, land-use/land-cover, distance from health facilities, distance from swamps and ponds, population density and distance from streams had different weight influence for the prevalence of malaria disease in Mecha District. Rainfall and altitude were the dominant factors for the existence of malaria disease as revealed from different statical results.

The total area and degree of vulnerability for malaria prevalence to the final malaria risk map and its layers (malaria hazard map, element at risk map and vulnerability map) are shown in Table 13.

Table 43: Summary of the results for malaria risk and its layers

Type of area	Area in (km^2)	Area in (%)	Degree of Vulnerability
Malaria hazard map	46.77	0.31	Very high
	64504.51	43.25	High
	76446.74	51.26	Moderate
	8122.58	5.44	Low
Vulnerability map	1878.04	1.26	Moderate
	39794.21	26.68	Low
	107446.73	72	very Low
Element at risk map	48523.66	32.54	Very high
	21365.29	14.32	High
	75556.48	50.66	Moderate
	3673.56	2.46	Low
Final Malaria risk map	33.59	0.225	Very high
	69305.82	46.47	High
	76830.96	51.52	Moderate
	2948.61	1.97	Low

4.8. Malaria risk levels of Mecha District Villages

As shown in Figure 24, all villages in the study area fall in the risk of malaria. One of them (Merawi town) was fall in very high malaria risk level and the rest fall in high to low level of malaria risk levels. The following figure shows the risk of malaria comparing villages in the study areas. In general, as shown in Figure 24 the whole district is in the risk of malaria. Most of the villages in the study area fall under high and moderate risk of malaria.

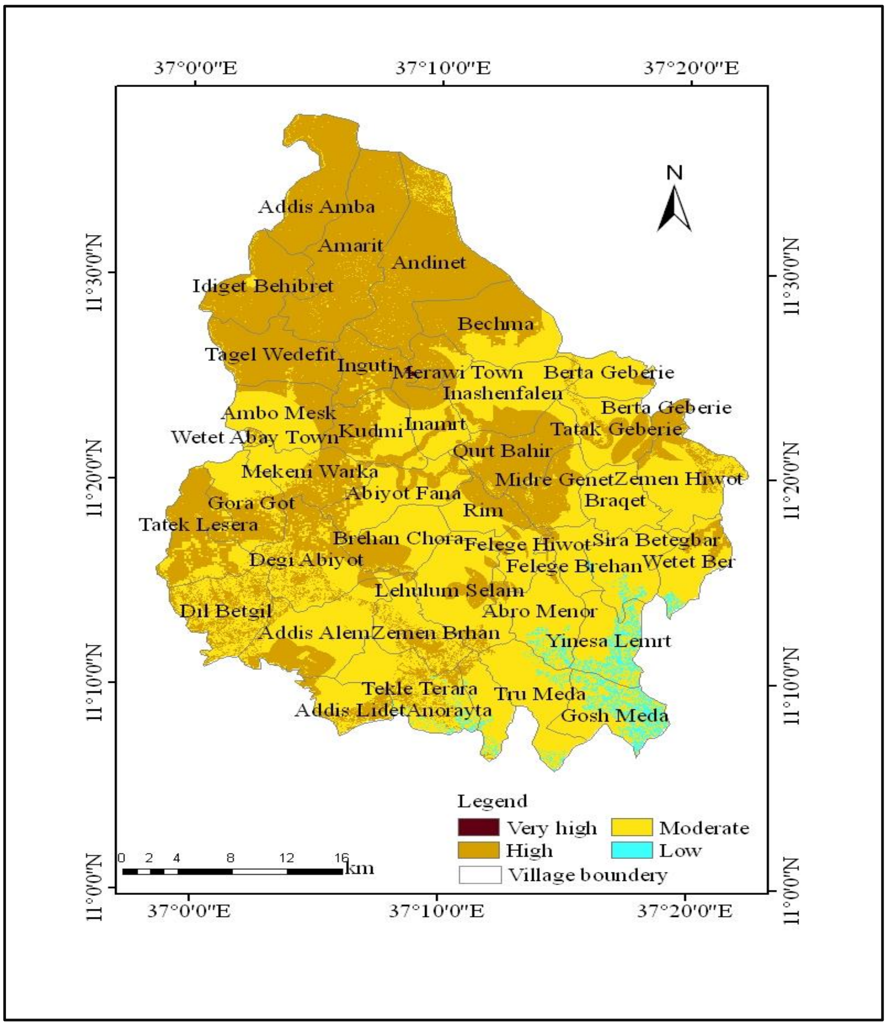

Figure 24: Malaria risk map per villages of the study area

CHAPTER V

DISCUSSION

Along with the development of personal computers and available software, GIS, has come to be used for lifeline management when disease occur. There are also global awareness of the importance of GIS techniques in providing priority for medical treatment (Carlos *et al*., 2010). GIS-based malaria incidence mapping has been used for risk assessment at national, regional, town and village level. Many maps of global malaria risk distribution in space and time have been prepared using GIS and RS. In the present study, ArcGIS, ERDAS Imagine and IDRISI software, which are capable of integration with spatial and aspatial data were used.

The distance to the streams showed a relationship with the disease prevalence. Some areas nearer the water bodies showed a low prevalence as a result of the fact that the main river is effectively being utilized as the river flows fast. There is no stagnation of the water body in the river. However, in some communities ponds are created close to the streams and rivers in order to store water for the dry season. Such ponds become stagnant points that enhances the breeding of mosquitoes that may increase the malaria prevalence at areas far off from the streams (Bautista *et al.*, 2006). But, breeding of mosquito is related with different water sources. Mosquito requires slow moving water to lay on its eggs and complete its life cycle to be an adult. Swamps and ponds are mentioned among several of these. In the present study, swampy area is broad that included swamps and ponds. The distribution of swampy areas is not inconsistent throughout the study area. A weak negative association was shown between distance from streams and malaria risk exists in the study area as the regression analysis revealed. Moreover, it has been previously shown that a negative association exists between the incidence of malaria incidence and water bodies (Abdulhakim, 2013; Aster and Meron, 2010 and Yihenew, 2007).

Higher elevation in general has long been recognized to be negatively associated with malaria due to its association with cooler temperatures that slows the development of anopheline vectors and the *Plasmodium* parasites they transmit. The relationship between malaria prevalence and altitude may be related to availability of optimal conditions for the development of malaria parasites in the mosquito vectors (Patz, *et* *al*., 2008). Malaria prevalence is decreases with increase in altitude. The fact that the elevation varied in some instances with the disease prevalence may have been as a result of differences in elevation was insignificant in areas above 2000 m altitudes (Bautista *et al.*, 2006). Transmission usually occurs at altitude <2000 m asl, but occur up to 2400 m (Patz *et al*., 2005). The present study shows higher negative correlation between monthly incidence of malaria and altitude. The strength of association between altitude and monthly incidence of malaria was high. Several workers from different places (Patz *et al*., 2005, Yazoume *et al*., 2008 and Yihenew, 2007) found the same results.

Rainfall resulted in an increase in the malaria prevalence. Rainfall increases parasitic density soon after the start of the rainy season because the rains provide good breeding sites for the mosquito vectors. As the vector habitants increases, vector breeding increase which accelerates the transmission of infection (Omukunda *et al*., 2013). The present study shows higher positive correlation between temperature and rainfall and monthly incidence of malaria. The correlation coefficient for the association between monthly rainfall and monthly incidence of malaria was found greater than that for the association between different explanatory variables and malaria incidence. This indicates that rainfall has an important role in the transmission of the disease than the others factors assessed. Several workers from different places (Yazoume *et al*., 2008 and Patz *et al*., *2003*) found the same results. Moreover, it has been previously shown that a strong positive association exists between the incidence of malaria incidence and rainfall. A rise in temperature in some locations, enhance the survival chances of *Plasmodium* and *Anopheles* mosquitoes and thus accelerates the transmission dynamics of malaria and spread it into populations that are currently malaria-free. The present study revealed both negative and positive relationships between monthly incidence of malaria and temperature. There is a negative relationship during the months January to April and August, when the study area had the minimum and maximum temperature. This indicated that the increase in temperatures does not actually mean an increase in the malaria transmission risk if this is accompanied by a decrease in rainfall. Although temperatures favor parasite development, the lack of water prevents vector development.

The habitants of vector mosquitoes differ according to the vegetation and the nature of local environment. Land-use/land-cover types with plantation and bush lands showed the strong association of malaria cases, indicating that this LU/LC may in fact be a proxy for predictors of elevated malaria risk (Richard Y. and Poccard, I. 1998). NDVI is a sensitive index for assessing disease associations evaluated the relationship between rainfall and temperature and malaria incidence. The relationship of Normalized Differential Vegetation Index (NDVI) to Entomological Inoculation Rate (EIR) is highly correlated. The lower the NDVI value indicates the lower the vegetation level and the area is thought to be dry (Ceccato et al., 2005). The present study result shows lower correlation between the incidence of malaria and water bodies and high in plantation due to the prevalence of high NDVI value. This finding is similar to the report of (Ehlkes *et al.*, 2014 ; Oliveira *et al*, 2013 and Richard Y. and Poccard, I. 1998).

Slope is a crucial factor water to be stagnated. This is because in areas with low slopes, water tends to be dammed, and this condition aggravated by the physical soil properties, which are lodged or impermeable. Therefore, in the absence of efficient water drainage systems can led to the creation of stagnant water pools and used as a crucial factor of water stagnates, which in turn, encourage the breeding and survival of mosquitoes (Madeleine *et al.*, 1999). The present study shows that slope gradient has negative influence on malaria incidence. This relationship could be attributed to the different slope types found on different geographic locations across the studied landscapes. The bottom areas and foot slopes characterized by flat or gentle slopes are mostly under irrigated vegetables swamps and water bodies. As slope increases from lower parts to middle and upper slopes the habitants of mosquitoes becomes uncomfortable.

Presence of health institutions in a particular area is very important for control of disease, awareness creation about different diseases and means of prevention (Meron, 2010). These in turn influence the prevalence of a particular disease. Absence and distant health institutions result in difficulties in accessibility and high cost of treatment. Therefore, people who are near to health institutions are safer relative to those who are at farther places. The identification of potential malaria risk localities helps the health authorities to minimize expenditure. The authors agree with this statement and in particular with establishment of an interrelationship between health facility availability and transmission of malaria. The present study shows negative correlation between monthly incidence of malaria and distance from health facilities. The relationship of distance from health stations and malaria incidence is statically significant. The maps will also help the regional state to prioritize risk areas for control activities.

The high population density in malaria free areas has caused movements, severe environmental degradation, leading to extensive drought and famine in many areas. These internal movements of the population, particularly from malaria free areas to malaria-prone areas have also resulted in transmission of malaria (Wakhari *et al.*, 2006). Malaria risk may increase in certain regions due to population movement by labor related to agriculture, mining, conflict and refugees, airport malaria, imported malaria (Marten, 2000). Work opportunities and resettlement programs in malaria endemic areas can easily attract a large number of people, making them vulnerable to the disease (Meron, 2010). Major environmental transformations like deforestation and new construction take place during resettlement, enhancing the proliferation of mosquito breeding sites, and result in malaria outbreaks (Kathleen, 2002). The present study shows strong positive correlation between monthly incidence of malaria and population density. The correlation coefficient for the association between population density and monthly incidence of malaria was strong. This finding is similar to the report of (Aster, 2010 and Martens, 1995).

CHAPTER VI

CONCLUSION AND RECOMMENDATION

6.1. Conclusion

This study was aimed at using GIS and RS tools for identification of malaria-prone areas to identify malaria risk level with reference to Mecha District. Research has shown that the technologies are available to create early warning system which could prevent risks and limit the scale of outbreaks. Furthermore, the final malaria risk map can be used to enable decision makers to use and ensure the scarce resources to the most high-risk areas to prevent or reduce cost of prevention with efficient targeting of the malaria risk areas. This study was achieved by selecting different parameters which are affect the prevalence of malaria with the integration of GIS and RS.

In the present study, model based malaria risk map was carried out by statistically establishing the relationship of various parameters using remote sensing and geographic information system. To identify the statistical correlations between malaria cases and climatic and non-climatic factors the regression analysis and NDVI value calculation were applied. Rainfall, data showed statistically positive correlation and dominant factor for mosquitoes breading and malaria transmission as revealed from the study.

The study carried out in Mecha District reveals that RS and GIS techniques are proved to be a significant in larval habitat identification and risk area mapping. The risk area identification map indicates affected area which varies for different villages. The final malaria risk map of the study area shows, that the entire study area has malaria-risk factors. The areas fall under very high, high moderate and low with risk areas. The malaria risk map obtained from the study is able to support decision makers in space and time so as to control malaria spread.

6.2. Recommendations

- Beyond the parameters used for malaria risk analysis in the study area, irrigation factor can contribute a great factor for malaria prevalence. Therefore, distance from irrigation factor should also be used as a factor for better exactness as the study area covered by a great irrigation area (Koga irrigation).
- Most of the local people in the area were used ponds for irrigation purpose in winter season and this creates suitable condition for malaria prevalence. Therefore, awareness service about the proper use of ponds is vital to control malaria breeding.
- Increase health institutions and advanced professionals is important for reduction and transmission of malaria.
- Identified malaria risk factors that are conductive for malaria prevalence are vital to take measures for malaria reduction or elimination.
- The District need to pay attention for malaria breeding and controlling methods using the output of GIS, RS and GPS technique.
- Based on the spatial distribution of malaria risk occur, the government and other responsible bodies need to pay attention to establish early warning system.
- The District should have proper database about health facilities, with reference to malaria cases.
- Future studies should incorporate additional criterion such as using high resolution satellite images.

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APPENDIX I

Pair-wise comparison of factor layers to Hazard map

Layers	Altitude	Rain fall	Streams	Swamp and ponds	Temperature
Altitude	1				
Rain fall	1	1			
Streams	1/7	1/9	1		
Swamp and ponds	1/5	1/7	1	1	
Temperature	1/7	1/9	1/3	1/2	1

Pair-wise comparison of factor layers to malaria risk map

AHP weight derivation			
	Hazard layer	Element at risk layer	Vulnerability layer
Hazard layer	1		
Element at risk layer	1/2	1	
Vulnerability layer	1/7	1/3	1

Land-use/land-cover type classification for malaria vulnerability

No.	Land-use/land-cover type	Rank	Degree of Vulnerability
1	Plantation	1	Very high
2	Shrub land	2	High
3	Grass land		
4	Settlement	3	Moderate
5	Farm land		
6	Water bodies		
7	Irrigation		
8	Wet land	4	Low
9	Bare land		

Keys

A→Koga irrigation main power and typical breeding site of its site
B→Typical breeding site irrigated by using ponds
C→Typical breeding site near to the school
D→Typical breeding sites near to residential areas
E→Typical breeding sites near to Birakat town
F→Shrub lands for malaria breeding.