Modelling Malaria Vulnerability Hotspot by Using Geospatial Techniques: The case of Kindo Koysha Woreda, Wolaita Zone, Ethiopia

By: Abel Daniel Banti

A Thesis Submitted to

The Department of Geomatics Engineering

School of Civil Engineering and Architecture

Presented in Partial Fulfillment of the Requirement for the Master of Science Degree in Geoinformatics Engineering

Office of Graduate Studies

Adama Science and Technology University

July-2021

Adama, Ethiopia

Modelling Malaria Vulnerability Hotspot by Using Geospatial Techniques: The case of Kindo Koysha Woreda, Wolaita Zone, Ethiopia

Abel Daniel Banti
Advisor: Dr. Tilahun Erduno

A Thesis Submitted to
The Department of Geomatics Engineering
School of Civil Engineering and Architecture

Presented in Partial Fulfillment of the Requirement for the Master of Science Degree in Geoinformatics Engineering

Office of Graduate Studies
Adama Science and Technology University

July-2021
Adama, Ethiopia

APPROVAL SHEET

I/we, the advisors of the thesis entitled “Modelling Malaria Vulnerability Hotspot by using Geospatial Techniques: The case of Kindo Koysha Woreda, Wolaita Zone, Ethiopia” and developed by Abel Daniel Banti, hereby certify that the recommendation and suggestions made by the board of examiners are appropriately incorporated into the final version of the thesis.

Tilahun Erduno (PhD)	____________________	____________________
Major Advisor	Signature	Date

We, the undersigned, members of the board of Examiners of the thesis by Abel Daniel Banti have read and evaluated the thesis entitled “Modelling Malaria Vulnerability Hotspot by using Geospatial Techniques: The case of Kindo Koysha Woreda, Wolaita Zone, Ethiopia” and examined the candidate during the open defense. This is, therefore, to certify that the thesis is accepted for partial fulfillment of the requirement of the degree of Master of Science in Geoinformatics Engineering.

Roba Gemechu (PhD)	____________________	____________________
Chairperson	Signature	Date
Yared Girma (PhD)	____________________	____________________
Internal Examiner	Signature	Date
Asfaw Mohammed (PhD)	____________________	____________________
External Examiner	Signature	Date

Finally, approval and acceptance of the thesis is contingent upon submission of its final copy to the office of Postgraduate Studies (OPGS) through the Department Graduate Council (DGC) and School Graduate Committee (SGC).

______________________________	____________________	____________________
Department Head	Signature	Date
______________________________	____________________	____________________
School Dean	Signature	Date
______________________________	____________________	____________________
Post-graduate Dean	Signature	Date

DECLARATION

I hereby declare that this Master Thesis entitled "Modelling Malaria Vulnerability Hotspot by Using Geospatial Techniques: The case of Kindo Koysha Woreda, Wolaita Zone, Ethiopia" is my original work. That is, it has not been submitted for the award of any academic degree, diploma, or certificate in any other university. All sources of material that are used for this thesis have been duly acknowledged through citation.

Name: Abel Daniel Banti Signature: ___________________________ Date______________

RECOMMENDATION

I/we, the advisor(s) of this thesis, hereby certify that I/we have read the revised version of the thesis entitled “Modelling Malaria Vulnerability Hotspot by Using Geospatial Techniques: The case of Kindo Koysha Woreda, Wolaita Zone, Ethiopia” prepared under my/ our guidance by Abel Daniel Banti submitted in partial fulfillment of the requirements for the degree of Master’s of Science in Geoinformatics Engineering. Therefore, I/we recommend the submission of the revised version of the thesis to the department following the applicable procedures.

Major Advisor

Name: Tilahun Erduno (Ph.D) Signature: ___________________ Date:_______________

ACKNOWLEDGEMENT

First and foremost, I want to thank almighty God, for helping me to complete this research work. Next, this work would not have been possible without the assistance of several people and organizations. So I would like to express gratitude from the bottom of my heart.

I would like to express my gratitude to Advisor Tilahun Erduno (PhD) for his supervision, support, and guidance, as well as for assisting me in overcoming obstacles and answering all of my questions during my research work. Special thanks to Adama Science and Technology University (ASTU) and Arba Minch University for financial assistance in pursuing my studies and related research activities to achieve my research goals.

I would also like to thank Daniel Alemayehu (PhD) for his advice and kindness, as well as Ato Behailu from the Wolaita zone health department for his assistance in gathering epidemiological data for this research. Last but not least, I would like to thank my parents, course instructors, and friends for their thoughtful encouragement throughout my research work.

TABLE OF CONTENTS

Contents **Page**

LIST OF TABLES

LIST OF FIGURES

Figure number and title **Page**

LIST OF ACRONYMS AND ABBREVIATIONS

ALOS	Advanced Land Observing Satellite
API	Annual Parasite Incidence
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
CSA	Central Statistical Agency
DEM	Digital Elevation Model
ERDAS	Earth Resources Data Analysis System
ESRI	Environmental Systems Research Institute
FMoH	Federal Ministry of Health
GIS	Geographical Information System
GPS	Global Positioning System
IDW	Inverse Distance Weightage
ITN	Insecticide Treated Net
IRS	Indian Remote Sensing
MCE	Multi-Criteria Evaluation
MSL	Mean Sea Level
NGO	Non-Governmental Organization
NIAID	National Institute of Allergy and Infectious Diseases
NMA	National Meteorological Agency
NRC	National Research Center
OLI	Operational Land Imager
PALSAR	Phased Array type L-band Synthetic Aperture Radar
Pf	Plasmodium falciparum
RS	Remote Sensing
SOI	Survey of India
SRTM	Shuttle Radar Topography Mission
TM	Thematic Mapper
USGS	United State Geological Survey
WHO	World Health Organization
WorHO	Woreda Health Office
WZHD	Wolaita Zone Health Department

ABSTRACT

Malaria is a serious, acute disease spread by female Anopheles mosquito bites. Malaria is caused by four parasite species. Plasmodium falciparum is the most common of the four human malaria parasites in Sub-Saharan Africa. Ethiopia, one of Africa's Sub-Saharan countries, is suffering from a malaria epidemic. Malaria is a major burden on public health services in Wolaita Zone approximately 85 percent of the population is at risk of malaria, and despite effective prevention and control interventions, the malaria outbreak continues. The traditional vector-borne disease control strategy is based on scientific evidence though full of doubts and ambiguities. Currently, the problem is becoming greater due to time-consuming prevention and control activities for malaria. The main objective of the current study is to apply Geospatial techniques for geographical, socioeconomic, and epidemiological parameters that increase certain conditions for malaria incidence to malaria vulnerability hotspot identification by using the multi-criteria evaluation method. GIS and remote sensing were used to create a malaria vulnerability hotspot map of the study area. GIS software is used to overlay and analyze various geographical datasets. All the parameters were rated based on their influence on mosquito breeding and suitability for mosquito habitat. The hotspot identification is done by applying the AHP to weight the factor for weighted overlay and finally the malaria vulnerability hotspot map identified by using the malaria hotspot identification algorithm. The findings of the current result show that very high and high vulnerable areas accounted for about 51 percent (224.14 km^2), moderate covers 26 percent (116.560 km^2), and Low vulnerable areas also account for 23 percent (103.600 km^2) of the study area. Mashenga, Mundena, and the Fajana Mata kebeles those very highly vulnerable hotspots from the Kindo Koysha Woreda kebeles and also Borkeshie, Dada Kare, Moliticho, Sere Finchawa, and Chereche are highly vulnerable. Generally, the western part of the study area which is near to Omo River with low elevation is highly vulnerable to malaria incidence. Reliable maps of malaria vulnerability hotspots are critical for estimating the scope of the problem and, consequently, the resources required to combat malaria. The current study confirmed that the Geospatial technology with the base of multi-criteria evaluation to model malaria vulnerability is more capable and efficient to apply. Similar research needs to be conducted in areas experiencing malaria epidemic prediction by using Geospatial techniques. It will be used as an input to the elimination program of malaria rather than control practice.

Keywords: *Epidemiology, GIS, Hotspot, Malaria, and Vulnerability*

CHAPTER I: INTRODUCTION

1.1. Background of the Study

Malaria is a severe, acute disease spread by the bites of infected female Anopheles mosquitoes, also known as "malaria vectors". Malaria remains a major cause of illness and death in children and adults around the world, with 87 countries reporting one or more cases of malaria in 2017 (WHO, 2019). Four parasite species cause malaria in humans, and two of these species Plasmodium falciparum and Plasmodium vivax-are the most common. Plasmodium falciparum accounted for 99.7 percent of the total cases of malaria in the WHO African Region in 2018, 50 percent of cases in the South-East Asia Region, and 71 percent of cases in the Eastern Mediterranean Region (*WHO*, 2020).

Plasmodium Falciparum is that the commonest of the four human malaria parasites across much of Sub-Saharan Africa. The distribution of Plasmodium vivax is concentrated within the Horn of Africa, covering Djibouti, Eritrea, Ethiopia, Somalia, and Sudan. Plasmodium Falciparum accounts for nearly all the malaria mortality in Sub-Saharan Africa, and it's often stated that the continent bears over 90 percent of the worldwide Plasmodium falciparum burden (Feachem & Jamison, 1991).

Ethiopia, one of the sub-Saharan countries in Africa is a victim of malaria (Kassaw et al., 2019). Malaria remains one of the leading causes of illness and death in Ethiopia (Eniyew, 2018). It's one of the most health problems within the country during which its cases are one of the highest and increasing at an alarming rate. However, exposure to malaria varies markedly by location and season (Ahmed, 2014). Ethiopians, living at altitudes −100 to >4220 m, the topography is a rich breeding ground for the Mosquitoes (Kassaw et al.,2019; Ahmed, 2014).

According to FMOH, (2020) malaria transmission in Ethiopia occurs primarily up to 2000 meters of altitude but may also sometimes impact areas up to 2300 meters of altitude. However, the levels of malaria risk and transmission intensity within these geographic ranges display marked seasonal, inter-annual, and spatial variability due to wide variations in climate (temperature, precipitation, and relative humidity), topography (altitude, surface hydrology, land cover, and land use, etc.) and characteristics of social settlement and population movement (FMOH, 2020). More than 50 million (68%) of the populace live in regions below 2000 meters above the mean sea level are at risk of malaria (Abdulahi et al., 2020; Manoharan et al., 2020). Most parts of the world have peak malaria incidence periods from September to December, after the main rainy seasons (June-September), and from March to May, during and after the minor rainy seasons (February-March) (FMOH, 2020).

Malaria is a major burden of public health services in the Wolaita Zone. According to WZHD (2019), about 85% of the population is at risk of malaria, despite effective prevention and control intervention. The outbreak of malaria is continuous in three woredas: Kindo Koysha, Boloso Sore, and Humbo. To overcome this problem it is important to use cost and time-effective preventive and control practices.

Prevention of malaria can be more cost-effective than treating the disease in the long run (Dana, 2018). Experts, specialists, or scientists working on vector-borne disease control are applying many traditional, conventional, and modern scientific methods. However, conventional approaches are laborious, costly, erroneous, and time-consuming (Manish, 2017). Recently, the Geographical Information System (GIS) has emerged as an innovative and important component of many projects in public health and epidemiology (Manoharan et al., 2020). One of the most useful functions of GIS in epidemiology continues to be its utility in basic mapping and it may also involve a more classy spatial analysis of disease occurrence (Manish, 2017).

Effective vector control requires a vast knowledge of the ecology of breeding and resting habitats as well as the actions of the different mosquito species, it is crucial to develop a tool with such functionality and great performance (Okogun, 2005, Pam *et al*., 2017). The Geographic Information System (GIS) and Remote Sensing (RS) are new technologies that have emerged as a frontrunner in malaria epidemiology research. By applying remote sensing and GIS techniques for mapping: vector environments, vector presence, abundance, and density, it also assesses the risk of vector-borne diseases, disease transmission, and spatial diffusion (Manish, 2017). Malaria continues to kill and harm a large number of people of all ages throughout Kindo Koysha Woreda at any given moment. Furthermore, Kindo Koysha has a substantial number of inpatient and outpatient malaria cases; it is a serious problem. The Woreda has suffered a great loss of life and money. As a result, research is necessary in Kindo Koysha, it is possible to model malaria cases linked to environmental, and socioeconomic variables very important. The modeling of these variables with the help of GIS and remote sensing techniques is very valuable for defining focal points of malaria transmission (Kassaw et al., 2019). Therefore, the current study focus is aimed to apply geographical, socioeconomic, and epidemiological parameters that facilitate conditions for malaria incidence, and to develop a malaria vulnerability hotspot map of the study area by using Geospatial techniques. The output of the current study map considered will be used as input to stakeholders for the betterment of preventive and control practices.

1.2. Statement of the Problem

Malaria is one of the common health problems in the world. To overcome this problem a wide range of measurements were taken but still, malaria is an epidemic in Africa countries mainly sub- Saharan countries. Ethiopia is also a victim of this epidemic of malaria. For Ethiopia, the burden of malaria is the loss of active employees due to sickness, school absenteeism, medical costs, and other indirect costs, such as adult workers who avoid working when infected. Kindo Koysha is a malarious district on the foot of Omo River in the Wolaita Zone. Malaria is a serious problem in Kindo Koysha, because of a large number of inpatient and outpatient cases. The data accessed from Kindo Koysha Woreda Health Office reveals that malaria is still epidemic in the area, with 3233, 2981, and 7008 consecutive data of malaria cases in the years 2017, 2018, and 2019 (WorHO, 2020).

Currently, the problem is becoming greater due to time-consuming prevention and control activities for malaria. According to Yadav *et al.,*(2012) that cited by (Qayum et al., 2015) Malaria control action plans are dying out due to improper implementation, inadequate surveillance, and lack of georeferenced information to pinpoint the trouble spots for timely preventive action. According to Kassaw et al., (2019) Geospatial technologies, i.e. GIS, RS, and GPS offer an opportunity for rapid assessment of malaria-endemic areas. These technologies coupled with prevalence/incidence data from health centers can provide reliable estimates of population at risk, predict disease distributions in areas that lack baseline data, and provide guidance for intervention strategies, so that, scarce resources can be allocated cost-effectively (Kumar *et al.*, 2012). The geospatial technology-based malaria risk assessment was used to identify the prone area to malaria risk by applying the geographical factors including; temperature, elevation, rainfall, land use/land cover, slope, and distance to stream (Ahmed, 2014). Also incorporated various parameters in addition to geographical factors were important to identify malaria hotspots, parameters like epidemiological and socioeconomic (Qayum et al., 2015). However, the previous research has not considered a spatial resolution and doesn't show the spatial extent of each degree of vulnerability at the village(Kebele) level.

Identification of extremely high and high-vulnerable areas ‘Hotspot’ is the most important issue in malaria vulnerability mapping and spatial analysis. Besides it uses in taking precautions in infrastructure assessment and resource allocation policy planning that made cost and time-efficient preventive and control practices. In the study area, the level of vulnerability for malaria was not identified previously. So to fill this gap the current study modeled the malaria hotspots of the study area by using environmental, socioeconomic, and epidemiological parameters with geospatial technologies to assess areas that are vulnerable to malaria incidence.

1.3. Objectives

1.3.1. General Objective

- To model malaria vulnerability hotspot based on Geospatial techniques by using the Multi-criteria evaluation method in the case of Kindo Koysha Woreda, Wolaita Zone.

1.3.2. Specific Objectives

The following are the specific objectives of the study.

- To identify potential malaria-causing factors in the study area.
- To develop the malaria vulnerability hotspots map of the study area.
- To compare the level of vulnerability for malaria between Kebeles of the study area.

1.4. Research Question

1. What are the potential factors that cause malaria in the study area?
2. Where is the high malaria vulnerability in the study area?
3. Which Kebeles of the study area are more vulnerable to malaria?

1.5. Significance

The findings of this study will help the Woreda health office to prioritize malaria prevention and control measures based on the vulnerability map, besides it helps the policymakers, concerned government bodies, and Nongovernmental organizations (NGOs) to make cost and time-efficient malaria prevention and control exercises.

1.6. Scope

This study is delimited geographically in Kindo Koysha Woreda, which is one of the Wolaita Zone Woredas, it covers an area of 444.30 sq. km. The study area Kindo Koysha was selected for the current study because to know the effect of the Omo River on the spread of malaria. The study content scope limited to develop Geospatial techniques based on malaria vulnerability hotspot map of Kindo Koysha woreda by applying Multi-criteria evaluation method to weight environmental, socioeconomic, and epidemiological parameters.

1.7. Limitation of the Study

The limitations of this study include a lack of well-documented data on malaria case studies and a lack of meteorological stations closer to the study area to perform an accurate interpolation process of temperature and rainfall maps.

1.8. Organization of the Thesis

This thesis is divided into five chapters. The first chapter contains; the background of the study, the problem statements, objectives, research questions, study significance, limitations, and scope of the study. The second chapter is a review of the literature. This includes the theoretical framework and an empirical framework that includes previous studies related to this study also contains the conceptual framework of the current study. Following that, chapter three delves deeper into the materials and methods. This chapter provides an overview of the study area, materials used, data processing and analysis methods, and the technical scheme of the study. The findings of the data analysis used to achieve the study’s objectives are presented in chapter four, along with their interpretation and discussion. The study's conclusion and recommendations for future research are found in chapter five.

CHAPTER II: LITERATURE REVIEW

This section explores theoretical, empirical, and conceptual frameworks. A Comprehensive review of malaria concepts and methods which are studied by different scholars in different countries is explored under a theoretical framework. An empirical framework explores the study of the malaria vulnerability hotspot identification in different countries. This section concluded with the conceptual framework of the current study that was developed from both theoretical and empirical frameworks.

2.1. Theoretical Framework

2.1.1. Malaria

Malaria is a mosquito-borne infectious disease that affects humans and other animals and is caused by parasitic protozoa or a group of unicellular microorganisms of the Plasmodium type (Dana, 2018). In humans the malarial parasites infect red blood cells, causing periodic chills and fever, and in some species of Plasmodium, the parasites can ultimately cause death (NRC, 2001). Plasmodium vivax and Plasmodium ovale are the most common while Plasmodium falciparum is the most deadly (NIAID, 2007).

Plasmodium falciparum is the cause of most malaria deaths, especially in Africa. The infection can appear out of nowhere and cause a variety of life-threatening complications. With timely and successful treatment, however, it is almost always curable (NIAID, 2007). Plasmodium vivax is geographically the most widespread species, causing less severe symptoms. However, relapses can last up to 3 years and debilitate chronic diseases. Plasmodium vivax was once distributed in temperate climates and is now mainly found in the tropics, particularly throughout Asia (NIAID, 2007).

Plasmodium malariae is an infection that not only causes typical malaria symptoms but can also persist in the blood for a very long time, possibly decades, without ever causing symptoms. However, an asymptomatic person (no symptoms) for Plasmodium malariae can infect others, either through blood donation or mosquito bites. Plasmodium malariae has been eradicated in temperate climates but persists in Africa (NIAID, 2007), and Plasmodium ovale is also rare, can cause relapses, and is generally found in West Africa (NIAID, 2007).

From the above listed four malaria type's current study focused on Plasmodium falciparum and plasmodium vivax because in Ethiopia only these species cause malaria. According to Mestewat, (2014) Among the Plasmodium species, Plasmodium falciparum and Plasmodium vivax are the most dominant malaria parasites in Ethiopia, distributed across the country and accounting for 60% and 40% of malaria cases, respectively. Plasmodium malariae accounts for less than 1% and Plasmodium ovale is rarely reported.

The malaria parasite, the human host, and the Anopheles mosquito all play a significant role in the disease's spread (Ahmad et al., 2017). The parasite is principally transmitted by the major mosquito vector known as Anopheles arabiensis. In some areas, Anopheles pharoensis, Anopheles funestus, and Anopheles nili also transmit the disease (WHO, 2020). High malaria incidence is primarily the cause of the drug resistance of the parasite. There is various other reason; including excessive deforestation, indiscriminate use of pesticide in agriculture, demographic shift for the enhanced rate of spread of malaria transmission (Qayum *et al*., 2015). The suitable habitat for vectors is surface water for production; humidity needed for adult mosquito survival, the influence of temperature for developmental rates of both vector and parasite populations (Ahmed et al. 2017). Climate, local ecology, and active control affect the ability of malaria parasites and Anopheles mosquito vector to co-exist long enough to enable transmission or endemicity depends on the density and infectivity of the Anopheles vector. These features depend on a range of climate, physical, and population characteristics (Feachem & Jamison, 1991).

2.1.2. Malaria Burden in World

Malaria is one of the most serious health problems in the world (Abdelsattar & Hassan, 2020). According to the WHO (2020), there were an estimated 229 million cases of malaria worldwide in 2019. The estimated number of malaria deaths in the 2019 report was 409,000. Children under the age of 5 are the most susceptible group to suffer from malaria; In 2019, they accounted for 67% (274,000) of all malaria deaths worldwide. The WHO African Region carries a disproportionately high share of the global malaria burden. In 2019, the region was home to 94% of malaria cases and deaths. Total funding for malaria control and elimination was estimated at $ 3 billion in 2019 (WHO, 2020).

2.1.3. Malaria Burden in Africa

Malaria is one of the world's most serious public health issues, with 300 to 500 million cases and approximately one million deaths reported to date, 90 percent of which have been reported from Sub-Saharan African countries. (Alelign & Dejene, 2018). Malaria remains one of Africa's most serious public health issues, causing significant morbidity and mortality. Anaemia is one of the most serious consequences of malaria in young children in Africa, especially in countries with high levels of chloroquine resistance (Samba, 2001). It is one of the most common diseases afflicting poor people in developing countries, as well as one of the leading causes of death, particularly among children and pregnant women (Alelign & Dejene, 2018). The immunological profile has been altered in some areas due to a temporary decrease in transmissions caused by a climatic and ecological change (Samba, 2001). The African region has been experiencing malaria epidemics, with an unacceptably high disease burden and high mortality in the epidemic-prone areas in East and Southern Africa. Sub-Saharan Africa bears the lion's share of the global malaria burden, accounting for 71% of cases and 86% of deaths (Alelign & Dejene, 2018).

Malaria costs both individuals and governments a lot of money. Individual and family costs include the purchase of drugs to treat malaria at home, expenses for travel to and treatment at dispensaries and clinics, missed days of work, absence from school, expenses for preventive measures, and expenses for burial in the event of death. Maintenance, supply, and staffing of health facilities; purchase of drugs and supplies; public health interventions against malaria, such as insecticide spraying or distribution of insecticide-treated bed nets; lost days of work with resulting loss of income; and lost opportunities for joint economic ventures and tourism are all costs borne by governments(Samba, 2001).

2.1.4. Malaria Burden in Ethiopia

In Ethiopia, malaria is one of the most serious public health issues. Transmission is bimodal: Major: September to December, following the main rainy season of June to August, and Minor: April to May, following a brief rainy season of February to March. (Alelign & Dejene, 2018). Malaria is pervasive in Ethiopia; 75 percent of the landscape below 2000 meters above sea level is malarial, which includes fertile low-lying areas suitable for agriculture. More than 54 million populations live in these areas and are at risk of malaria (Alelign & Dejene, 2018). Efforts to combat the disease are constrained by a shortage of trained manpower, particularly of vector control supervisors at zonal level and technicians at sector and district levels in all regions, weak surveillance systems, shortage of drugs and laboratory supplies, shortage of spray pumps, and shortage of field logistics. Above all, operational finances are inadequate. Traditionally the malaria problem has been seen as a challenge for the health sector alone with little or no involvement by other sectors or the general community (Ethiopian public health institute, 2016).

Overall, the malaria transmission pattern in the country is seasonal and unstable, often characterized by focal and large-scale cyclic epidemics. A relatively long transmission season exists in the western lowland areas, river basins, valleys, and irrigation schemes. Due to the unstable and seasonal transmission of malaria, protective immunity is generally low and all age groups of the population are at risk of the disease (Ethiopian public health institute, 2016). The central highlands, which are >2500m above mean sea level, are generally free of malaria. The rest of the country, however, has a varied pattern of malaria transmission, with the transmission season ranging from less than three months to greater than six months. The map in (Figure 2.1) below shows the pattern of malaria in Ethiopia. According to WHO (2020). There are four major eco-epidemiological strata of malaria in the country: Malaria-free highland areas above 2500-meter altitude, Highland fringe areas between 1500 – 2500 meters (which are affected by frequent epidemics), Lowland areas below 1500 meters (with the seasonal pattern of transmission), and Stable malaria areas (characterized by all year round transmission). Because of climate and ecological diversity, there is variation in the epidemiology of its transmission (Tesfaye et al., 2011).

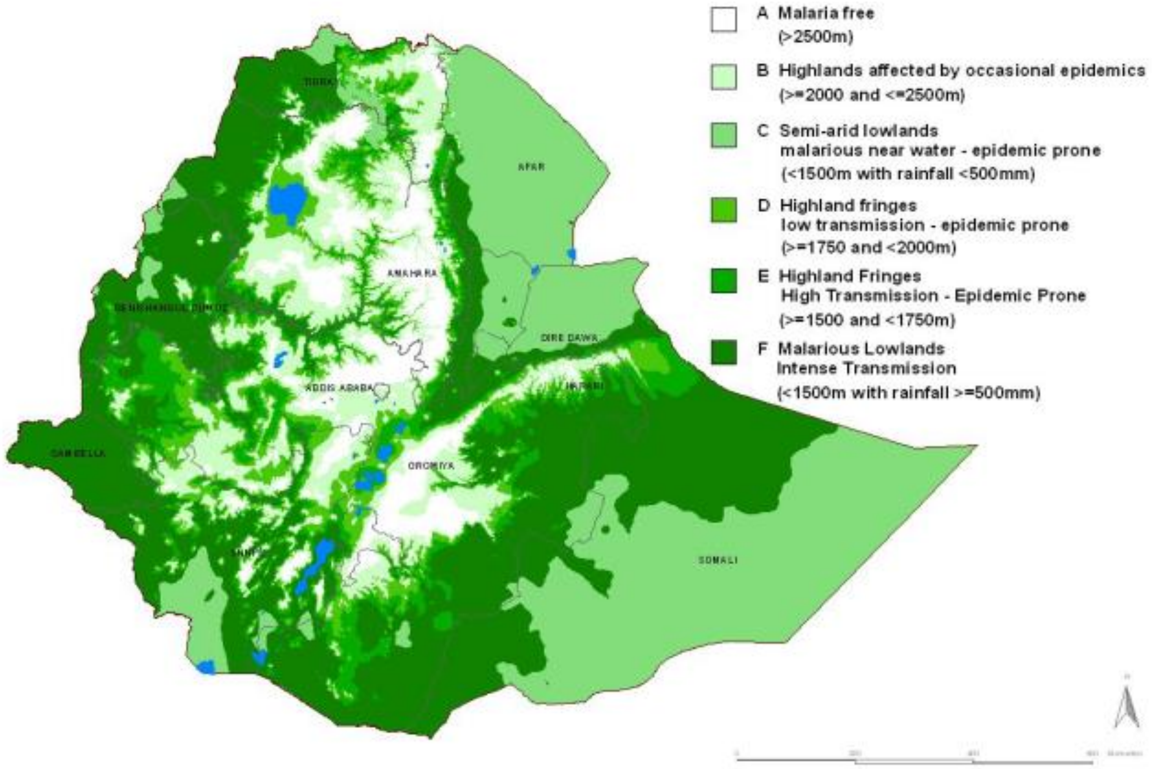


Figure 2.1 Malaria pattern in Ethiopia

Source:(Ethiopian public health institute, 2016)

2.1.5. Geospatial Technologies

Geospatial technology, which has been adopted successfully in other malaria control programs in developing countries, includes Geographic Information System (GIS), Global Positioning System (GPS), and remote sensing (RS) (Kirk et al., 2015).

Geographic Information System (GIS) is a computer-aided system with which all types of geographic data can be recorded, stored, manipulated, analyzed, managed, and presented

(Ishaya, 2019). It is also defined as an organized collection of computer hardware, software, geographic data, and personnel designed to efficiently collect, store, update, manipulate, analyze and display all forms of geographically referenced information (ESRI 1990).

Remote sensing can be defined as any process by which information about an object, area, or phenomenon is gathered without coming into contact with it. Because of this more general definition, the term has been associated more specifically with the measurement of interactions between the earth's surface materials and electromagnetic energy. Remote sensing data enables scientists to study the biotic and abiotic components of the earth (Beck et al., 2000). Several studies have used remote sensing imagery and geographic information system techniques to map the distribution of vector species on various spatial scales such as around the world, continent, national, regional, and even at the small village level (Akinbobola & Ikiroma, 2018).

Google Earth is a virtual globe, map, and geographic information program originally called Earth Viewer 3D and developed by Keyhole, Inc., a Central Intelligence Agency (CIA) funded company that was acquired by Google in 2004 (Mohammed et al., 2013).

2.1.6. Application of Geospatial Techniques in Malaria Vulnerability Mapping

When satellite data of various resolutions are combined with a Geographical information system (GIS), it opens up enormous possibilities for analyzing large amounts of data at a low cost, with accuracy, and in an efficient manner (Ahmad et al., 2017). The habitats of the anopheles mosquitoes and the chances of malaria risk to the human population can be detected by remote sensing and GIS (Bhatt, 2020). Analyses resulting from the combination of GIS and Remote Sensing (RS) have improved knowledge of the biodiversity influencing malaria (Ceccato et al., 2005). The availability of an up-to-date map of mosquito vector distribution plays an important role in mosquito control programs (Jemal & Al-thukair, 2016). Maps have long been used as evidence by national stakeholders to inform policy priorities, approaches, and interventions (Ghilardi et al., 2020). The use of remote sensing, GIS, and GPS have not only limited to mapping the habitats of mosquitoes but are also used for the spatial relationship between the malaria cases and the environmental changes of the particular areas (Bhatt, 2020).

a) GIS application

The GIS computer system can describe, analyze, and predict disease patterns using the feature (cartographic) and attribute data. GIS has been used in many epidemiological applications including disease mapping, rate smoothing, cluster or hotspot analysis, and spatial modeling, and has been reported and applied in small territorial units such as urban-rural and lower levels of government (Tewara et al., 2018). GIS has many applications to the study of vector-borne diseases, as many of the underlying processes influencing the distribution of insect vectors of disease are spatially heterogeneous. During the last twenty years, the development of Geographical Information Systems (GIS) and satellites for earth observation have made it possible to make important progress in the monitoring of the environmental and anthropogenic factors which influence the reduction or the re-emergence of the disease (Ceccato et al., 2005).

b) Remote sensing application

Remotely sensed data has been used to map characteristics on the earth's surface since the launch of Landsat-1. A growing number of health studies, notably in the field of vector-borne diseases, have used remotely sensed data for monitoring, surveillance, or risk mapping (Beck *et al*., 2000). Remote Sensing, an instrument for Earth observation on satellite platforms, offers information on landscape features and climatic factors and can be used to relate these factors to the risk of vector-borne diseases. New sensor systems are in orbit, or soon to be launched, whose data may prove useful for characterizing and monitoring the spatial and temporal patterns of infectious diseases (Beck *et al*., 2000).

c) Google Earth application

Google earth aimed to provide viewers with “a more realistic view of the world” (Mohammed et al., 2013). It uses in malaria vulnerability hotspots to taking coordinates and assessment of geographical locations (Akinbobola & Ikiroma, 2018).

The current study was performed by applying all the above listed geospatial technologies with their right functionality; GIS for data processing and analysis through the data obtained from remote sensing, and Google Earth.

2.1.7. Multi-criteria Decision Evaluation Method and GIS

The display and analysis of data to help the process of environmental decision-making are some of the most important applications of GIS. A decision can be represented as a choice between alternatives, where different actions, places, objects, and the like may have been the alternatives. For instance, it might be necessary to choose the best location for a waste disposal plant or even decide which areas are best suited for new construction (Eastman, 2012.). Geographical Information Systems in conjunction with MCDA, sometimes referred to as GIS-MCDA or Spatial MCDA, could help provide insight into the impact of spatial restrictions such as zoning, land use, or demographics on program management in public health and other settings (Zhao et al., 2020).

2.7.1.1. Multi-criteria Evaluation Methods

The widely-used methods in this domain are the analytical hierarchy process (AHP), and FAHP

a) AHP

The AHP aims to solve the hierarchical model by incorporating into the model the criteria that are effective in the decision-making process by adding layers of the second or higher-order to the scaling techniques (Sahin & Yurdugul, 2018). To make comparisons, a scale needs numbers that indicate how many times more important or dominant one element is over another element for the criterion or property concerning which they are compared. (Saaty, 2008). The advantage of AHP allows for the participation of both experts and stakeholders in providing input and intuitive understanding of the apportionment of the whole into its parts (Vargas, 1990). Such framework allows the incorporation and accommodation of both qualitative and quantitative criteria and the input of expert knowledge and this approach is that it can be done quickly utilizing the data processing and capabilities of GIS.

b) Fuzzy AHP

Decision-makers are faced with numerous and increasingly complex situations and are often unsure whether it is a matter of assigning evaluation points as a crisp value. Therefore, the design of an MCDA incorporating the fuzzy set theory can address this uncertainty. A fuzzy AHP (FAHP) is the inclusion of fuzzy logic nuances in the assessment of the AHP criteria. In the fuzzy environment, evaluation is conducted by allowing uncertainty associated with an individual’s subjective judgment, expressed as a membership function of the fuzzy set representation in which fuzzy numbers represent a decision maker’s subjective judgment (Karami & Guo, 2012).

The current study used AHP from the Multi-criteria evaluation methods because it is easy to perform and user-friendly rather than others. It’s also used consequently in the previously worked researches. One of the Multi-criteria evaluation techniques, which were known as Weighted Overlay and Weighted sum in the GIS environment, was shown to be useful for delineating areas at different ratings in terms of malaria hazard and malaria risk. Moreover, The allocation of weights and their calculation in the AHP module, developed through a collection of pairwise comparisons of the relative significance of factors in the fitness of pixels the activity being assessed, has generated valuable information (Kassaw et al., 2019).

2.2. Empirical Framework

Different scholars focused on identifying malaria hotspots and malaria risk assessment and also the few scholars try to predicate the occurrence of malaria and monitoring by using Geospatial technologies. Malaria is a local and focal disease, because of this the parameters that are applied to map the vulnerability hotspot of malaria mainly depend on various variables some empirical views of previously worked literature are explored as follows.

2.2.1. Global Experience in Malaria Vulnerability Hotspot Identification

Kumar Ra et al.,(2012) research was conducted to produce a malaria distribution map and malaria susceptibility models using multivariate linear regression analysis through Remote Sensing data and GIS techniques. They apply several factors i.e. Land Use, NDVI, climatic factors, distance to the location of existing government health centers, population, distance to ponds, streams, and roads. Which are related to malaria transmission. Climatic factors, particularly rainfall, temperature, and relative humidity are known to have a strong influence on the biology of mosquitoes. The research was concluded that the Percentage of malaria areas is very much related to distance to health facilities.

Qayum et al., (2015) study was carried out to create socio-economic and climatic factors, geographical parameters, and a clinical-data-based GIS-integrated databank. It entails compiling a list of all those villages/pockets (so-called malarial hotspots). This study concluded. With the advancement of technology, information tools such as GIS have captured almost every field of scientific research, particularly in the field of vector-borne diseases such as malaria. Malaria mapping enables policymakers to produce cost-effective malaria control measures in endemic areas by allowing for easy information updates and easy access to geo-referenced data (Qayum et al., 2015).

Ahmad et al., (2017) the research aimed to apply GIS tools on RS and ancillary data for visualizing and analyzing the various environmental socioeconomic, and epidemiological data to reveal trends and interrelationships toward malaria incidence and to obtain a malaria risk map or vulnerability map of the target malaria endemic zone. They used remote sensing data Landsat 8 OLI having a 30m resolution and Aster DEM with the same resolution to extract environmental factors. Their result reveals that major hotspot regions have waterlogging, high rainfall, and proximity to forest areas, combined with poor socioeconomic conditions.

Akinbobola & Ikiroma, (2018) evaluated the environmental risk factors that influence malaria prevalence and the Spatio-temporal distribution of malaria incidence to delineate the hardest hit area in Ibadan, Southwest, and Nigeria. They found that there is a strong association between climatic factors and malaria incidence, particularly maximum temperature and relative humidity.

Table 2.1 Summary of the Empirical review

No	Author	Study area	Data used	Methods used
1	(Kumar Ra et al.,2012.)	Varanasi District, INDIA	IRS-1C LISS III and SOI Topo maps Ancillary data	Multiple Linear regression models With GIS and remote sensing
2	(Qayum et al., 2015)	Uttar Pradash, India	Ancillary data	Weight matrix with GIS
3	(Ahmad et al., 2017)	Chakardharpur, India	Landsat 8 OLI and ASTER DEM	–MCE with Geospatial tools.
4	(Akinbobola & Ikiroma, 2018)	Ibadan, southwest, Nigeria	Landsat 8 OLI, SRTM DEM, Soil map, and ancillary data	–MCE (AHP) with GIS and Remote sensing

2.2.2. National Experience in Malaria Vulnerability Hotspot Identification

Kassaw et al., (2019) research was conducted to identify malaria epidemic-prone areas hotspot risk map using GIS and spatial MCE technique for the betterment of malaria intervention and control program service in Majang zone, Gambella Ethiopia, finally, they concluded large area of the zone is found on risk area for malaria and this research justified that by combining GIS with MCE was capable to integrate all the malaria hazard causative factors and the components of malaria risk as well.

Previously worked research both at the global and national level used Geospatial techniques to identify the malaria hotspot in a particular area in addition to that they used methods that moderate the accuracy of the data and reliable technologies for analysis and processing. They tried to show the main malaria incidence causing parameters in the area and show the direction for the stakeholders to prioritize the preventive and control action. However, they never consider the spatial resolution of both satellite image and DEM therefore this study comes up with the fine resolution of both these data types.

2.3. Conceptual Framework

This section of the current study developed from the theoretical framework and empirical framework, the previously worked both national and international levels literature are as input to identify parameters, data sources, as well as methodologies in the current study. Based on the literature review the parameters that are used to perform the current study are categorized into three main groups that contain about thirteen factors are Environmental socioeconomic and epidemiological parameters.

Commonly the frequently used environmental parameters include elevation, slope, aspect, wetness, land use/cover, drainage buffer, temperature, rainfall, and proximity to river different scholars share this environmental parameter in the percent range from 60 – 80% to the malaria incidence. The second most important parameter that causes malaria incidence in a particular area is the epidemiological parameter these are API and Pf cases. The third parameter for malaria incidence is the socioeconomic factor contains population and proximity to a hospital. After all these factors were identified the remained task was to select the appropriate data with high accuracy and reliability. Based on the literature review the data used to perform the malaria hotspot modeling includes Satellite images, DEM, Topographic maps, and ancillary data from different organizations. After the data collection, the next task for successful termination of the study depends on the technologies and the right method for data process and analysis.

Geospatial technologies like GIS, remote sensing play a key role in malaria control and preventive action, the previously worked research applies these technologies for processing and analysis of raw data. The malaria vulnerability hotspot is independent of the thematic map of individual factors but it is dependent on different techniques these include classification, interpolation, spatial analysis, buffering, geospatial technology, and weight allocation. So to avoid the weight mistake the AHP user-friendly method was selected from the multi-criteria evaluation methods. Finally, the malaria hotspot algorithm was performed to get the final output of the study. The overall conceptualized literature review for the current study is summarized below in (Figure 2.2).

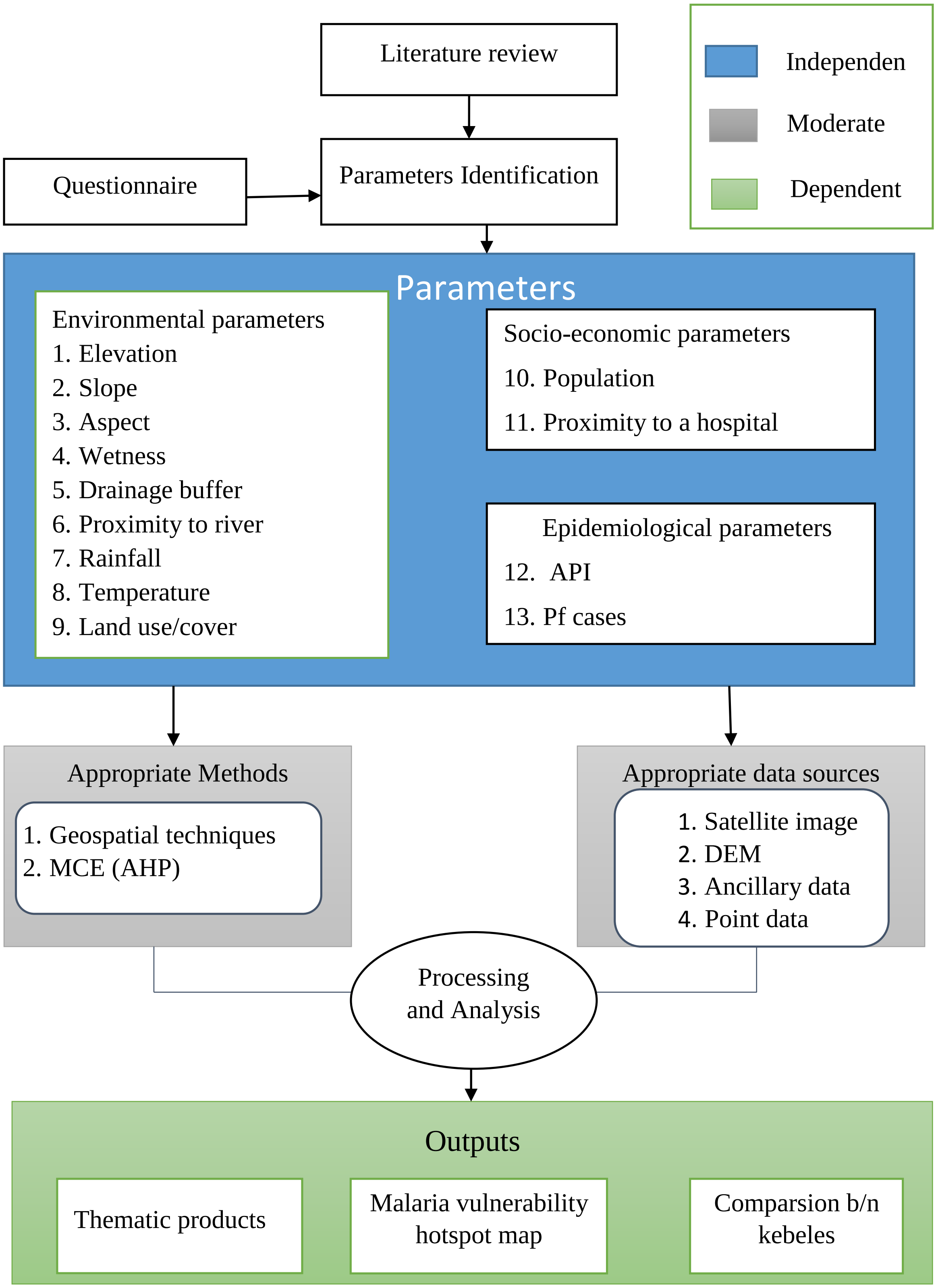


Figure 2.2 Conceptual Framework of the current study

CHAPTER III: MATERIALS AND METHODS

3.1. Description of the Study Area

The study area Kindo Koysha Woreda is one of the Woredas in the Wolaita Zone of the South Nation Nationalities and People Regional state. Which is located at 37˚24– 37˚38 E longitude and 6˚48-7˚04 N latitude, 431 km southeast of Addis Ababa and 36 km west of Wolaita Sodo town. The Woreda has a total area of 444.30 square kilometers, administratively divided into 19 Kebeles and one town administration called Bele Town with a total population of nearly 139,316. It is composed of 2 agro-ecological zones: 21% midland temperate ("Woinadega"), and 79% lowland ("Kolla"), with altitude ranging from 687 meters at the foot of the Omo river valley to 2,164 meters above sea level (Buke, 2016). The area has an average maximum and minimum temperature of 30.7^{0}c and 18.2^{0}c respectively and the annual rainfall has characteristic monthly variation, with peak rainy seasons usually observed during March through May (autumn), locally termed as "belg," and July through September (summer to partially spring), locally termed as "kremt" to partially "tsedey." In the woreda are currently one primary hospital, 3 health centers, and 28 health posts. The map in (Figure 3.1) below shows the location of the study area.

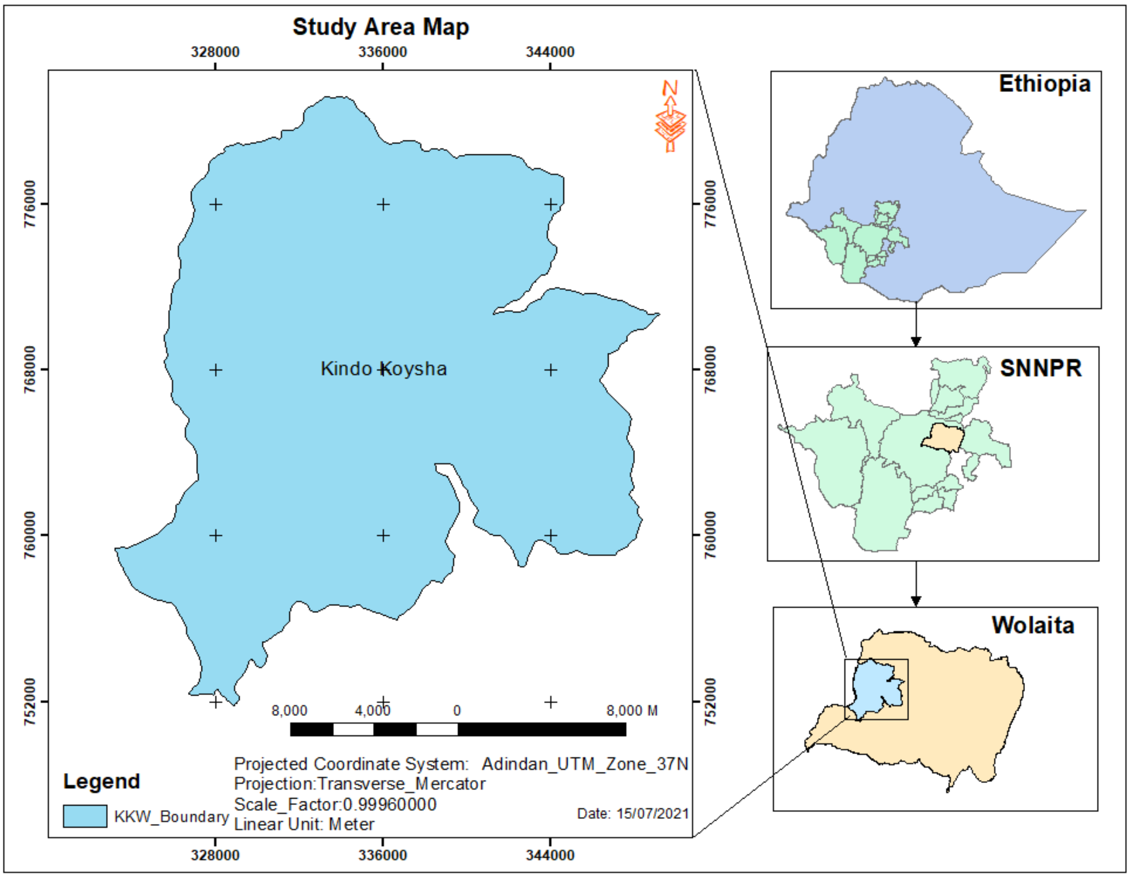


Figure 3.1 Study area map

3.1.1. Population

According to CSA data of 2007, Kindo Koysha Woreda has a total population of 104564 people, of whom 51150 males and 53414 females. Per the CSA's 2020 projection population, the population of Kindo Koysha is 139316 from whom 68116 and 71200 male and female respectively. Based on the CSA data, from the total population of Kindo Koysha Woreda about 20766 members of the population have households, of whom 10221 male and 10545 are females. The below (Figure 3.2) shows the current population distribution between kebeles of the study area.

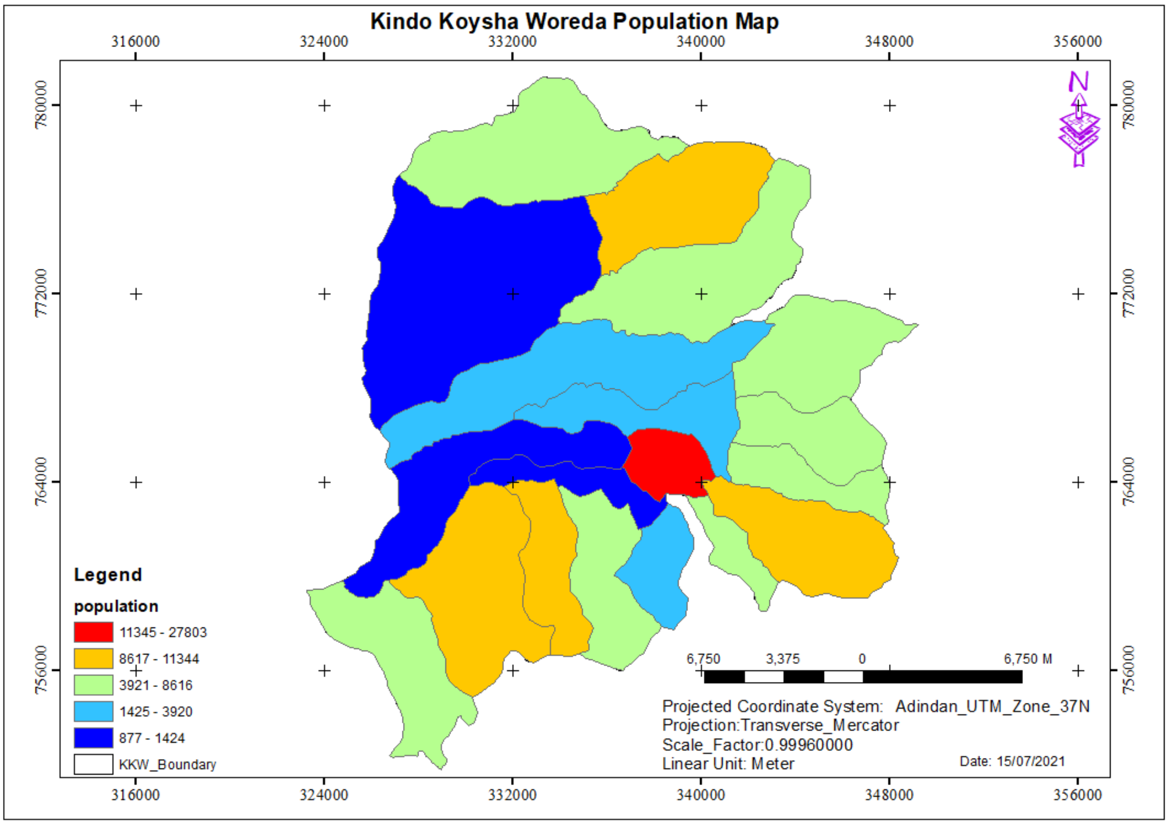


Figure 3.2 Kebele Population map of Kindo Koysha Woreda

3.1.2. Topography

The topography of the study area contains flat, gentle, and mountainous. Its altitude varies from 678 to 2164 m above mean sea level. Most of the northern, southern, and eastern parts of the study area have altitudes above 1200 m above mean sea level (amsl) and the eastern and central parts of the study area have an altitude below 1200 m altitude. Based on the topography of the study area, the agro-ecological strata of the Kindo Koysha woreda share only midland temperate and lowland zones. The below (Figure 3.3) shows the elevation difference in the study area.

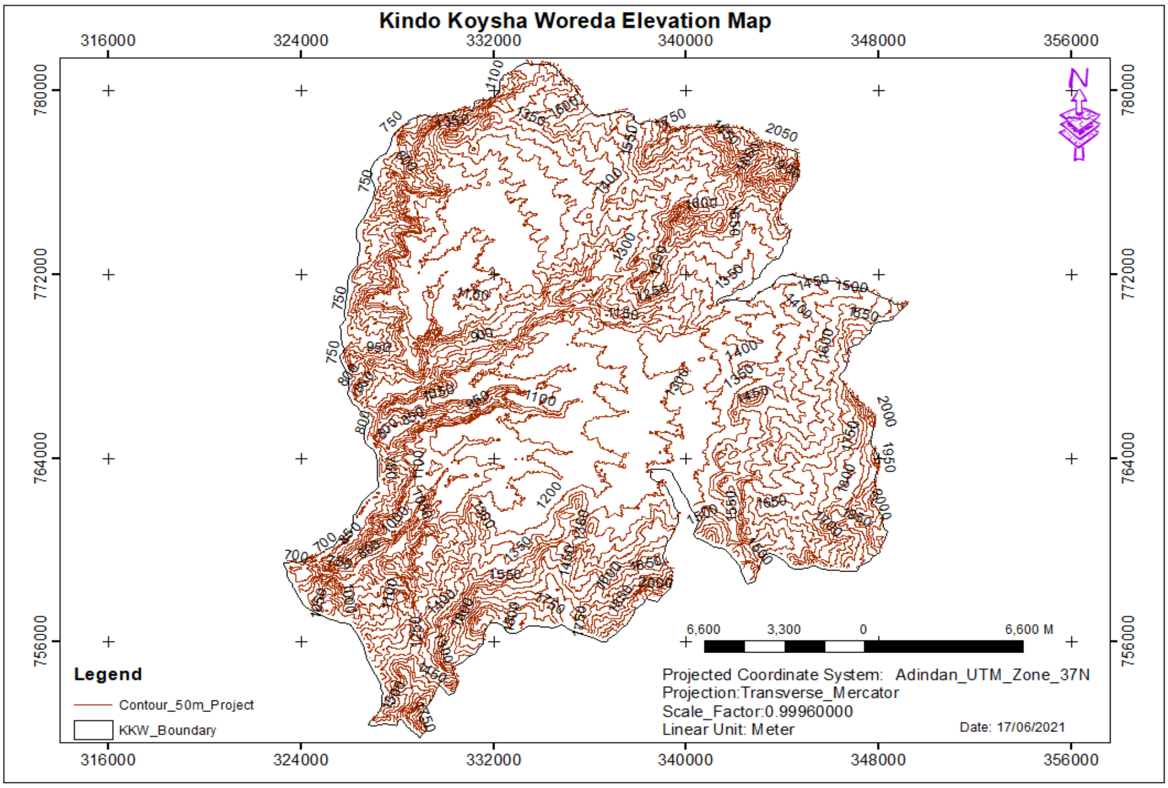


Figure 3.3 Topographic map of the study area

3.1.3. Climate

Based on the data obtained from the National meteorological agency at Bele station the mean monthly temperature ranges from 18^0c (May) to 24^0c (January and March). The Average monthly maximum of the study area ranges 23^0c (May) to 32^0c (December) and the average monthly minimum temperature of the study area ranges between 12^0c (June) to 32^0c to17^0c (January). (Table 3.1) gives the average monthly maximum, mean, and minimum temperature value of the Bele station.

Table 3.1 Monthly Average Max, Mean, and Min Temperature

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Max	31	27	31	30	23	28	28	27	25	28	30	32
Mean	24	21	24	22.5	18.5	20	21	21	20.5	21.5	22	22
Min	17	15	17	15	14	12	14	15	16	15	14	12

Source; NMA, Bele station

The below (Figure 3.4) shows the monthly average maximum, mean, and minimum temperature of the study area by using the diagram of the month versus the amount of average monthly max, mean, and min value.

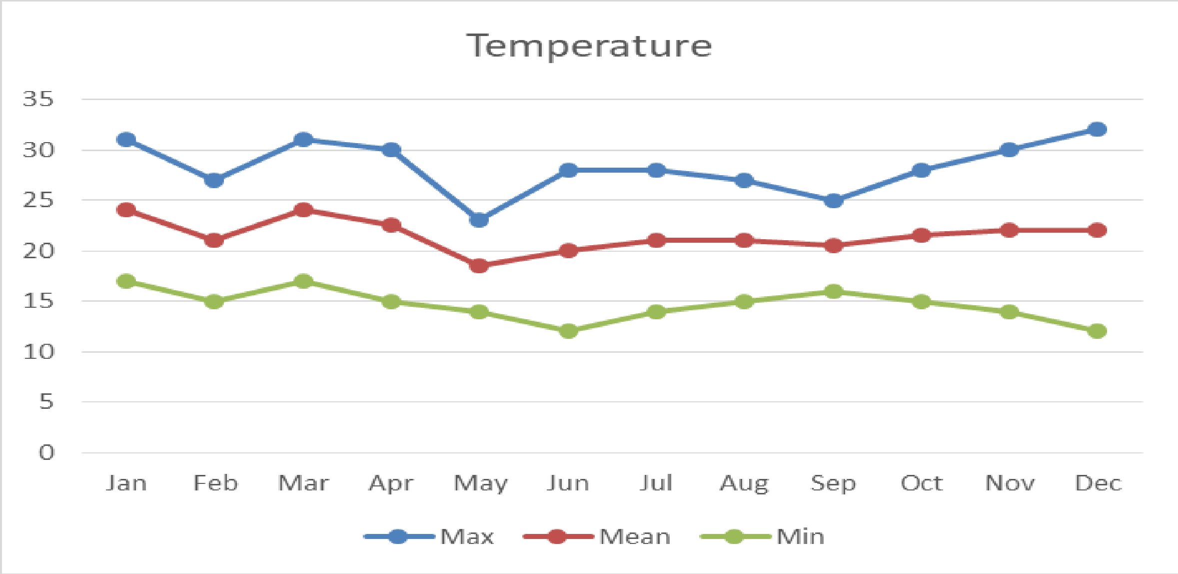


Figure 3.4 Average Monthly Max, Mean, and Min temperature of the Bele station

Regarding the rainfall pattern mean monthly rainfall ranges from 14.7 to 192.4. The annual rainfall ranges from 1000 to 1400mm and the average rainfall is 120.6 mm. The (Table 3.2) depicts the average data of 16 years at Bele station.

Table 3.2 Sixteen year monthly rainfall data of Bele station

Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Rainfall	29.6	37	91.7	126.1	151.9	162.5	192.4	186.1	137.1	73.2	46.1	14.7

Source; NMA, Bele station

From the average data diagram shown in (Figure 3.5), January present has a peak rainfall.

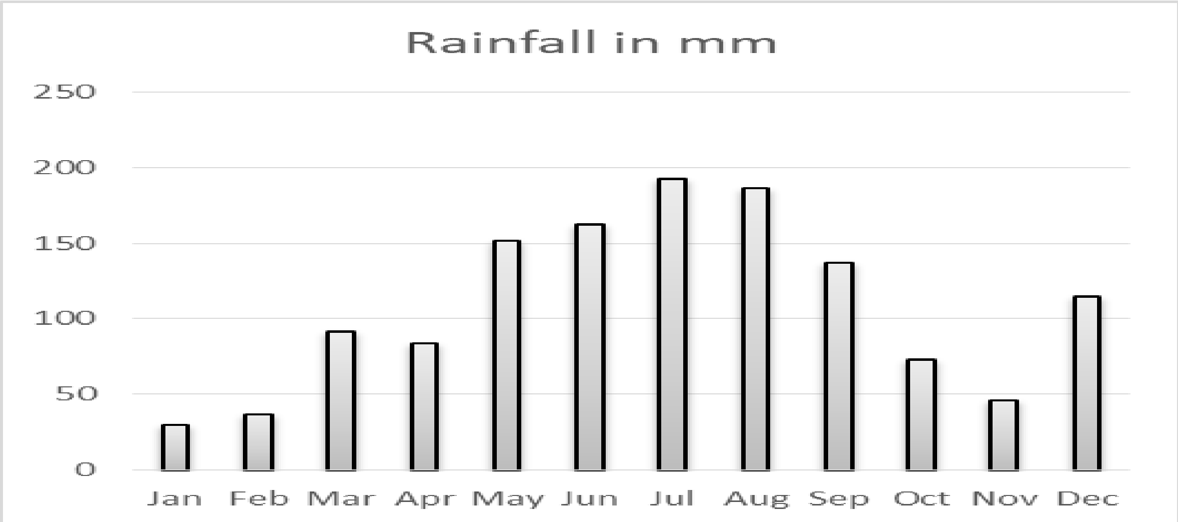


Figure 3.5 Sixteen-year Average rainfall data of Bele station

3.1.4. The Trend of Malaria Cases

According to five-year data obtained from the Kindo Koysha Woreda Health Office, the number of malaria cases in the study area is high and the malaria trend is not static. Due to various preventive measures taken by the Woreda Health Office and other related agencies, it has shown a downward trend in the years 2009 and 2010. However, these actions were taken malaria cases increased again in 2011 and 2012, and became the biggest problem till today. The trend of malaria cases in five years is shown below in (Table 3.3).

Table 3.3 Five year trend of malaria cases in Kindo Koysha Woreda

Year	**2008 EC**	**2009 EC**	**2010EC**	**2011 EC**	**2012 EC**
Malaria cases	9663	3233	2981	7008	5817

Source: Kindo Koysha Woreda health office *EC- Ethiopian calendar*

The diagram in (Figure 3.6) depicts the trend of malaria cases in the study area.

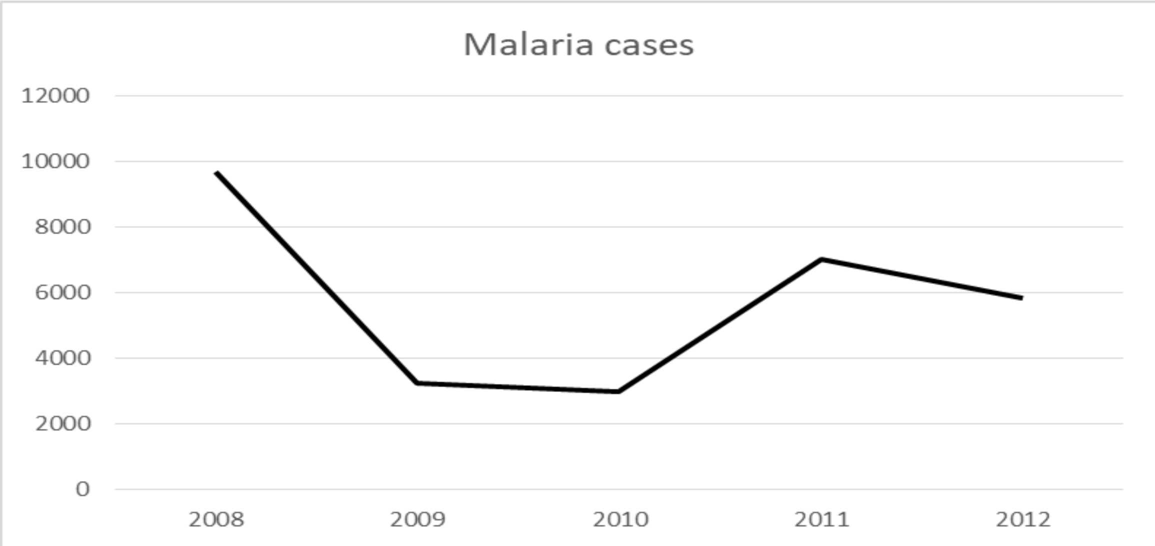


Figure 3.6 Malaria cases trend in the study area

3.2. Research Design

The conceptual structure or the design of the research project that the researcher followed in conducting the research is essential to clearly define and visualize the whole image of the work. Defining the research design highly contributes towards result findings by showing overall highlights of methods. Therefore, before the commencement of the research techniques, it is imperative to prepare tracks of the research by assembling all the requirements for the problem-solving objective.

3.2.1 Approaches to the Research

In this study, both Quantitative and Qualitative research approaches are implemented to get the final result and it can be known as Mixed Approach. Even though the qualitative side has more weightage than the quantitative, it is difficult to attain the objective of the study without the involvement of both.

3.2.2. Research Type

It is known that there are different types of researches to be employed based on the goal (purpose), Type of data, Field of study, or the aim (objective) of the research. Therefore, this study is categorized under the applied research type. Because the result can be applied to solve real-world problems.

3.3. Data Sources and Types

The current study was performed by using both primary and secondary data sources.

i. Primary Data Source

The primary data source includes the questionnaire only that used for parameter identification and weight allocation; it was done by six experts on malaria selected randomly from the Kindo Koysha district to list and order the factors in the study area according to their influence on malaria incidence and two experts were selected to assign weights for the ordered parameter by using satay's scale.

ii. Secondary Data Source

The required data for the study area were collected from different secondary data sources are Climate data from NMA, Population data from CSA, and epidemiological data from health centers, and satellite imagery for study area Sentinel-2 is downloaded from the USGS Earth Explorer website and ALOS DEM downloaded from the ASF website. The location of different land uses/cover and health centers in the study area were collected from Google earth carried out to verify image classification. The sources and type of data used for the current study are listed in (Table 3.4) below.

Table 3.4 Data Sources, scale, year, and types

No	Data Type	Data scale	Year	Source	Data Acquisition
1	Sentinel-2B	10 m	2020	https://earthexplorer.usgs.gov/	Land use/cover, and water bodies
2	ALOS DEM	12.5 m	2011	https://www.asf.alaska.edu/sar--data/palsar/	Aspect, slope, elevation, wetness, and drainage buffer
3	Census data	-	2017-2019	CSA	Population
4	Climate data	-	2010-2019	NMA	Temperature and rainfall data
5	Clinical data	-	2017-2019	Health centers	API and Pf
6	Point data	2m	2021	Google earth	Hospital Coordinate
7	Topographic map	1:50,000	1979	Ethiopia Geospatial Information Institute	Coordinates to georeferencing

3.4. Software's and Materials

Software like ArcGIS and ERDAS Imagine and other materials are listed in (Table 3.5) below were used for conducting the current study successfully.

Table 3.5 Software's and materials

NO	Name	Purpose
1	Computer with 8GB RAM	Processing raw data and report writing
2	ERDAS Imagine 2014	Image preprocessing and classification
3	ArcGIS 10.8	Data processing and thematic map preparation
4	Microsoft word, excel	Integrating attribute data and compositing final thesis
5	IDRISI Selva 17	For weight computation

3.5. Methodology

This study structure and setting are based on a combination of geographic, socioeconomic, and epidemiological Parameters. The first task was to identify the main parameters that cause malaria incidence in the study area, followed by assessing and determining the data source and finally distinguishing the interaction of factors for malaria transmission, and the weight computation was performed by using AHP which is a user-friendly multi-criteria evaluation method. GIS software is used to overlay and analyze various geographical datasets to generate meaningful maps and outputs.

The main parameters used in the current study were identified through a literature review as well as a questionnaire, and they are environmental (elevation, slope, aspect, wetness, and also drainage buffer, proximity to a river, rainfall, temperature, and land use/land cover), epidemiological (API and Pf cases), and socioeconomic parameters (population and hospital proximity). After the parameters were identified, buffering, interpolation, reclassification, and the zonal statistical process were performed using Arc GIS tools, and land use/cover supervised classification is performed using ERDAS Imagine.

Both geospatial techniques and the multi-criteria evaluation method were used to achieve the objectives of the current study. These methods were chosen for the study because they are very effective and easy to apply, and a malaria hotspot identification algorithm was used to compute the parameters and zonal statistics were used to determine to what extent vulnerability degree in each Kebele shares in the study area.

The multi-functionality of Arc GIS is used to drop-down lists of acceptable data values, and data is automatically derived where possible, data has been automatically derived from previously entered values. (Figure 3.7) shows the overall workflow of a current study.

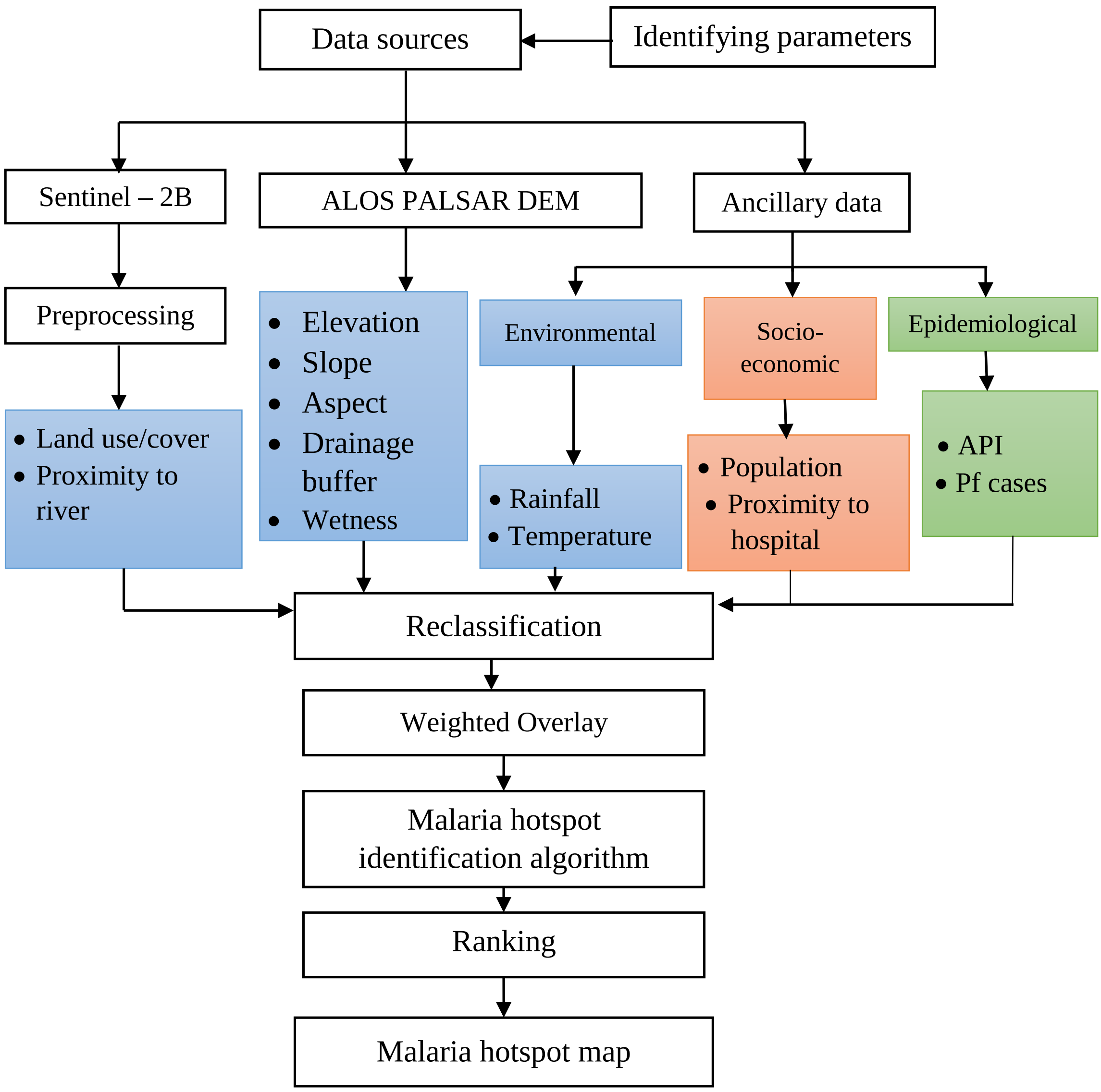


Figure 3.7 Technical scheme

3.6. Data Processing and Analysis

Data processing and analysis were done with the use of ArcGIS software and ERDAS imagine software. The data used for analysis was sentinel-2B having 10m spatial resolution, the satellite image data was downloaded from United States Geological Survey (USGS) website was obtained in 13 bands. The satellite image was radiometrically and geometrically corrected and various individual bands with the same spatial resolution (Band 2,3,4 and 8) layer stacked to obtained composite images for further analysis and the image was downsampled to 12.5m by using nearest resampling techniques to get similar resolution with

ALOS DEM the vector layer of the study area used to extract the image. ALOS Digital Elevation Model (DEM) 12.5m spatial resolution was downloaded from the Alaska satellite facility (ASF) portal. A subset was done by using the vector layer of the study area.

3.6.1. Parameters Contributing to Malaria Incidence

According to WHO,(2020) in Ethiopia, altitude and climate (rainfall and temperature) are the most important determinants of malaria transmission, Transmission is seasonal and largely unstable. The major transmission of malaria follows the June – September rains and occurs between September - December while the minor transmission season occurs between April – May following the February – March rains. Areas with bimodal patterns of transmission are limited and restricted to a few areas that receive the small/Belg rains (WHO, 2020). Three parameters (environmental, socioeconomic, and epidemiological parameters) are shared on the previously worked researches. Environmental parameters include wetness, elevation, drainage buffer, slope, aspect, land use/cover, rainfall, temperature, and proximity to the river while socioeconomic parameters were categorized as a population and proximity to a Hospital, and Epidemiological factors are the Annual parasite Index and Plasmodium falciparum cases (Kassaw et al., 2019; Ahmad et al., 2017; Qayum et al., 2015)**.**

3.6.1.1.Environmental Parameters

Malaria transmission is strongly associated with environmental parameters, which control mosquito breeding and parasite growth (Ahmad et al., 2017). According to Kassaw et al., (2019) about 70-90% of the risk of malaria is considered due to environmental factors which in turn influence the abundance and survival of vectors. Environmental factors such as elevation, slope, aspect, wetness, and also drainage buffer, proximity to a river, rainfall, temperature, and land use/land cover were used to identify the malaria vulnerability hotspot area based on literature review and experts' advice. The ALOS PALSAR DEM with 12.5m resolution was used to generate accurate topographic parameters in different research work, these are for landslide (Rabby & Ishtiaque, 2020), soil erosion (Saxena et al., 2020), and other studies also applied the ALSO PLASAR for topographic factors because of this ALOS DEM used in the current study to generate parameters include elevation, slope, aspect, drainage, and wetness index factors of the study area. Temperature and rainfall maps generated from NMA data using Inverse Distance Weightage (IDW) interpolation, and land use/land cover maps generated from Sentinel-2B imagery.

a) Elevation

The elevation is an important factor in the transmission of malaria because the elevation greatly determines the temperature and the temperature, in turn, affects mosquito breeding as the length of the immature stage in the life cycle (Kebede et al., 2017). Accordingly, at high temperatures, the egg, larval, and pupil stages are shortened, so that turnover is increased and the length of the saprogenic cycle of the parasite within the mosquito host is also influenced, i.e. when the temperature rises, the period of the saprogenic cycle is short-circuited (Ahmed, 2014). Altitude is directly related to climate, and mosquitoes prefer warmer climates and lower altitudes. Lower altitudes increase the turnover of the mosquito population, which means a higher risk of transmission. Since the temperatures decrease with increasing altitude, the temperature accordingly determines the altitude limit of stable malaria transmission (Vajda & Webb, 2017).

Based on prior research, the altitude was reclassified depend on the relationship between altitude and malaria incidence. Malaria is most common in areas where the altitude is less than 1500 meters, and malaria-free areas are those where the altitude is greater than 2500 meters. The study area is classified into five sections: 687-1000 m, 1000-1200 m, 1200-1400 m, 1400 m-1600 m, and >= 1600 m. Each category of the classification assigned ranks based on the vulnerability degree: very high (5), high (4), moderate (3), low (2), and very low (1).

b) Slope

The slope is another environmental parameter that may be associated with mosquito larval habitat formation, is the measurement of the rate-change of the land per unit distance which may affect the stability of the aquatic habitat (Kebede et al., 2017; Ahmed, 2014). Regarding the relationship between slope and malaria case, water appears to be logged in regions with low-lying slopes, and in such a case speeds up the possibilities, of water stagnation. According to Munga (2006) as cited by Ahmed et al., (2017) the steeper slopes are known to allow faster water movement and to affect the stability of aquatic habitats. Surface water movement is nearly stagnant on gentle slopes, creating a fertile environment for mosquito breeding sites (Ahmad et al., 2017). So gentle slopes equal higher vulnerable areas for malaria incidence.

According to Lemessa, (2011) plain and gentle slopes favor mosquito breeding than sloppy areas. Based on previous research, an area with a gentle slope (0 – 5) % is more favorable for malaria because water stagnation occurs, which increases mosquito breeding. The slope of the study area is classified into five classes. Then there are the classes 0–5%, 5%–10%, 10%–20%, 20%–40%, and 40 and above the rank assigned to each class were very high (5), high (4), moderate (3), low (2), and very low (1).

***c)* Aspect**

As stated by Ahmad et al., (2017) aspect is another important parameter that influences the transmission of malaria. The northern aspect ranges from NW340 to NE70 and is known as the shadow area. In the shadow area due to the lack of direct sunlight, the moisture content is high and, compared to the other aspects, there is relatively dense vegetation. Shadow influences the larval distribution for the risk of malaria. An aspect map was generated from the digital elevation model and reclassified into two classes based on either shadow or non-shadow, the rank was assigned as high (4) and very low (1) respectively.

***d)* Wetness Index**

The wetness index can affect the availability of mosquitoes in a given area. The wetness index factor contributes to the risk of malaria, as the wetness of the soil increases the water holding capacity of the area and this would create a breeding ground for the mosquito (Ahmed, 2014). The topographical wetness index is obtained by the following equation.

$$\text{TWI} = \text{Ln}\left(\frac{\text{A}}{\tan\alpha}\right) \quad \textit{Equation 3.1}$$

Where;

A = Area of a specific catchment and

α = Slope gradient of the specific area

The DEM model was used to generate a wetness index map, and the study area wetness index is classified into five classes: 12-24, 8-12, 6-8, 5-6, and below 5. the rank was assigned as very high (5), high (4), moderate (3), low (2), and very low (1).

***e)* Drainage buffer**

Drainage may affect the availability of the aquatic habitat in the area (Kassaw et al., 2019). The closeness of the populated area to drainage structures is an important parameter for malaria vector breeding sources (Kumar Ra et al. 2012). Drainage factors contribute to the risk of malaria as the moisture of the land increases the water holding capacity of the land and this would create a breeding ground for the mosquito (Kebede et al., 2017).

The ALOS DEM was used to generate a drainage buffer map of the study area by applying the fill, flow direction, and flow accumulation processes, as well as the stream order determined by the hydrology tool then by using the Euclidean distance tool drainage buffer, was performed. The sample was obtained by the generated class were 0 – 200, 200 – 500, 500 – 800, 800-1200, and 1200 – 1500. The rank was assigned to each class as follows: very high (5), high (4), moderate (3), low (2), and very low (1).

***f)* Proximity to the river (distance to breeding)**

One important parameter that sometimes plays an important role to increase malaria parasites and malaria disease is the distance to the river. Wetlands provide habitats for the juvenile (immature) stages (egg, larvae, pupae) of the malaria vectors. Monitoring the state of small water bodies and wetlands using satellite data is therefore very useful in identifying the source of malaria vectors (Ahmad et al., 2017).

As stated by Kassaw et al., (2019) female anopheles mosquitos can only fly a maximum of 2 km per day, so areas near rivers are more likely to be infected with malaria. Proximity to river map was created by using the Euclidean distance method to determine which areas are more vulnerable than others. The distance from the river is divided into five categories: 0-1000, 1000-2000, 2000-3000, 3000- 4000, and 4,000-11,000m. The rank was assigned to each class as follows; very high (5), high (4), moderate (3), low (2), and very low (1).

***g)* Rainfall**

Rainfall is considered to be the most important malaria triggering parameter causing soil saturation and a rise in pore water pressure (Kumar Ra et al.,2012.). According to previous researches, rainfall is the most important malaria-causing parameter, and its spatial variation shows a strong positive correlation with malaria incidence. Because heavy rains cause flooding, there is a lot of runoff, which disrupts the breeding grounds of the anopheles mosquito. The rainfall map was created using climatic data, typically from a ten-year NMA data, and IDW interpolation was used to cover the entire weather range of the study area. The following thirteen stations were used for interpolation: Wolaita, Boditi School, Bele, Awassa, Billate, Dilla, Werabe, Arba Minch, Danna 1, Sewula, Tercha, Chida, and Hossana the meteorological station distribution shown in (Appendix 3) and tabular data for meteorological station show in (Appendix 4).

According to President's Malaria Initiative (2012) areas with annual rainfall amount greater than 1000 mm are malarious and have intense malaria transmission, but areas with rainfall amount between 500 and 1000 mm have seasonal transmission. Since very high rainfall is not suitable for vector immature stages, areas having >1600 mm annual rainfall are unfavorable for mosquito breeding. Rainfall of the study area reclassified into five class intervals: < 1245, 1245 - 1250, 1250 - 1255, 1255-1260, and >= 1260. Each class have various vulnerability degree and rank these are very high (5), high (4), moderate (3), low (2), and very low (1).

***h)* Temperature**

Temperature-dependent growth of both the vector and the parasite. In female Anopheles, the optimal temperature range for parasite development is between 25°C and 30°C and below 16°C for growth (Feachem & Jamison, 1991). Altitude and temperature are closely related to a decrease in altitude of 0.50°C per 100 m increase. According to Pam et al., (2017) Plasmodium falciparum (the main cause of malaria mortality, especially in Africa) is limited by temperatures below 16°C to 19°C and cannot occur even at temperatures above 33°C to 39°C. This suggests that rising temperatures may limit malaria transmission in some geographic areas. Essentially, this means that high altitude and high-temperature regions experience little or no malaria transmission (Pam et al., 2017).

The temperature map of the study area was prepared from climatic data of the same stations of the rainfall. The Kindo Koysha temperature obtained by IDW interpolation was reclassified concerning previously worked researches into five classes, are < 27.4, 27.4 – 27.6, 27.6 -27.9, 27.9 – 28.2, and >= 28.2. The rank assigned to each class is very low (1), Low (2), Moderate (3), High (4), and Very high (5) respectively.

***i)* Land use /cover**

According to Manish (2017), land-use changes are cited as a major driver of disease outbreaks, particularly those caused by wildlife. Areas around the settlement have been highly susceptible to the reproduction of female Anopheles mosquitoes (Kassaw et al., 2019). The dense forest produces a lot of leaves which, after decomposition, produce litters with a high moisture content, which provide the mosquitoes with a better environment for laying eggs, the production of larvae, the growth of malaria vector pupae compared to the open forest (Ahmed et al., 2017).

Land-use/land-cover is a critical environmental factor associated with vector-borne disease (Lemessa, 2011). The sentinel-2 data was downloaded on Feb 28, 2020, from the USGS Website. Sentinel-2 is widely used for research (Miranda, 2018). Various spectral signatures of the vegetation and various topography suggest that the spectral data of the Sentinel-2 satellite with its fine spatial resolution (10 and 60 m), fine temporal resolution (five days), and fine spectral resolution (13 spectral bands) can be particularly good and suitable for the classification of land use/cover (Nguyen et al., 2020, Miranda, 2018).

i. Preprocessing

Image preprocessing is the initial task of correcting radiometric, atmospheric, and geometric distortions in the original image data (Muluken, 2019). Scene lighting, atmospheric factors, display geometry, and instrument response characteristics that may require correction are all examples of radiometric correction. The preprocessing function involves those operations that are usually required before master data analysis and information extraction, and are usually classified as radiation or geometric correction. Atmospheric effects will cause the dynamic range of the image to be limited to which appears as blur or reduced contrast.

ii. Image classification

In the supervised image classification method, the maximum likelihood algorithm is used to classify images to map the current land use/cover of the study area. Supervised classification is the process of using the known identity of a specific location in remote sensing data, representing a homogeneous example of land cover type to classify the rest of the image. The maximum likelihood classifier is one of the most popular classification methods among Remote sensing technologies. The maximum likelihood classification is a classification system in which the unknown pixels are assigned to the specific class by using the likelihood of contours around the training area using the maximum likelihood approach (Miranda, 2018). Qayum et al. (2015) stated that all types of land except for barren land have a strong influence on the incidence of malaria, considering epidemiology as one dimension, while the barren land itself has almost no influence on any of the three dimensions. The current study classified the land use/land cover into four categories these are settlement, water, farmland, and forest with the rank of very high(5), high(4), moderate(3), and low(2) respectively.

3.6.1.2.Socioeconomic Parameters

The socio-economic parameter is the important parameter for the spread of malaria incidence includes population and hospital proximity (Kassaw et al., 2019). In this study, the socioeconomic factors were divided into two categories: proximity to a hospital and population.

a) **Population**

It is one of the most significant socioeconomic factors directly linked to the rising risk of malaria (Ahmad et al., 2017). The growth of population and urbanization is another factor in the determination of health events such as epidemics of malaria (Degife, 2009).

According to the literature, the densely populated area is more vulnerable than the sparsely populated area, so the population distribution of the Kindo Koysha woreda is also used as one of the socio-economic factors. The study area population distribution map was generated from CSA data. The study area population is classified into five classes according to their effect on the spread of malaria cases. These are <5000, 5000 – 10000, 10000 -15000, 15000 – 20000 and > 25000. The new value assigned to each class as Very low (1), Low (2), Moderate (3), High (4), and Very high (5) respectively.

b) **Proximity to a hospital center**

Distance from the house to the nearest health center or facility was another risk factor for malaria incidence (Kebede et al., 2017). Malaria can easily become life-threatening if not treated. Access to health clinics and hospitals would also significantly impact the insecurity of the population. Closeness or distance may have a huge effect on the treatment and care of patients with malaria. Proximity consideration (hospital distance) is linked to the patient's economic and physical capacity to access and receive the requisite hospital service (Kassaw et al., 2019).

It was only one government hospital in Kindo Koysha woreda, which was located in Bele town. The study area Proximity to the hospital map generated from the Google earth collected control point by using the Euclidean distance analysis tool. The closeness and farness to the hospital affect the spread of malaria. Classification for current study based on the previous research that areas in the radius of 3 km to hospital lowly vulnerable to malaria (Muluken, 2019). The distance from the hospital is reclassified into five classes are below 1500, 1500 – 3000, 3000 – 4500, 4500 - 6000, and 6000 – 16600. The new value assigned to each class as Very low (1), Low (2), Moderate (3), High (4), and Very high (5) respectively.

3.6.1.3.Epidemiological Parameters

Malaria distribution is strongly related to the spatial distribution pattern of epidemiological parameters, providing unique information on its significance for malaria hotspots (Ahmad et al., 2017). The Epidemiological parameters include Annual parasite incidences (API) and plasmodium falciparum cases (Pf cases).

a) API

API (Annual parasite incidence) is used to identify the hotspot of malaria in a specific way through the following formula (Qayum et al., 2015, Ahmad et al., 2017).

API=$\left(\frac{\text{The total positive case for infection}}{\text{Total population data}}\right) 1000$……………………………….*Equation 3.2*

Where; API –Annual parasite incidence

The API map of the study area was obtained from both the population and total malaria cases of Kindo Koysha by applying the IDW interpolation, the higher API value shows the area is more favorable to the spread of malaria than the low API value. After processing, the API value map of the study area is classified into five classes, which are <50, 50-100, 100-150, 150-200, and >= 200. The new value assigned to each class as Very low(1), Low(2), Moderate(3), High(4), and Very high(5) respectively.

b) Plasmodium falciparum cases

Since P. falciparum is responsible for mortality from malaria and also indicates re-transmission, Pf cases were considered to identify the hotspots (Srivastava et al., 2009). The study area's Pf cases map derived from Kindo Koysha malaria cases by applying IDW interpolation the higher the Pf cases value, the more favorable the area is for the spread of malaria. The lower the Pf cases value, the less favorable the area is for the spread of malaria. After processing, the study area's value map is divided into five categories: < 500, 500-1000, 1000-1500, 1500-2000, and >=2000. Very low(1), Low(2), Moderate(3), High(4), and Very high(5), within this order.

All the parameters listed in the above section are used as input for the current study to identify the malaria vulnerability hotspot in the study area. These are environmental (elevation, slope, aspect, wetness, drainage buffer, proximity to river, temperature, rainfall, and land use/cover), epidemiological (API and Pf cases) and socioeconomic parameters (population and distance to hospital). Generally, the Malaria hotspot evaluation was developed specifically in the following manners; the determination of parameters that proliferation the transmission of malaria in the study area based on the previously worked literature review, and the expert is a primary task of the study and data collection for the parameters also a key one. After the collection of all the essential parameters data, it was easy to develop a malaria hotspot map of the study area. Every parameter in the study was been identified and the layer created in ArcGIS software and further analysis was performed by using GIS tools.

3.6.2. Malaria Hotspot Identification Algorithm

The hotspot identification was done by applying the multi-criteria evaluation method to weight the factor for weighted overlay and finally the vulnerability hotspot map identified by the malaria hotspot identification algorithm. Hotspot refers to an area or geographical region of relatively higher importance which is based on parameters such as symptomatic cases and asymptomatic, Malaria hotspot identification algorithm used as was done by (Qayum et al., 2015, Ahmad et al., 2017).

$$\mathbf{MHS = HS_{se} \times HS_{epidemiology} \times HS_{env}} \quad \textit{Equation 3.3}$$

Where,

MHS is a Malaria hotspot,
HS_{se} is a hotspot for socioeconomic parameters,
$HS_{epidemiology}$ is a hotspot for epidemiology,
HS_{env} is a hotspot for environmental parameters.

3.6.3. Weight Computation

All the parameters were rated based on their influence on mosquito breeding and suitability for mosquito habitat. Because each factor has a different degree of influence, it was necessary to determine the weight of each factor. Previous works and literature were used to assign weights to the factors (Muluken, 2019, Ahmad et al., 2017, Kassaw et al., 2019, Mestewat, 2014), and a discussion with malaria experts by using a questionnaire to get the appropriate weights for the parameters (Appendix 6). The Analytical Hierarchy Process (AHP), which is one of the techniques for multi-criteria decision making, is used to attain the weights by obtaining the main eigenvectors of the reciprocal square matrix of pairwise comparisons between criteria. In the multi-criteria evaluation process using a weighted linear combination, the sum of the weights must be one (Saaty, 2008; Eastman, 2012). The comparison involves determining the relative importance of the two criteria involved in a given goal. Scores are provided on a continuous 9-point scale for pairwise comparison by using this computation of the current study performed (Appendix 5). The following (Table 3.6) gives the information about all the factors that used in the current study.

Table 3.6 Weights and classification of parameters

	Weight	Factors	Weight	Class interval	Ranks	Vulnerability Degree
Environmental parameters	70 %	Elevation	0.2682	< 1000	5	Very high
				1000 – 1200	4	High
				1200 – 1400	3	Moderate
				1400 – 1600	2	Low
				>= 1600	1	Very low
		Temperature	0.1710	< 27.4	1	Very low
				27.4 – 27.6	2	Low
				27.6 – 27.9	3	Moderate
				27.9 – 28.2	4	High
				>= 28.2	5	Very High
		Slope	0.0762	< 5	5	Very high
				5 – 10	4	High
				10 -20	3	Moderate
				20 – 40	2	Low
				>= 40	1	Very low
		Aspect	0.0476	Shadow	4	High
				Non-shadow	1	Very low
		Wetness index	0.0371	< 5	1	Very low
				5 – 6	2	Low
				6 – 8	3	Moderate
				8 -12	4	High
				>= 12	5	Very high
		Proximity to river	0.0334	< 1000	5	Very high
				1000 – 2000	4	High
				2000 – 3000	3	Moderate
				3000 – 4000	2	Low
				>= 4000	1	Very low
		Drainage buffer	0.0265	< 200	5	Very high
				200 -400	4	High
				400 -600	3	Moderate
				600 -800	2	Low

				>= 800	1	Very low
		Rainfall	0.0224	< 1245	5	Very high
				1245 – 1250	4	High
				1250 – 1255	3	Moderate
				1255 – 1260	2	Low
				>= 1260	1	Very low
		Land use/cover	0.0164	Settlement	5	Very high
				Water	4	High
				Forest	3	Moderate
				Farmland	2	Low
Epidemiological Parameters	20%	API	0.1566	< 50	1	Very low
				50 – 100	2	Low
				100 – 150	3	Moderate
				150 -200	4	High
				>= 200	5	Very high
		Pf cases	0.0404	< 500	1	Very low
				500 – 1000	2	Low
				100 -1500	3	Moderate
				1500 – 2000	4	High
				>= 2000	5	Very high
Socio-economic parameters	10%	Proximity to Hospital	0.0883	< 1500	1	Very low
				1500 – 3000	2	Low
				3000- 4500	3	Moderate
				4500- 6000	4	High
				>= 6000	5	Very High
		Population	0.0160	< 5000	1	Very low
				5000-10000	2	Low
				10000-15000	3	Moderate
				15000-20000	4	High
				>= 20000	5	Very high
	100%		1.00			

CHAPTER IV: RESULT AND DISCUSSION

In this section, the study findings are interpreted and discussed concerning a research objective, empirical framework, and methodology.

4.1. Result

The findings of the current study were a combination of thirteen factors classified into three categories based on their influence on the spread of malaria incidence and facilitation of mosquito breeding. Based on the data gathered the analysis performed the output of the research shown by using thematic products from (Figure 4.1) to (Figure 4.18) and the statistical information includes class interval, rank, and area coverage both by square kilometer and percent presented from (Table 4.1) to (Table 4.18).

4.1.1. Relationship of Environmental Parameters with Malaria Incidences

The environmental factors include Elevation, slope, aspect, wetness index, drainage buffer, distance to rivers, rainfall, temperature, and Land use/ land cover were presented in this section for what extent each factor shares the degree of vulnerability in the study area.

4.1.1.1. Elevation

The current study reclassified elevation map shows from the total are coverage 58.357 km^2 as very high, 118.997 km^2 high, 127.889 km^2 Moderate, 84.599 km^2 low, and 54.458 km^2 very lowly vulnerable to malaria. According to FMOH areas with less than 1500 m elevations are intensively favorable for mosquito breeding, so 80 % of the study area has elevations ranging from 687 to 1500 m amsl, which could be favorable for mosquito breeding. The reclassified map has five degrees of vulnerability with a rank of 1 up to 5 the following (Table 4.1) gives the information for classification and area coverage of the elevation factor in the study area.

Table 4.1 Elevation classification and area coverage

S. no	Class interval(m)	Rank	Vulnerability degree	Area (Km^2)	Percent
1	< 1000	5	Very high	58.357	13
2	1000 - 1200	4	High	118.997	27
3	1200 -1400	3	Moderate	127.889	29
4	1400 - 1600	2	Low	84.599	19
5	>= 1600	1	Very low	54.458	12
		Total		**444.30**	**100**

The elevation shows a gradual increment from west to eastward in the study area. From the below (Figure 4.1) it is possible to decide 39% of the study area is very high and highly vulnerable to malaria incidence.

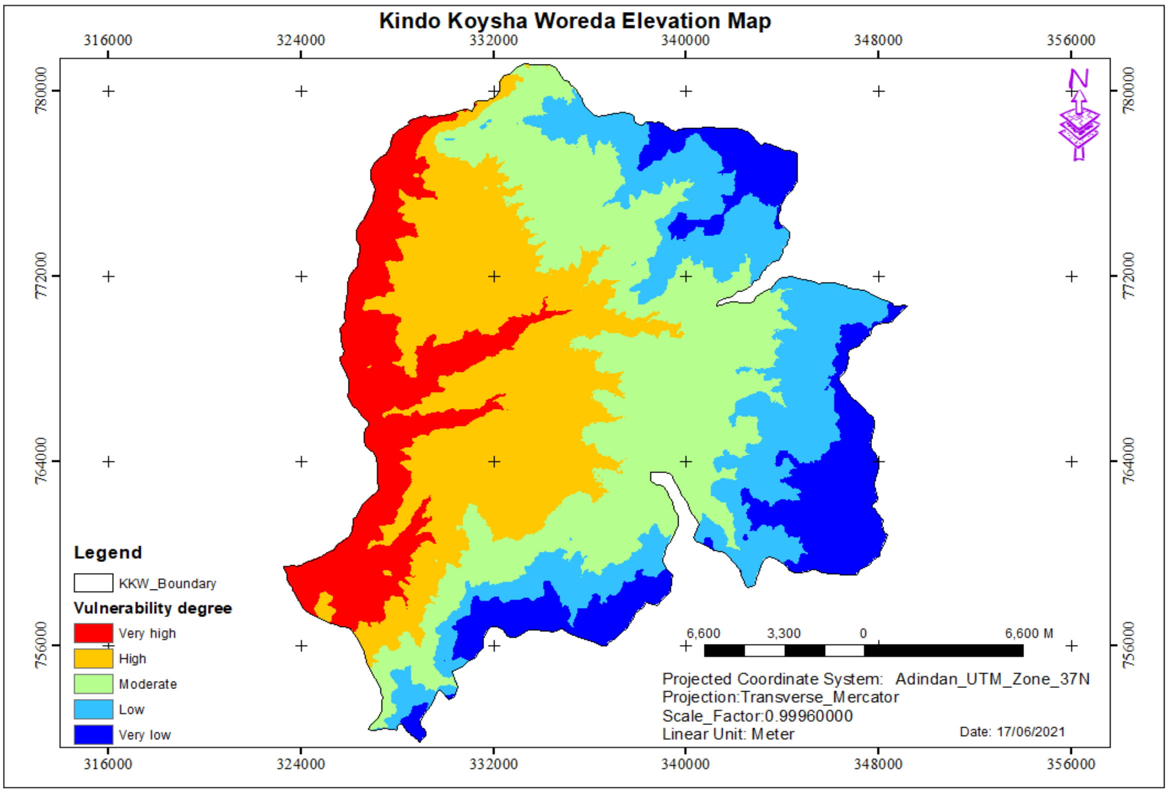


Figure 4.1 Reclassified elevation map of the study area

4.1.1.2. Slope

To the assessment of identifying a suitable area for mosquito breeding, the reclassified slope map reveals that approximately 22% are very highly vulnerable to malaria incidence, 28% are high, 31% are moderate, 18% are low, and 1% are very low with area coverage of 99.002 km^2, 125.362 km^2, 137.674 km^2, 78.233 km^2, 4.029 km^2 respectively. The slope classification and area coverage of the classes are shown in (Table 4.2) below.

Table 4.2 Slope classification and area coverage

S. no	Class interval (%)	Rank	Vulnerability degree	Area (Km^2)	Percent
1	< 5	5	Very high	99.002	22
2	5 – 10	4	High	125.362	28
3	10 -20	3	Moderate	137.674	31
4	20- 40	2	Low	78.233	18
5	>= 40	1	Very low	4.029	1
		Total		**444.30**	**100**

The map in (Figure 4.2) below depicts the slope difference distribution in the study area; near to central part of the study area is more suitable for water stagnation, which facilitates mosquito breeding.

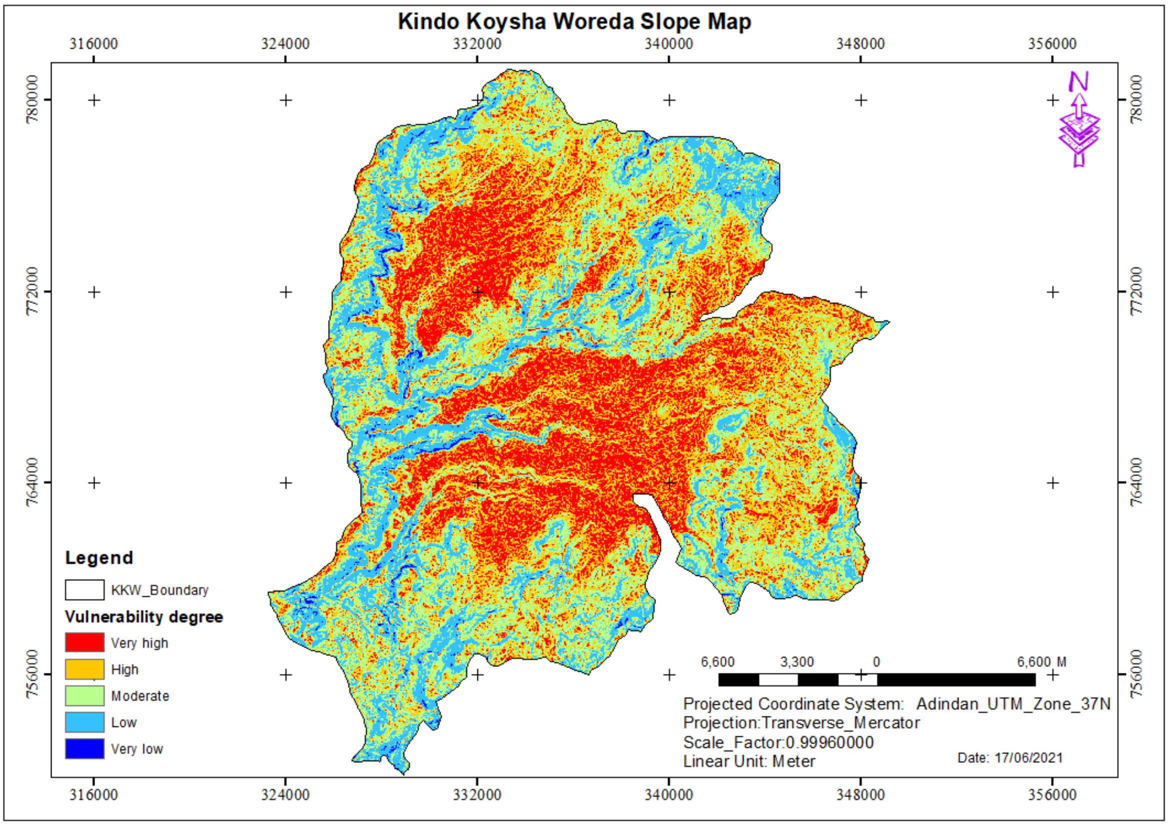


Figure 4.2 Reclassified slope map of the study area

4.1.1.3. Aspect

The presence of shadow helps the soil to hold moisture that creates a favorable site for mosquito breeding; based on reclassification, the study area can be divided into two categories: high 15 percent, with an area coverage of 68.693 km^2, which is suitable for breeding, and low 85 percent with an area coverage of 375.607 km^2, which have a lesser influence on the breeding system. (Table 4.3) gives details about the classification and area coverage of aspect in the study area.

Table 4.3 Aspect classification and area coverage

S. no	Classes	Rank	Vulnerability degree	Area (Km^2)	Percent
1	Shadow	4	High	68.693	15
2	Non shadow	1	Low	375.607	85
		Total		**444.30**	**100**

The below map in (Figure 4.3) shows the randomly distributed pattern of Aspect of the study area that can be categorized into two classes.

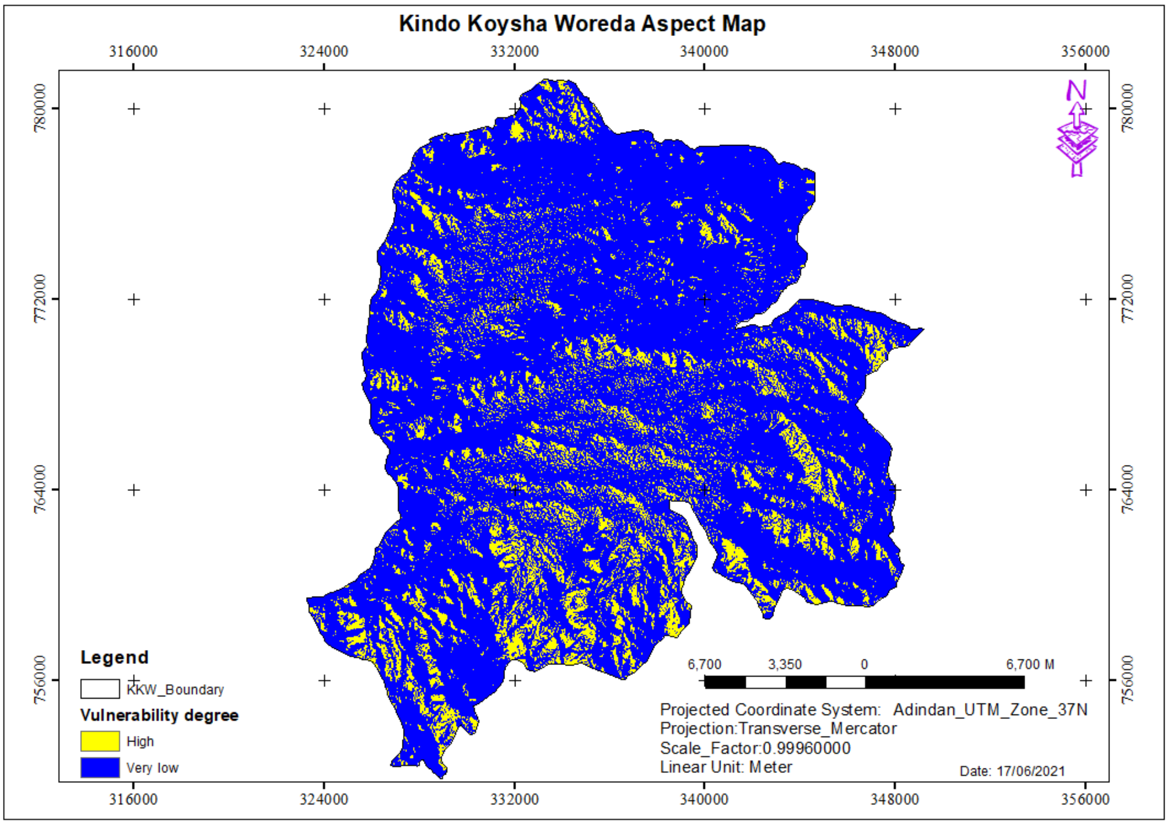


Figure 4.3 Reclassified aspect map of the study area

4.1.1.4. Wetness Index

The reclassified wetness index map reveals that approximately 59 percent of the study area is favorable for mosquito breeding, with the remaining percent shares being moderate, low, and very low, with values of 28, 11, and 2, respectively. The study area covers the classes very high and high 262.78 km^2, moderate 124.950 km^2, and very low and low about 56.57 km^2 of the study area. (Table 4.4) shows detail about classification and area coverage.

Table 4.4 Wetness index classification and area coverage

S. no	Class interval	Rank	Vulnerability degree	Area (Km^2)	Percent
1	< 5	1	Very low	8.523	2
2	5 – 6	2	Low	48.047	11
3	6 – 8	3	Moderate	124.950	28
4	8- 12	4	High	133.957	30
5	>= 12	5	Very High	128.823	29
		Total		**444.30**	**100**

The below map in (Figure 4.4) shows the wetness index of the study area. The reclassified image with very high and high vulnerability degrees have covered around 59 percent of the study area.

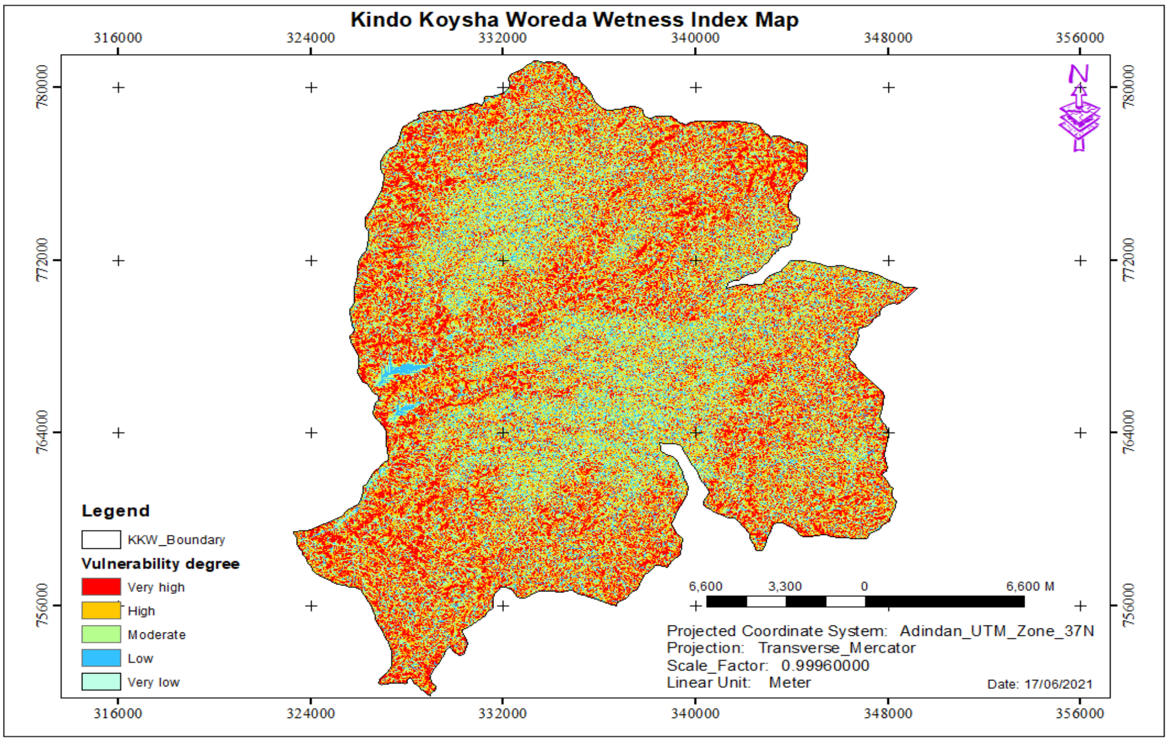


Figure 4.4 Reclassified wetness index map of the study area

4.1.1.5. Drainage Buffer

The reclassified drainage buffer covers a total of 89 percent of the study area covered by two classes: very high (52 percent) that covers an area of 231.828 km^2 and highly vulnerable (37 percent) that has 166.58 km^2 area coverage. The remained classes covered 11 percent of the study area these are Moderate 9 percent (41.220 km^2), low 1 percent (3.728 km^2), and very low 1 percent (0.944 km^2) the following (Table 4.5) gives the details about the area coverage and classification for drainage buffer factor of the current study.

Table 4.5 Drainage buffer classification and area coverage

S. no	Class interval (m)	Rank	Vulnerability degree	Area (Km^2)	Percent
1	< 200	5	Very high	231.828	52
2	200 - 400	4	High	166.58	37
3	400 - 600	3	Moderate	41.220	9
4	600 - 800	2	Low	3.728	1
5	>= 800	1	Very low	0.944	1
		Total		**444.30**	**100**

The map in (Figure 4.5) depicts the drainage distribution in the study area and classification based on their degree of influence for mosquito breeding in the study area.

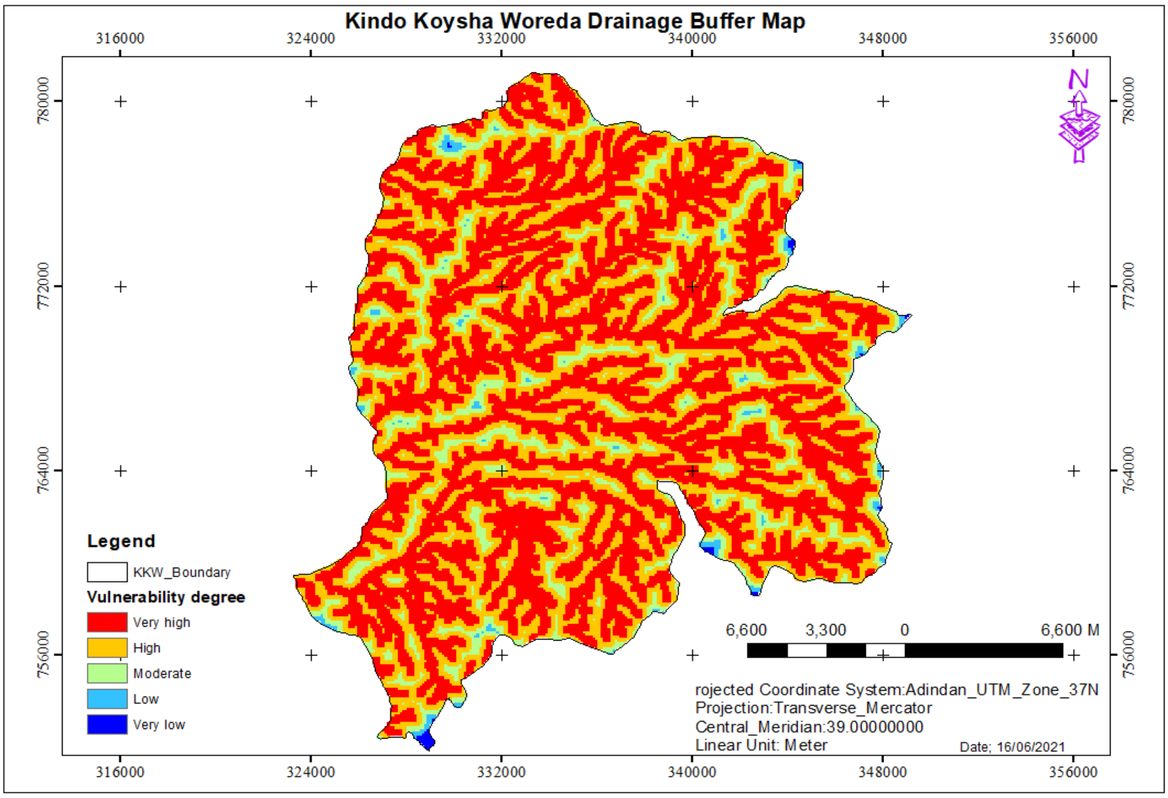


Figure 4.5 Reclassified drainage buffer map of the study area

4.1.1.6. Proximity to the River

According to the classified proximity to river class, 40 percent of the study are is vulnerable for malaria incidence with the degree of extremely high and highly vulnerable, the area coverage of these two classes is about 135.134 km^2, the moderately vulnerable are cover 13 percent of study area 57.646 km^2, and both low and very lowly vulnerable classes cover about 56 percent about 251.52 km^2 of the study area. (Table 4.6) below depicts the classification and area coverage proximity to the river.

Table 4.6 Proximity to river classification and area coverage

S. no	Class interval (m)	Rank	Vulnerability degree	Area (Km^2)	Percent
1	< 1000	5	Very high	71.098	16
2	1000 – 2000	4	High	64.036	14
3	2000 – 3000	3	Moderate	57.646	13
4	3000 – 4000	2	Low	54.309	12
5	>= 4000	1	Very low	197.211	44
		Total		**444.30**	**100**

The below thematic map (Figure 4.6) shows the proximity to the river for the study area in five classes of vulnerability degree.

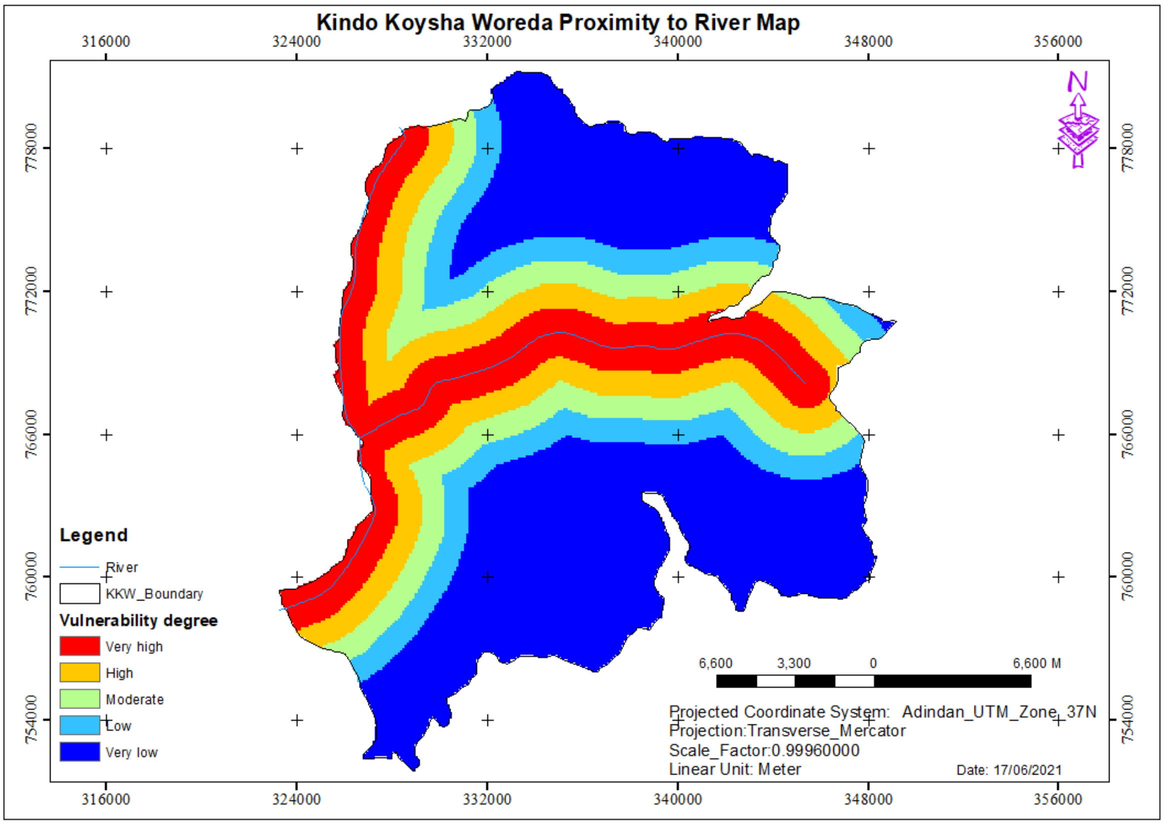


Figure 4.6 Reclassified proximity to river map of the study area

4.1.1.7. Rainfall

Based on the classification the 60 percent of the study area is highly vulnerable to malaria with an area coverage of 266.953 km^2, a moderate cover of about 54.292 km^{2,} and a very low and low share of about 16 percent 69.993 km^2 of the study area. The rainfall class interval, classification, and area coverage are shown in (Table 4.7) below.

Table 4.7 Rainfall classification and area coverage

S. no	Class interval (mm)	Rank	Vulnerability degree	Area (Km^2)	Percent
1	< 1245	5	Very high	53.062	12
2	1245 – 1250	4	High	266.953	60
3	1250 -1255	3	Moderate	54.292	12
4	1255 -1260	2	Low	53.784	12
5	>= 1260	1	Very low	16.209	4
		Total		**444.30**	**100**

The below map in (Figure 4.7) shows the rainfall distribution in the study area the large portion of the study area is covered by a highly vulnerable rank for mosquitoes breeding.

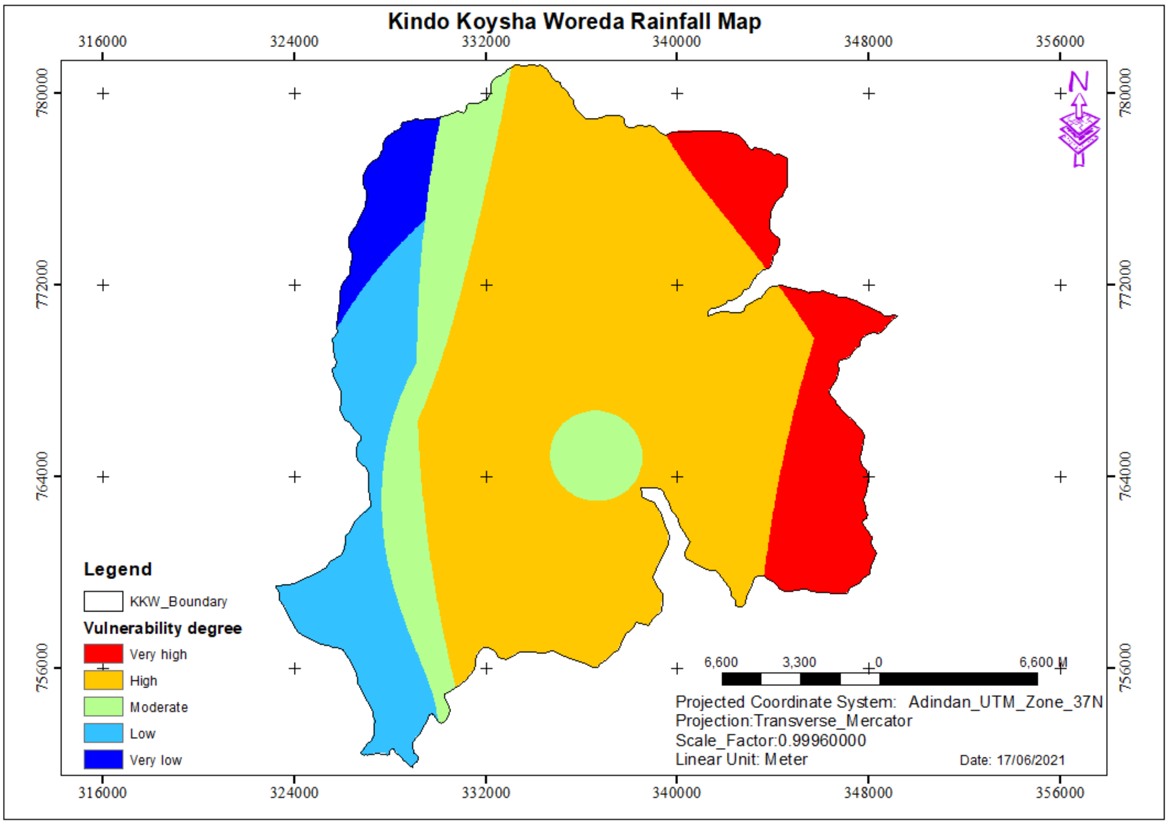


Figure 4.7 Reclassified rainfall map of the study area

4.1.1.8. Temperature

Temperature plays a key role in the breeding system of mosquitoes. According to the classification classes, about 57 percent (254.830 km^2) of the study area is extremely high vulnerable to malaria spread, and about only1 percent (2.495 km^2) is very low vulnerable to the Malaria epidemic. The below (Table 4.8) depicts the classification and area coverage of the study area.

Table 4.8 Temperature classification and area coverage

S. no	Class interval(^{0}c)	Rank	Vulnerability degree	Area (Km^2)	Percent
1	< 27.4	1	Very low	2.495	1
2	27.4 – 27.6	2	Low	6.700	1
3	27.6 – 27.9	3	Moderate	30.823	7
4	27.9 – 28.2	4	High	149.452	34
5	>= 28.2	5	Very High	254.830	57
		Total		**444.30**	**100**

The map in (Figure 4.8) below shows that the pattern of the temperature decrease from the west to the eastward in the study area.

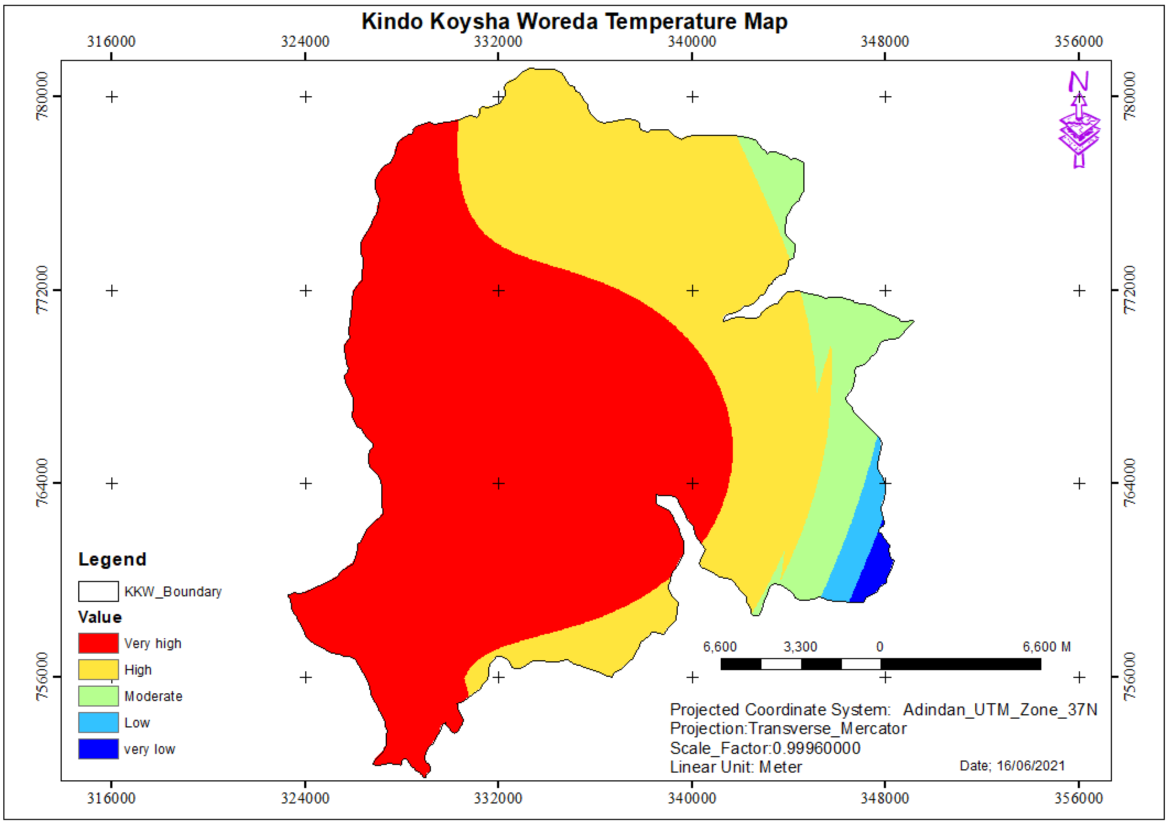


Figure 4.8 Reclassified temperature map of the study area

4.1.1.9. Land Use/Cover

Land use/cover affects the breeding of the mosquitoes directly, supervised maximum likelihood classification is applied to get the four class feature. According to the classification, 23 percent (101.977 km^2) of the total area share extreme high and high rank, and about 7 percent (30.751km^2) of the study area fall in a moderate and very low and low degree of vulnerability with area coverage of 342.323 km^2. (Table 4.9) show the detail of classification and area coverage of the study area.

Table 4.9 Land use/cover classification and area coverage

S. no	Classes	Rank	Vulnerability degree	Area (Km^2)	Percent
1	Settlement	5	Very high	71.226	16
2	Water	4	High	30.751	7
3	Forest	3	Moderate	195.415	44
4	Farm land	2	Low	146.908	33
		Total		**444.30**	**100**

The distribution of land use/land cover is clearly shown below in (Figure 4.9).

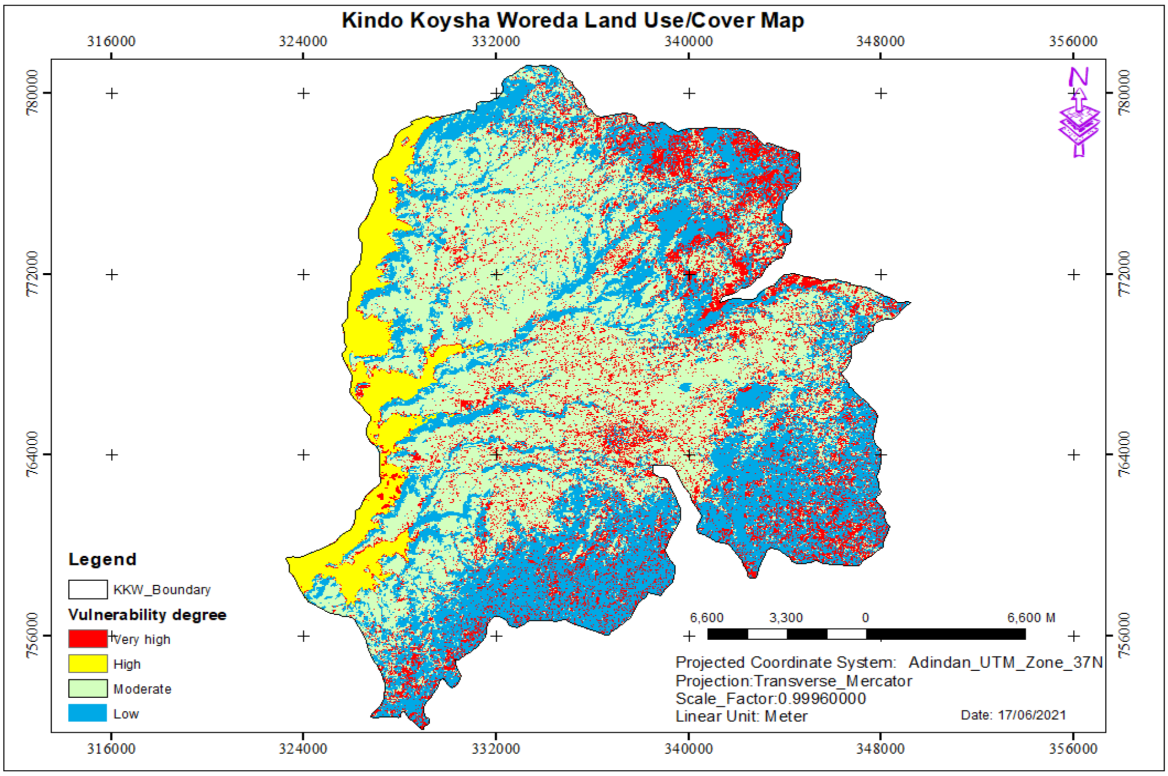


Figure 4.9 Reclassified land use/cover map of the study area

4.1.2. Relationship of Socioeconomic Parameters with Malaria Incidences

The total population distribution between the study area and proximity to the hospital are the two factors that are considered in socioeconomic parameters.

4.1.2.1 Population

Based on the classification about 95 percent of the study area held on very low and low vulnerability degree with an area coverage of 421.921km^2 the rest classes share only 6 percent area of the woreda these are Moderate (4 percent), high, and very high (2 percent). (Table 4.10) below shows the classification and area coverage of the study area.

Table 4.10 Population distribution classification and area coverage

S. no	Class interval	Rank	Vulnerability degree	Area (Km^2)	Percent
1	< 5000	1	Very low	110.770	25
2	5000 – 10000	2	Low	311.157	70
3	10000 – 15000	3	Moderate	15.873	4
4	15000 – 20000	4	High	3.713	1
5	>= 20000	5	Very High	2.787	1
		Total		**444.30**	**100**

The below map in (Figure 4.10) shows the distribution of population in the study area and vulnerability degree.

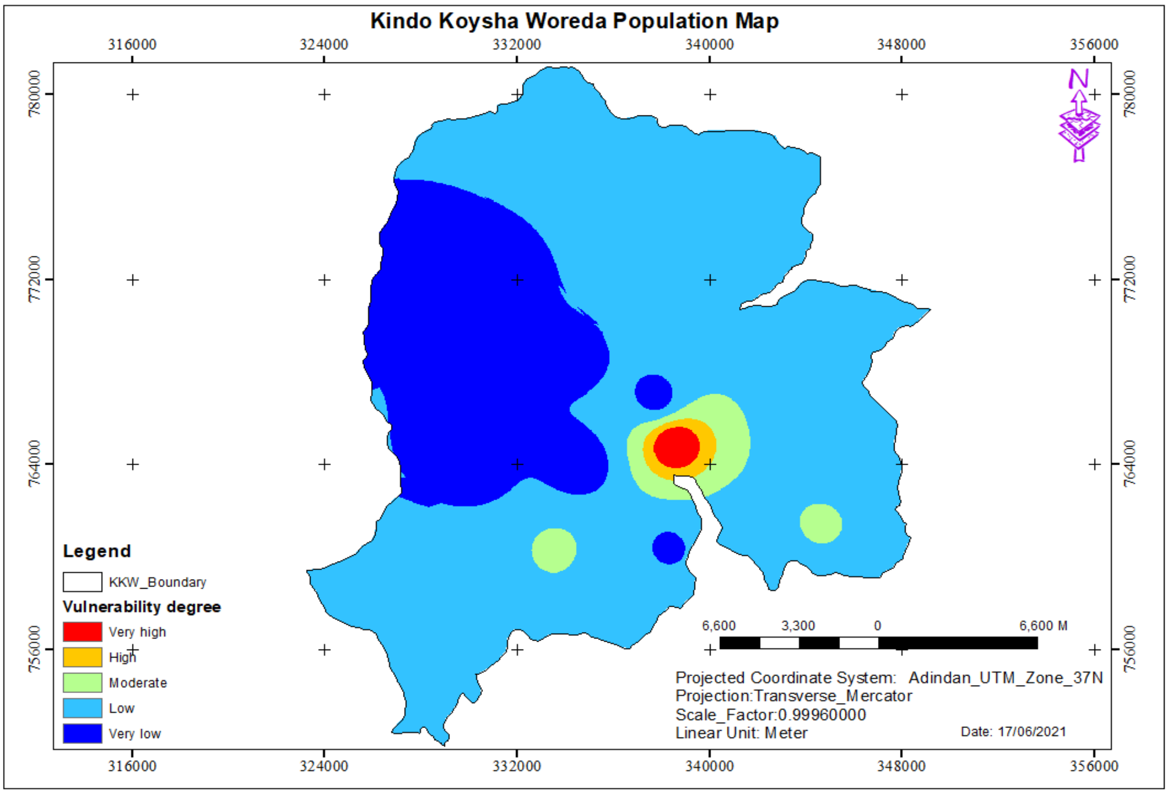


Figure 4.10 Reclassified population map of the study area

4.1.2.2. Proximity to Hospital

Based on classification from a total land area of 444.30 km^2 (75 percent) was identified as very highly vulnerable for malaria incidence in the case study area, with a proximity distance of above 6000 m from a hospital. Whereas a buffer distance of less than 1500 m from the hospital was classified as extremely low vulnerable, representing a total land area of 7.243 km^2 (2 percent) and also about 34.596 km^2 area moderately vulnerable for malaria. The below (Table 4.11) shows classification and area coverage.

Table 4.11 Proximity to hospital classification and area coverage

S. no	Class interval(m)	Rank	Vulnerability degree	Area (Km^2)	Percent
1	< 1500	1	Very low	7.243	2
2	1500 – 3000	2	Low	20.638	5
3	3000 – 4500	3	Moderate	34.596	8
4	4500 – 6000	4	High	47.375	11
5	>= 6000	5	Very high	334.448	75
		Total		**444.30**	**100**

The map in (Figure 4.11) shows the farness and closeness to the hospital in the study area.

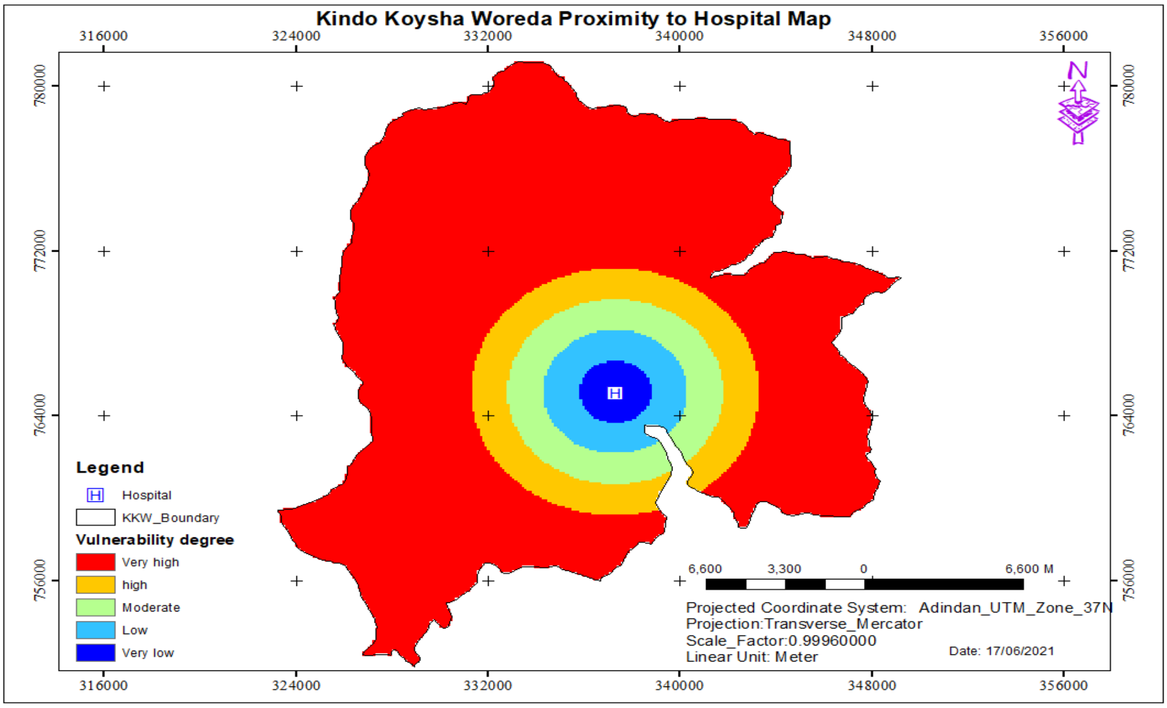


Figure 4.11 Reclassified proximity to hospital map

4.1.3. Relationship of Epidemiological Parameters with Malaria Incidences

The epidemiological parameters of the study are classified into two these are API and Pf cases both of them contribute to their parties in the spread of malaria in the study area.

4.1.3.1. API

The API obtained from the combination of both population and confirmed positive cases average of three consecutive years based on classification about 53 percent of the study area lives in very high and high vulnerable and 30 percent lives in moderate rank also only 17 percent share low and very low classes. (Table 4.12) shows the classification and area coverage.

Table 4.12 API classification and area coverage

S. no	Class interval	Rank	Vulnerability degree	Area in Km^2	Percent
1	< 50	1	Very low	0.423	0
2	50- 100	2	Low	73.947	17
3	100- 150	3	Moderate	134.126	30
4	150 – 200	4	High	72.004	16
5	>= 200	5	Very High	163.800	37
		Total		**444.30**	**100**

The map in (Figure 4.12) below shows the pattern of API distribution in the study area.

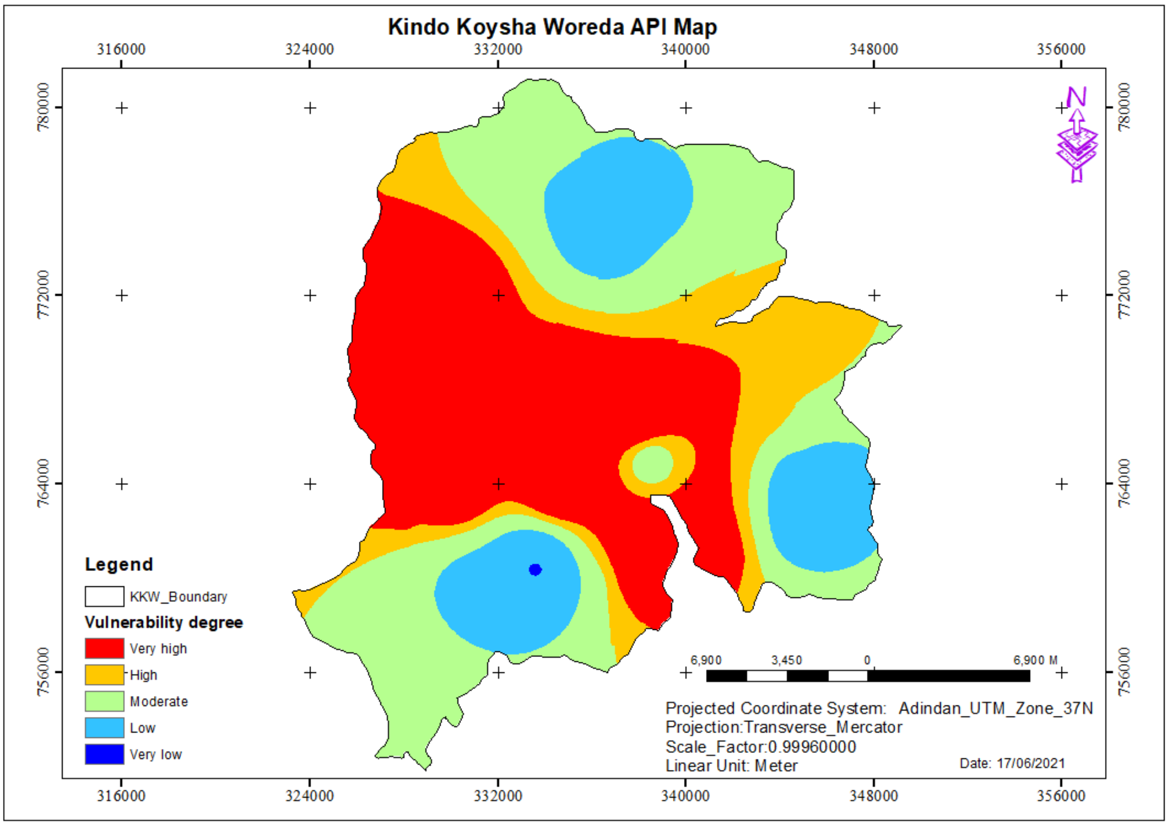


Figure 4.12 Reclassified API map of the study area

4.1.3.2. Plasmodium Falciparum Cases

The reclassified Pf cases of the study are cover about 79 percent very low and low with area coverage of 351.399 km^2 and only about 8 percent of the study area falls in very high and a high degree of vulnerability. Moderately vulnerable to malaria area covers 55.675 km^2 of the study area. The below (Table 4.13) depicts the classification and area coverage of plasmodium falciparum cases in the study area.

Table 4.13 Pf cases classification and area coverage

S. no	Class interval	Rank	Vulnerability degree	Area (Km^2)	Percent
1	< 500	1	Very low	43.597	10
2	500- 1000	2	Low	307.802	69
3	1000- 1500	3	Moderate	55.675	12
4	1500 – 2000	4	High	23.356	5
5	>= 2000	5	Very High	13.870	3
		Total		**444.30**	**100**

The map in (Figure 4.13) shows the distribution of plasmodium falciparum in the study area in the five classes.

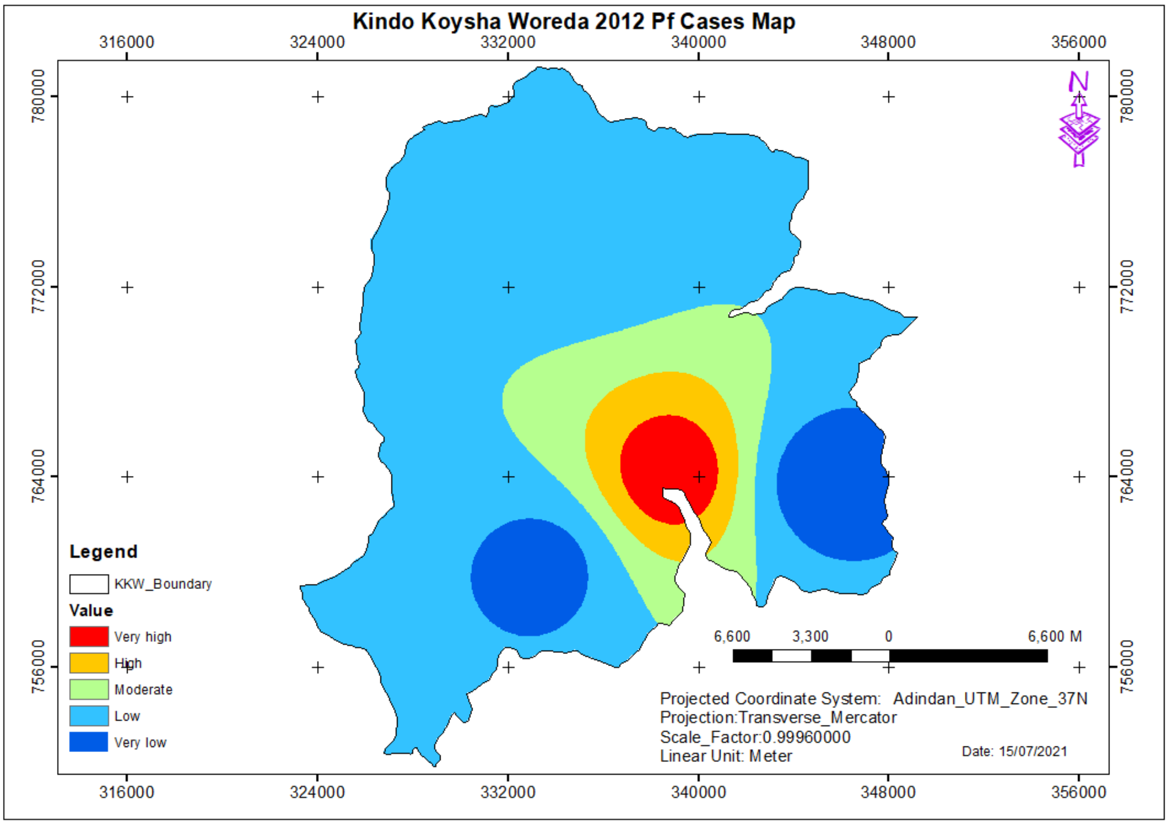


Figure 4.13 Reclassified Pf cases map of the study area

4.1.4. Malaria Vulnerability Analysis

Malaria vulnerability hotspots were identified using a weighted combination of three parameters: environmental (70 %), epidemiological (20 %), and socioeconomic parameter (10 %). The weight was assigned to the parameters with the help of experts and a review of the literature.

4.1.4.1 Hotspot for Environmental Parameters

The malaria hotspot for environmental parameters was computed using the identified environmental variables such as elevation, aspect, slope, wetness and buffer distance to Drainage, Land Use/cover, rainfall, Temperature, and breeding sites (Proximity to the river) was developed and weighted by using IDRISI, and the overlaying process performed by using weighted linear combination.

$\mathbf{HS_{env}}$ =[(Elevation × 0.2682) + (Slope× 0.0762) + (Aspect× 0.0476) + (Wetness× 0.0371) + (Drainage buffer × 0.0265) + (Proximity to river × 0.0334) + (Temperature × 0.1710) + (Rainfall × 0.0224) + (Land use/cover× 0.0164)] ………………………….. *Equation 4.1*

The below (Table 4.14) shows that about 45 percent (200.397 km^2) of the total area coverage is extremely high and highly vulnerable to malaria, 25 percent (109.710 km^2) moderate, and 30 percent (174.253 km^2) of the study area fall in a very low and low degree of vulnerability.

Table 4.14 Hotspot for environmental parameters classification and area coverage

Rank	Vulnerability degree	Area in Km^2	Percent
1	Very low	47.895	11
2	Low	86.358	19
3	Moderate	109.710	25
4	High	115.627	26
5	Very High	84.770	19
Total		**444.30**	**100**

The overlay of the nine environmental parameters gives the following result for the study area the map in (Figure 4.14) depicts the hotspot pattern for environmental factors in the study area.

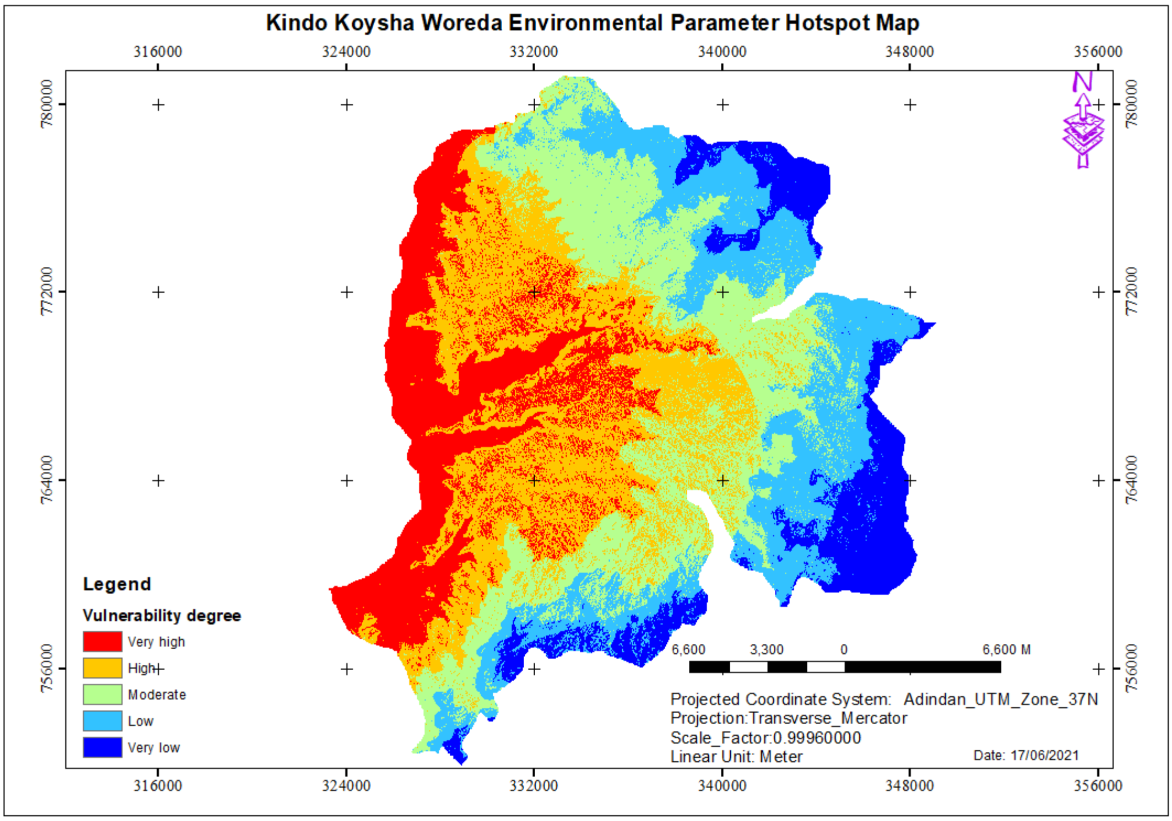


Figure 4.14 Reclassified environmental parameters hotspot map

4.1.4.2 Hotspot for Epidemiological parameters

The hotspot for Epidemiological parameters obtained from API and Pf cases by applying the Weighted linear combination;

$$\mathbf{HS_{epidemiology}} = [(\text{API} \times 0.1566) + (\text{Pf cases} \times 0.0404)] \ldots\ldots\ldots\ldots\ldots\ldots \textit{Equation 4.2}$$

The classification shows about 47 percent (206.31 km^2) of the study area have very low and low vulnerability degrees and about 38 (168.219km^2) percent of the study area share very high and high vulnerability degrees. The area coverage and classification information for epidemiological factors hotspot shown in the below (Table 4.15).

Table 4.15 Epidemiological parameters hotspot classification and area coverage

Rank	Vulnerability degree	Area (Km^2)	Percent
1	Very low	74.486	17
2	Low	131.824	30
3	Moderate	69.771	16
4	High	92.723	21
5	Very High	75.496	17
	Total	**444.30**	**100**

The below (Figure 4.15) depicts an epidemiological parameters hotspot for malaria with their degree of vulnerability in the study area.

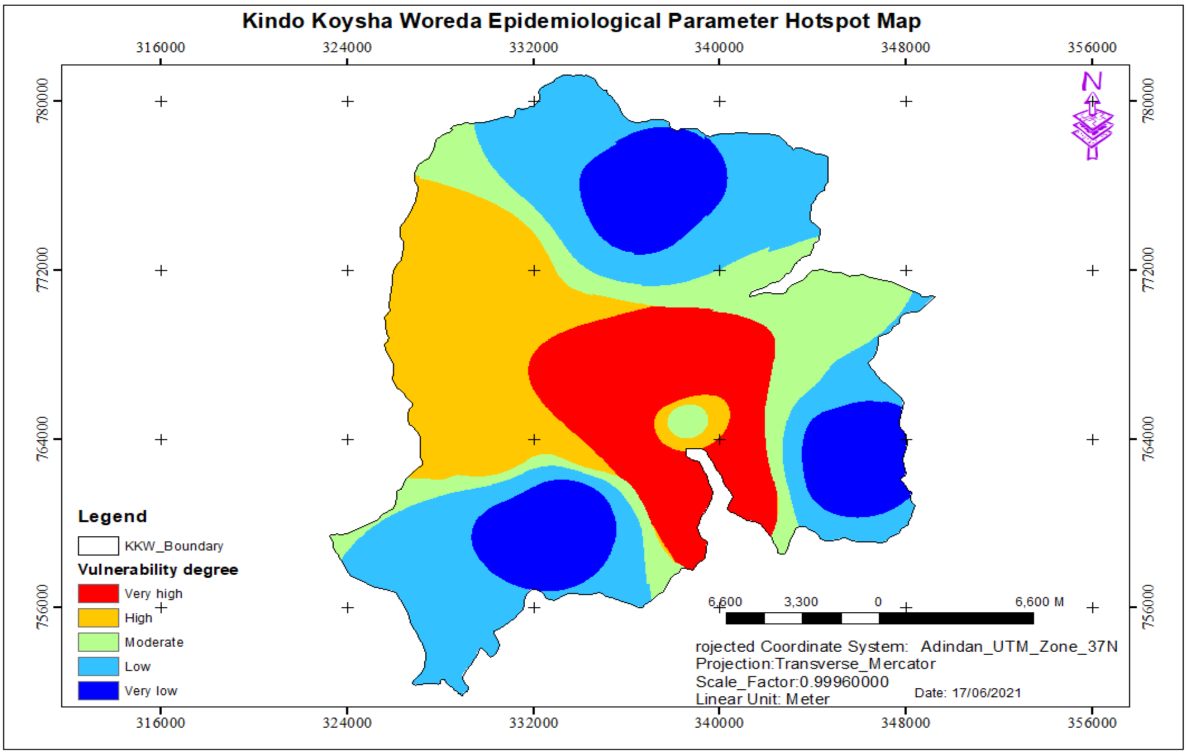


Figure 4.15 Reclassified epidemiological parameters hotspot map

4.1.4.3 Hotspot for Socioeconomic Parameters

The socioeconomic parameters were calculated and weighted using socioeconomic variables such as population and hospital proximity.

$\mathbf{HS_{se}}$= [(hospital proximity × 0.0883) + (population × 0.0160) ………………..*Equation 4.3*

According to classification, approximately 86 percent of the study area is extremely high and highly favorable to the spread of malaria. The classification and area coverage of the classes in the study area are shown in (Table 4.16.)

Table 4.16 Hotspot for socioeconomic parameters classification and area coverage

Rank	Vulnerability degree	Area (Km^2)	Percent
1	Very low	7.508	2
2	Low	19.539	4
3	Moderate	35.901	8
4	High	47.856	11
5	Very High	333.496	75
	Total	**444.30**	**100**

The map in (Figure 4.16) depicts the study's socioeconomic hotspot distributions.

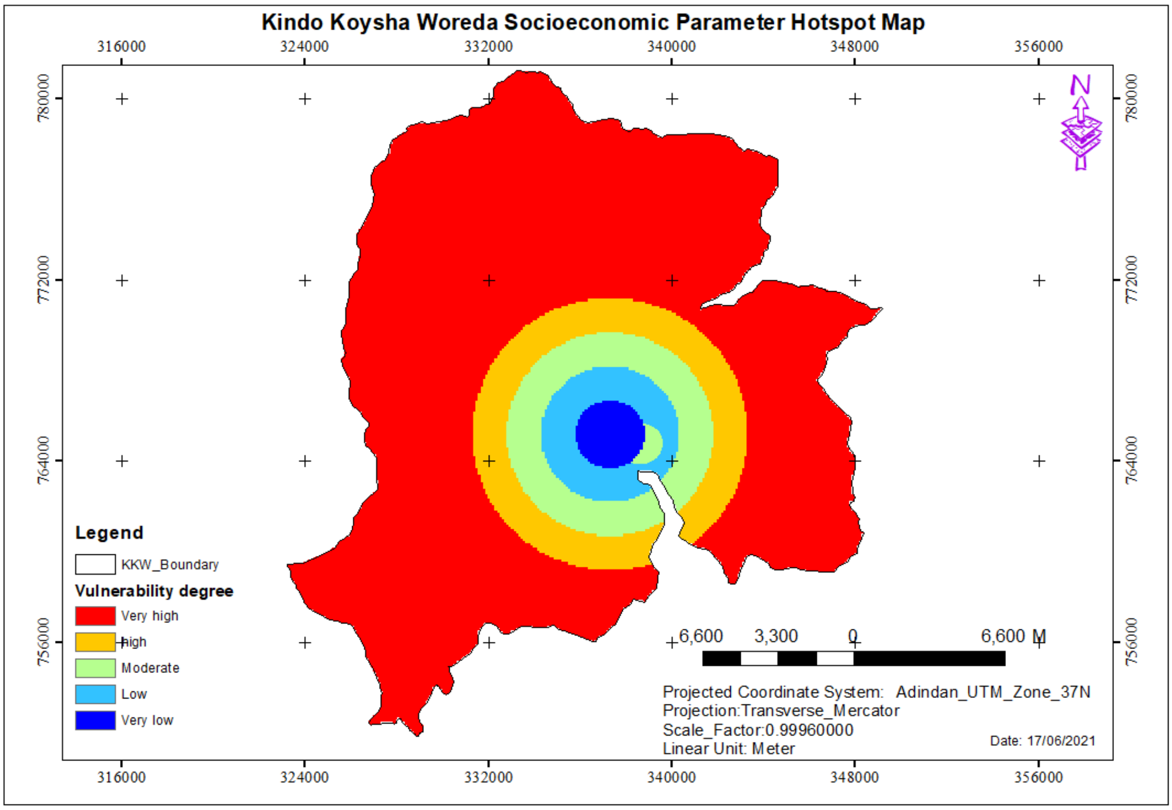


Figure 4.16 Reclassified socioeconomic parameters hotspot map

4.1.5. Malaria Vulnerability Hotspot

The malaria vulnerability hotspot is calculated by the output of the three parameters based on their influence on the mosquito breeding system by applying a malaria hotspot identification algorithm. The output is classified into four by using natural break, according to the malaria hotspot map, approximately 23 percent of the study area 103.600 km^2 is lowly vulnerable to malaria, 26% of the study area 116.560 km^2 is moderately vulnerable, and approximately 51percent (224.14 km^2) is extremely high and highly vulnerable to malaria.

Table 4.17 Malaria hotspot classification and area coverage

Rank	Vulnerability degree	Area (Km^2)	Percent
1	Low	103.600	23
2	Moderate	116.560	26
3	High	119.592	27
4	Very High	104.548	24
	Total	**444.30**	**100**

The map in (Figure 4.17) below depicts the malaria hotspots in the study area in four malaria incidence vulnerability degrees.

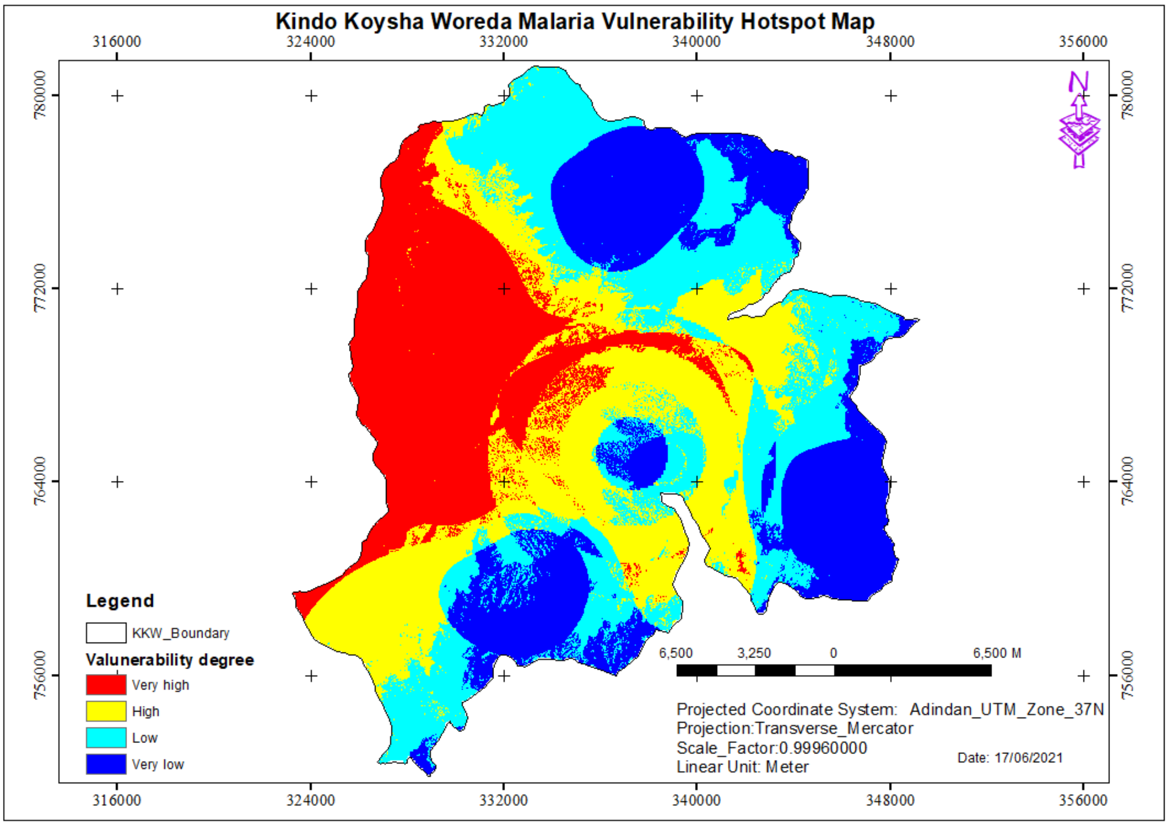


Figure 4.17 Malaria hotspot map of the study area

The probability of a malaria outbreak is influenced by some interrelated environmental, epidemiological, and socioeconomic factors. All of these factors were taken into account in the current study to identify mosquito-friendly regions. The final result was divided into four malaria hotspot categories:

Very high: The area that is very highly vulnerable to malaria in the study area obtained on the contributions of the parameter like elevation, wetness index, proximity to the river, temperature, land use/cover, proximity to a hospital, and API. The delineated area as very highly vulnerable has low elevation with high temperature that affect the breeding cycle of mosquitoes also it's near to Omo River and water cover this increase the wetness it makes suitable habitat for mosquito facilitation and the API value in this area is low to high and also the area share moderate to the high value of proximity to a hospital. Based on ranking it covers 24 percent 104. 029 km^2 of total area,

High: The area is dominated by high elevation with suitable temperature for breeding, gentle slope, high drainage density, near to river with high rainfall and high API value. The area covers 27 percent (119.073 Km^2).

Moderate: These areas are covered by moderate to high value of proximity to a hospital, moderate to the high population with the coverage of forest, high temperature, and rainfall value, low to high value of distance to the river with high value of wetness. The delineated are coverage for moderately vulnerable are is 26 percent (116.041 km^2).

Low: This area was found that areas of low priority are more likely to be in the Northeast and Southeast part of the study area with a low population, moderate to high slope, low Pf cases, and low proximity to river value accounted 23 percent (102.559km^2) of the study area.

4.1.6. Comparison Between Kebele Based on Malaria Vulnerability Level

By superimposing the malaria vulnerability hotspot map and the Kebeles boundary map, the malaria vulnerability levels of different Kebeles were observed by using zonal statistics. Mundena, Mashenga, Fajana Mata, and the majority of Chereche, Sere Finchawa, Borkeshie, and a portion of Moliticho, and Dada Kare, kebeles are very high and highly vulnerable to malaria incidence. Tulicha, Kindo Angala, Bele town and parts of Doge Laroso, Sorto, Menara, Fechana, and Hanaze are moderate malaria vulnerable areas. Oyldu Chama and Bede Weyde are almost completely low vulnerable areas in the Kindo Koysha woreda. As a result, when it comes to preventing malaria-related damage, health offices and responsible government offices should concentrate on these high-vulnerable areas. The below map in (Figure 4.18) illustrates the malaria vulnerability hotspot of Kindo Koysha Woreda.

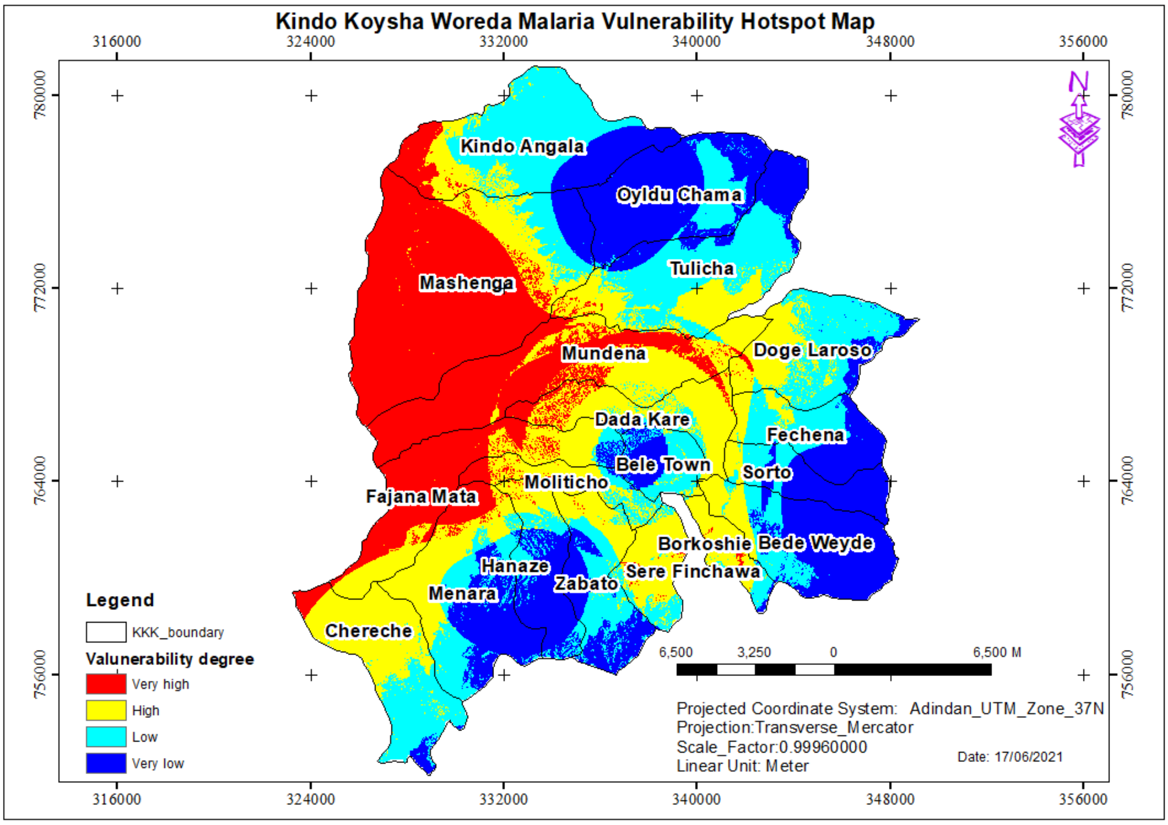


Figure 4.18 Malaria hotspot b/n Kebeles map of the study area

Based on the area covered with the degree of vulnerability Oydu Chama and Bede Weyde have no chance of being very highly vulnerable to malaria incidence, but they have less chance to be moderately vulnerable. Oyldu Chama has the lowest vulnerability degree when compared to the remaining from the delineated area about 21.657km^2 lowly vulnerable, moderate (5.614), and about only 0.012km^2 of the area is extremely high and highly vulnerable.

Based on the Zonal statistical analysis report Mundena, Mashenga, and a majority of Fajana Mata are modeled as very highly vulnerable from the 19 kebeles of the study area. The very high portion of Mashenga kebele is very highly vulnerable with an area coverage of (49.942 km^2) follows high (7.967 km^2), moderate (4.661 km^2), and low (3.446 km^2). Next to Mashenga, Mundena the second vulnerable kebele from the 19 Kindo Koysha kebeles with the highly vulnerable degree covers about 24.460 km^2 follows high (13.495 km^2), moderate (0.516 km^2), and low (0) malaria incidence vulnerability. Fajana Mata; is the third very highly vulnerable area for malaria incidence in the study area. The data for all the 19 kebeles in the study are shown in the following (Table 4.18).

Table 4.18 Comparison of vulnerability degree between kebeles of the study area

S.no	Kebele name	Low	Moderate	High	Very high
1	Oyldu Chama	21.627	5.614	0.012	0.000
2	Tulicha	7.061	17.665	9.496	0.383
3	Kindo Angala	6.593	20.657	5.153	3.804
4	Mashenga	3.446	4.661	7.967	49.942
5	Mundena	0.000	0.516	13.495	24.460
6	Fechena	6.007	6.649	2.225	0.013
7	Doge Laroso	1.987	12.598	7.946	0.199
8	Sorto	7.140	2.999	1.128	0.000
9	Borkoshie	0.188	1.239	4.566	0.257
10	Bede Woyde	16.126	4.725	3.245	0.000
11	Dada Kare	0.355	1.831	11.384	2.566
12	Bele Town	3.595	4.540	0.611	0.000
13	Fajana Mata	0.752	0.882	9.365	16.146
14	Moliticho	0.191	1.890	5.367	1.438
15	Sere Finchawa	0.041	2.241	7.410	0.272
16	Zabato	6.953	6.872	4.200	0.047
17	Hanaze	8.629	3.371	2.702	0.151
18	Menara	11.054	8.600	9.584	3.320
19	Chereche	0.814	8.492	13.215	1.031
Total value of vulnerability degree		**103.600**	**116.560**	**119.592**	**104.548**
The total area of the study area			444.30		

4.2. Discussion

The current study analyzed and developed a Malaria vulnerability hotspot map by using the Geospatial Technology with a multi-criteria evaluation method for the chosen environmental, socioeconomic, and epidemiological parameters for Kindo Koysha Woreda. The result of the current study delineated in four malaria hotspot ratings with the value of very high and high accounted about 51 percent (224.14 km^2), moderate covers 26 percent (116.560 km^2), and the lowly vulnerable area also accounts for 23 percent (103.600 km^2).

Mashenga, Mundena, and Fajana Mata kebeles those very highly vulnerable hotspots from the Kindo Koysha Woreda kebeles and also Borkeshie, Dada Kare, Moliticho, Sere Finchawa, and Chereche are highly vulnerable. Generally, the Western part of the study area which is near to Omo River with low elevation is highly vulnerable to malaria incidence.

Based on the malaria susceptibility of the current study, very highly susceptible areas have low altitudes with high temperatures affecting the mosquito breeding cycle. API value in this area is low to high, high wetness, low to high slope, and area covered by water bodies. As stated by Ahmad et al., (2017), the very high rating malaria hotspot area is highly dominated by tribal population, covered with dense forest, high wetness, high rainfall with a lot of perennial streams with a gentle slope and moderate to low elevation provide a most conducive environment for the growth of malaria parasite, in addition to the above factor high amount of API value is used to identify the highly vulnerable area (Kassaw et al., 2019).

Low vulnerable area of the current study was found that areas of low priority are more likely to be in the Northeast and Southeast part of the study area with a low population, moderate to high slope, low Pf cases, and high proximity to the river. Previously worked researches states low vulnerable area with low population in general and low to the sparse population. It is covered with open forest to the dense forest, low wetness, low rainfall, high slope, and high elevation, which provides less favorable conditions for the malaria parasite to grow (Ahmad et al., 2017; Kassaw et al., 2019), so current study fairly agreeable with previously worked researches that worked on the area of malaria vulnerability hotspots.

The findings of the current study use as input for malaria prevention and control activities, the identification of the malaria hotspots in woreda use to allocate the preventive materials like an insecticide-treated bednet (ITN), medicines, and other materials to the right population in the study area. It also uses as input for policymakers and NGOs.

Several interesting aspects may be explored further by applying Geospatial techniques with other technologies to predict the outbreak of malaria, and malaria diffusion. It may be used as input in the country to achieve the elimination program of malaria that is scheduled in 2025. In addition that it’s important to consider population migration and deforestation as factors because these two are more take place currently especially population migration in our country and all over the world due to COVID-19 pandemic disease.

5. CONCLUSION AND RECOMMENDATION

The current study is aimed to model the malaria vulnerability hotspot map of Kindo Koysha woreda using environmental, epidemiological, and socioeconomic factors. It is also intended to determine the level of susceptibility of Kebeles found in the study area concludes the following stopping points and recommendations on the study.

5.1. Conclusion

The current study discussed the malaria vulnerability hotspot modeling in a Kindo Koysha Woreda area with the help of different data types, technologies, and interpretations. Malaria is the most silent killer disease around the world even though it is a treatable disease. To minimize the spread as well as elimination it's important to applying the new technologies rather than using conventional methods at all. Reliable maps of malaria hotspot areas are critical for estimating the scope of the problem and, consequently, the resources required to combat malaria. Thematic products serve as a benchmark for assessing control progress and indicate which geographic areas should be prioritized.

The final result is obtained by applying the multi-criteria evaluation method, weight was computed using pair-wise comparison in the AHP module based on the influence of factors that considering the importance of each factor to the facilitation of mosquito breeding and the interrelationships between the factors. Weighted Overlay was used to map malaria vulnerability zones in the study area. Thematic products were used to show the extent of the individual factors in the study area.

The results of the current study show that very high and highly vulnerable areas make up around 51 percent (224.14 km^2), medium coverage 26 percent (116.560 km^2) and lowly vulnerable areas also make up 23 percent (103.600 km^2) of the study area. Mashenga, Mundena, and the Fajana Mata Kebeles These very endangered hotspots from the Kindo Koysha Woreda Kebeles and also Borkeshie, Dada Kare, Moliticho, Sere Finchawa, and Chereche are highly vulnerable. In general, the western part of the study area near the Omo River with low elevation is very prone to malaria incidence.

Finally, the current study confirmed that the Geospatial technology with the base of multi-criteria evaluation to model malaria vulnerability is more capable and efficient to apply. It can be said Geospatial technologies recently the front runner to solve the problem in the entire world to fulfill seeks of humankind, appropriate use of these technologies make a safe environment response; the application of Geospatial technologies is not limited in the mapping, the beyond application includes; data processing, display, analyze, query, data collection, and processing. The current study used GIS for data processing, analysis and to produce thematic maps, and Google earth and remote sensing were used as input data for GIS processing.

5.2. Recommendation

The findings of this particular study have shown that remote sensing, GIS, and multi-criteria evaluation models are useful tools for studies of Malaria vulnerability hotspot identification. The following are also recommended as potential research recommendations, based on the results of the study:

- One of the most results noticed that area near to Omo River is highly vulnerable to malaria in the study area. The Kindo Koysha woreda health office and stakeholders should have to give priority to the three kebeles in prevention and control practice, these are Mashenga, Mundena, and Fajana Mata.
- The preventive action of the woreda health and data handling system in malaria cases is conventional. Therefore the Woreda health office should design a digital system rather than an analog.
- Similar research needs to be conducted in areas experiencing malaria epidemic prediction by using Geospatial techniques. It will be used as an input to the elimination program of malaria rather than control practice.
- The future researcher should have to consider population migration and deforestation as factors.

REFERENCE

Abdulahi, A., Wudad, A., & Abajihad, M. (2020). Malaria Hazard and Risk Analysis Using GIS and Remote Sensing in Korahey Zone of Somali Regional State , Eastern Ethiopia. *American Scientific Research Journal for Engineering*, *68*, 20–39.

Ahmad, F., Goparaju, L., & Qayum, A. (2017). Studying Malaria Epidemic for Vulnerability Zones: Multi-Criteria Approach of Geospatial Tools. *Journal of Geoscience and Environment Protection*, *05*(05), 30–53. https://doi.org/10.4236/gep.2017.55003

Ahmed, A. (2014). GIS and remote sensing for malaria risk mapping, Ethiopia. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives*, *40*(8), 155–161. https://doi.org/10.5194/isprsarchives-XL-8-155-2014

Akinbobola, A., & Ikiroma, I. A. (2018). Determining Malaria Hotspot Using Climatic Variables and Geospatial Technique in Central Urban Area of Ibadan, Southwest, Nigeria. *Journal of Climatology & Weather Forecasting*. https://doi.org/10.4172/2332-2594.1000225

Alelign, A., & Dejene, T. (2018). *Current Status of Malaria in Ethiopia : Evaluation of the Burden , Factors for Transmission and Prevention Methods*. *7*(1), 1–6. https://doi.org/10.5829/idosi.apg.2016.7.1.10273

Beck, L. R., Lobitz, B. M., & Wood, B. L. (2000). *New Sensors and New Opportunities*. *6*(3), 217–227.

Bhatt, B. J. (2020). Study on the satellite based assessment of malaria mosquitogenic conditions in and around Dehradun. *International Journal of Mosquito Research*, *7*(1), 08–15.

Buke, T. (2016). *The Effect of Np Fertlizer Rates on the Yield and Yield Components of Taro (Colocasia esculenta (L .) Schott .) in*. *5*(3), 329–340.

Ceccato, P., Connor, S. J., Jeanne, I., & Thomson, M. C. (2005). Application of Geographical Information Systems and Remote Sensing technologies for assessing and monitoring malaria risk. *Parassitologia*, *47*(1), 81–96.

Dana, D. D. (2018). *Spatial Modelling of Malaria Risk in Bayesian Setting : A Case Study of Wolaita and Dawuro Zones in SNNPR , Ethiopia*. *8*(15), 68–74.

Degife, A. (2009). Vulnerability analysis and malaria risk mapping in Awassa and Wondogenet woredas. *Unpublished Masters' Thesis*, 1–64.

Eastman, J. R. (2012). *Multi-criteria evaluation and GIS*. 493–502.

Eniyew, S. (2018). Modelling of malaria hotspot sites using geospatial technology in the north-western highlands of Ethiopia. *International Journal of Mosquito Research*, *5*(5), 59–70.

Ethiopian public health institute. (2016). *Ethiopian National Malaria Indicators Survey*.

Feachem, R. G., & Jamison, D. T. (1991). Disease and mortality in sub-Saharan Africa. In *Disease and mortality in sub-Saharan Africa*. https://doi.org/10.2307/524757

Ghilardi, L., Okello, G., Nyondo-Mipando, L., Chirambo, C. M., Malongo, F., Hoyt, J., Lee, J., Sedekia, Y., Parkhurst, J., Lines, J., Snow, R. W., Lynch, C. A., & Webster, J. (2020). How useful are malaria risk maps at the country level? Perceptions of decision-makers in Kenya, Malawi and the Democratic Republic of Congo. *Malaria Journal*, *19*(1). https://doi.org/10.1186/s12936-020-03425-z

Jemal, Y., & Al-thukair, A. A. (2016). Combining GIS application and climatic factors for mosquito control in Eastern Province , Saudi Arabia. *Saudi Journal of Biological Sciences*. https://doi.org/10.1016/j.sjbs.2016.04.001

Karami, A., & Guo, Z. (2012). A fuzzy logic multi-criteria decision framework for selecting IT service providers. *Proceedings of the Annual Hawaii International Conference on System Sciences*, *April 2015*, 1118–1127. https://doi.org/10.1109/HICSS.2012.59

Kassaw, M., Zewdie, A., & Ameneshewa, W. (2019). Identifying Malaria Epidemic Prone Area Hotspot Map by Using Geospatial Technologies and Spatial Multi Criteria Evaluation Techniques : The Case of Majang Zone , Gambella Region , Ethiopia. *IOSR Journal Of Humanities And Social Science (IOSR-JHSS)*, *24*(11), 65–79. https://doi.org/10.9790/0837-2411056579

Kebede, Y., Edmealem, W., & Alemayehu, B. (2017). *Malaria Hazard and Risk Mapping Using GIS Based Spatial Multicriteria Evaluation Technique (SMCET) in Tekeze Basin Development Corridor , Amhara Region , Ethiopia*. *7*(5), 76–87.

Kirk, K. E., Zahirul Haq, M., Alam, M. S., & Haque, U. (2015). Geospatial technology: A tool to Aid in the Elimination of Malaria in Bangladesh. *ISPRS International Journal of Geo-Information*, *4*(1), 47–58. https://doi.org/10.3390/ijgi4010047

Kumar Ra, P., Singh Nathawat, M., & Onagh, M. (n.d.). HEALTH SCIENCE JOURNAL ® Application of Multiple Linear Regression Model through GIS and Remote Sensing for Malaria Mapping in Varanasi District, INDIA. In *Health Science Journal* (Vol. 6, Issue 4). iMedPub. Retrieved December 22, 2020, from www.hsj.gr

Lemessa, A. (2011). GIS and Remote sensing based malaria risk mapping in Fentale Woreda, East Shoa Zone, Ethiopia. *Unpublished Masters' Thesis*, 1–81.

Malaria. (2020). WHO. https://www.who.int/news-room/fact-sheets/detail/malaria

Malaria | FMOH. (2020). Retrieved December 23, 2020, from http://www.moh. gov.et/ejcc /en/malaria

Manish, K. (2017). Malaria Risk Zonation and validation using Remote sensing and GIS in Haora district and Kolikata Municipal Corporation, West Bengal. *Masters' Thesis*, 9–64.

Manoharan, R., Alemu, M., Legesse, B., & Abajihad, M. (2020). Malaria Hazard and Risk Analysis Using Geospatial Techniques in the Case of Selected Woredas of Jimma Zone, Oromia Region, Ethiopia. *Earth Systems and Environment*, *FMoH 2009*. https://doi.org/10.1007/s41748-020-00170-w

Mestewat, S. (2014). Geographic Information System and Remote Sensing Based Malaria Risk Mapping Using Environmental Factors: A Case of Arba Minch Zuria Woreda, Southern Nations Nationalities and Peoples' Regional Stat. *Unpublished Masters' Thesis*, 21–30.

Miranda, E. (2018). *Classification of Land Cover from Sentinel-2 Imagery Using Supervised Classification Technique*. *September*. https://doi.org/10.1109/ICIMTech.2018.852812

MOH, W. (2019). *Malaria outbreak in Wolaita zone*. https://www.facebook.com/www. wzgo/

Mohammed, N. Z., Ghazi, A., & Mustafa, H. E. (2013). Positional accuracy testing of Google Earth. *International Journal of Multidisciplinary Sciences and Engineering*, *4*(6), 6–9. http://www.ijmse.org/Volume4/Issue6/paper2.pdf

Muluken, B. (2019). GIS and Remote sensing based malaria risk assessment znd mapping in Raya Kobo Woreda, North Wollo, Ethiopia. *Unpublished Masters' Thesis*.

Nguyen, H. T. T., Doan, T. M., Tomppo, E., & McRoberts, R. E. (2020). Land use/land cover mapping using multitemporal sentinel-2 imagery and four classification methods-A case study from Dak Nong, Vietnam. *Remote Sensing*, *12*(9), 1–27. https://doi.org/10.3390/RS12091367

NIAID. (2007). *Understanding malaria : fighting an ancient scourge.* U.S. Dept. of Health and Human Services National Institutes of Health National Institute of Allergy and Infectious Diseases.

NRC. (2001). *The national academies press*. https://doi.org/10.17226/10025

Okogun, G. R. A. (2005). Life-table analysis of Anopheles malaria vectors: Generational mortality as tool in mosquito vector abundance and control studies. *Journal of Vector Borne Diseases*, *42*(2), 45–53.

Pam, D. D., Nigeria, Omalu, I. C. J., Akintola, A. A., Dan, A. Y., Kalesanwo, A. O., Babagana, M., Muhammad, S. A., Ocha, I. M., & Adeniyi, K. A. (2017). The role of GIS and remote sensing in the control of malaria. *Online Journal of Health and Allied Sciences*, *16*(3), 1–4.

Qayum, A., Arya, R., Kumar, P., & Lynn, A. M. (2015). Socio-economic, epidemiological and geographic features based on GIS-integrated mapping to identify malarial hotspots. *Malaria Journal*, *14*(1). https://doi.org/10.1186/s12936-015-0685-4

Rabby, Y. W., & Ishtiaque, A. (2020). *Evaluating the E ff ects of Digital Elevation Models in Landslide Susceptibility Mapping in Rangamati*.

Saaty, T. L. (2008). *Decision making with the analytic hierarchy process*. *1*(1).

Sahin, M., & Yurdugul, H. (2018). A Content Analysis Study on the Use of Analytic Hierarchy Process in Educational Studies. *Eğitimde ve Psikolojide Ölçme ve Değerlendirme Dergisi*, *9*(4), 376–392. https://doi.org/10.21031/epod.373784

Samba, E. (2001). The malaria burden and Africa. *The American Journal of Tropical Medicine and Hygiene*, *64*(1_suppl), ii–ii. https://doi.org/10.4269/ajtmh.2001.64.ii

Saxena, A., Kumar Jat, M., & Kumar, S. (2020). Uncertainty Analysis of high-resolution open source DEM for modelling soil erosion. *Roorkee Water Conclave*.

Srivastava, A., Nagpal, B. N., Joshi, P. L., Paliwal, J. C., & Dash, A. P. (2009). Identification of malaria hot spots for focused intervention in tribal state of India: A GIS based approach. *International Journal of Health Geographics*, *8*(1), 1–8. https://doi.org/10.1186/1476-072X-8-30

Tesfaye, S., Belyhun, Y., Teklu, T., Mengesha, T., & Petros, B. (2011). Malaria prevalence pattern observed in the highland fringe of Butajira , Southern Ethiopia : A longitudinal study from parasitological and entomological survey. *Malaria Journal*, *10*(1), 153. https://doi.org/10.1186/1475-2875-10-153

Tewara, M. A., Mbah-Fongkimeh, P. N., Dayimu, A., Kang, F., & Xue, F. (2018). Small-area spatial statistical analysis of malaria clusters and hotspots in Cameroon;2000–2015. *BMC Infectious Diseases*, *18*(1), 1–15. https://doi.org/10.1186/s12879-018-3534-6

Vargas, L. G. (1990). An overview of the analytic hierarchy process and its applications. *European Journal of Operational Research*, *48*(1), 2–8. https://doi.org/10.1016/0377-2217(90)90056-H

WHO. (2019). Guidelines for Malaria Vector Control. In *Guidelines for Malaria Vector Control*. https://apps.who.int/iris/bitstream/handle/10665/310862/9789241550499-eng.pdf?ua=1%0Ahttp://www.ncbi.nlm.nih.gov/pubmed/30844152

WHO. (2020). Malaria in Ethiopia. *Report*, 1–3.

WorHO. (2020). *Disease Registration - Kindo Koyisha WorHO Disease Registration - Kindo Koyisha WorHO*. 1–4.

Zhao, X., Thanapongtharm, W., Lawawirojwong, S., Wei, C., Tang, Y., Zhou, Y., Sun, X., Cui, L., Sattabongkot, J., & Kaewkungwal, J. (2020). Malaria risk map using spatial multi-criteria decision analysis along yunnan border during the pre-elimination period. *American Journal of Tropical Medicine and Hygiene*, *103*(2), 793–809. https://doi.org/10.4269/ajtmh.19-0854

APPENDICES

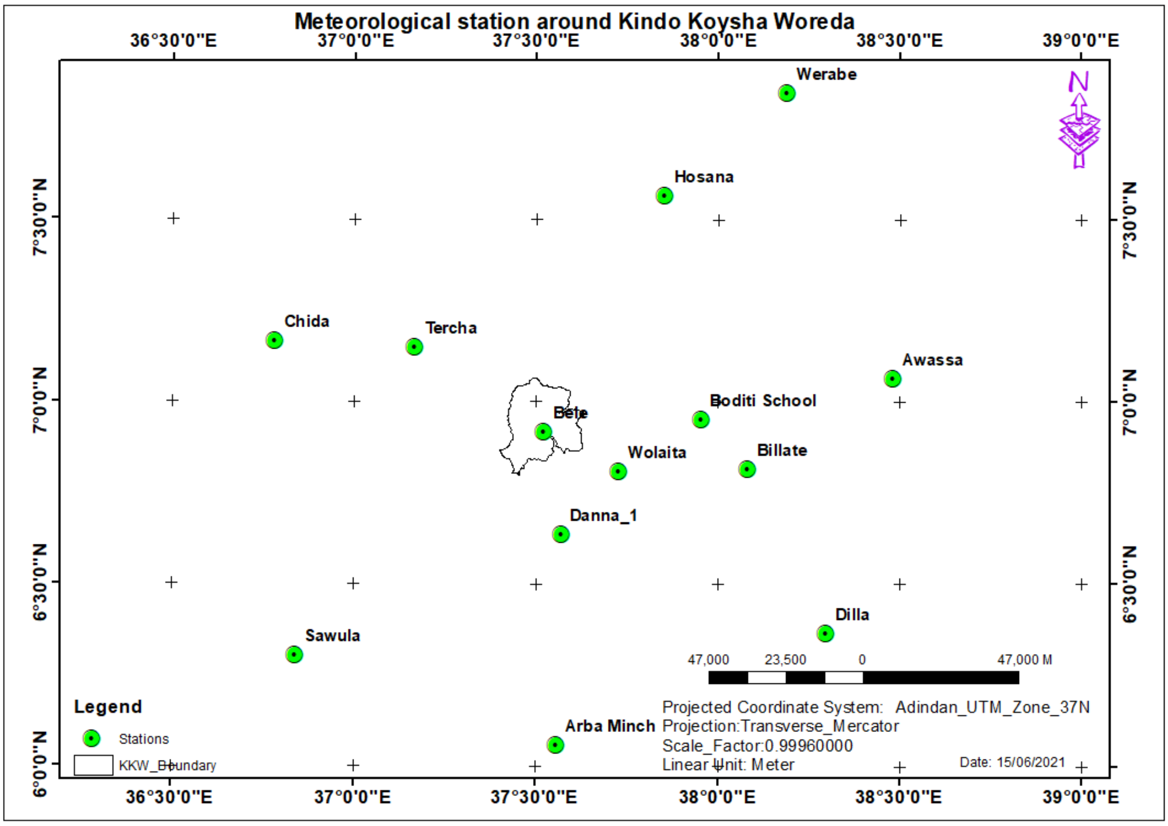
Appendix 1. Kebele population data of Kindo Koysha woreda of 2012

S. No	Name Of Kebele	Male	Female	Total
1	Kindo Angala	3398	3564	6962
2	Mashenga	684	656	1341
3	Oyldu Chama	4492	4812	9304
4	Tulicha	3919	3786	7705
5	Mundena	1789	1796	3586
6	Dada Kare	1566	1167	2734
7	Doge Laroso	3251	3332	6584
8	Fechena	3243	3366	6610
9	Sorto	3688	3948	7637
10	Bede Weyde	5228	5475	10703
11	Sere Finchawa	1925	1995	3920
12	Borkoshie	2840	3191	6032
13	Moliticho	383	494	877
14	Fajana Mata	707	717	1424
15	Menara	4880	4940	9821
16	Hanaze	5139	6204	11344
17	Zabato	4127	4489	8616
18	Chereche	3904	3841	7745
19	Bele Town	12492	15311	27803

Appendix 2. Accuracy assessment of ML classification

Data Classified	Water	Forest	Farm Land	Settlement	
Water	28245	0	0	0	
Forest	15	33321	73	439	
Farm Land	4	13	145327	767	
Settlement	4	21	98	13652	
					220545
Column Total	28268	155	172398	28458	229279
Overall Accuracy			96.19067		

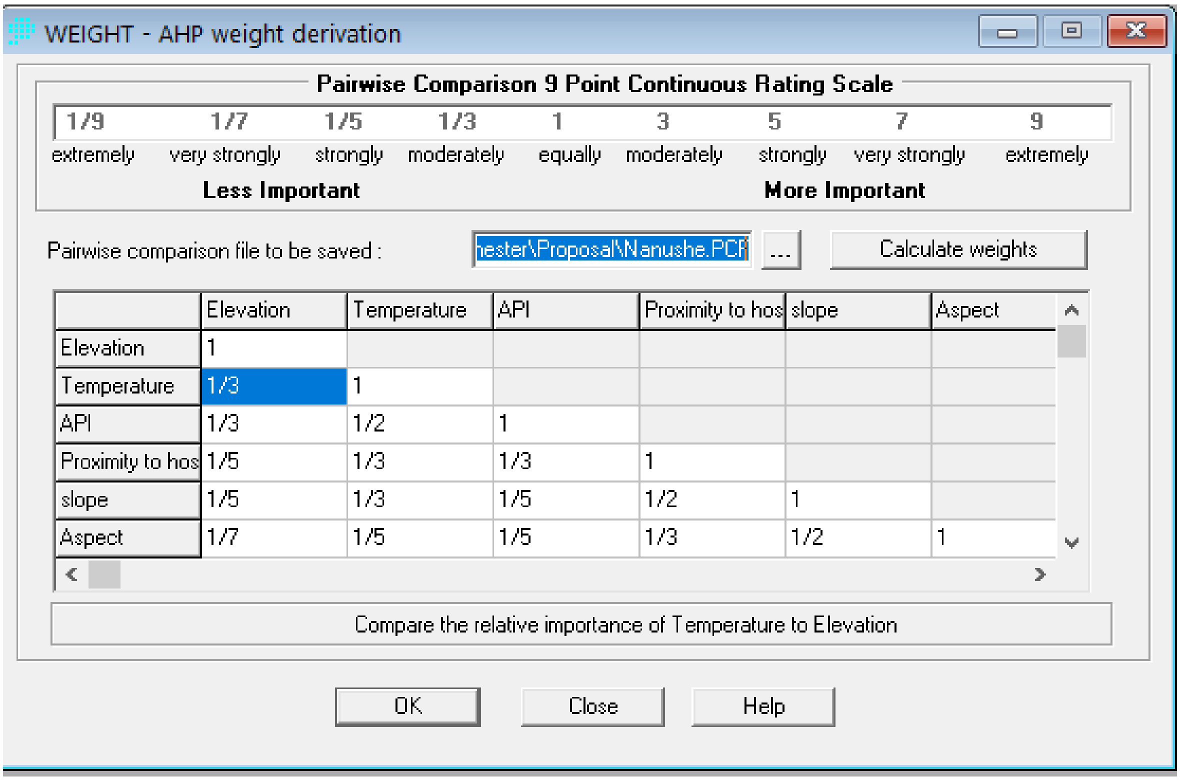
Appendix 3. Meteorological station around the study area



Appendix 4. Temperature and rainfall data study area and surrounding stations.

Stations	code	Easting	Northing	Elevation	Rainfall	Av.max temp
Wolaita	SIWOLA11	359657.4	752860.7	1854	1279.564	25.05088733
Bele	SIBEL12	336917.14	764988.413	1350	1250.1	28.33333
Boditi School	SIBODI13	384559	768684.1	2043	1021.545	25.72572181
Awassa	SIAWAS32	442909.1	780894.7	1694	944.15	27.8689899
Billate	SIBILL11	398707.8	753509.7	1361	850.5242	30.93560606
Dilla	SIDILL11	422581.4	703728.6	1579	1431.974	27.8875
Werabe	SIWERA11	410812.2	867777.3	2057	1239.098	25.41033951
Arba Minch	GGARBA12	340393.1	669674.6	1207	947.95	31.04806397
Danna_1	GGDANN41	342027.2	733596.7	1282	1235.458	29.82142256
Sawula	GGSAWU31	261168.6	697338.2	1348	1295.147	30.43257576
Tercha	GGTERC21	297672.3	790520	1335	1341.409	30.08510101
Chida	KFCHID11	255190.3	792692.3	1659	1367.007	28.01242063
Hosana	SHHOSA11	373552.9	836552.9	2307	1194.573	23.41330808

Appendix 5. Weight computation for the parameters



	Elevation	Temperature	API	Proximity to hos	slope	Aspect
Elevation	1					
Temperature	1/3	1				
API	1/3	1/2	1			
Proximity to hos	1/5	1/3	1/3	1		
slope	1/5	1/3	1/5	1/2	1	
Aspect	1/7	1/5	1/5	1/3	1/2	1

```
The eigenvector of weights is :

   Elevation : 0.2682
  Temperature : 0.1710
    API : 0.1566
 Proximity to hospital : 0.0883
    slope : 0.0762
    Aspect : 0.0476
   PF_case : 0.0404
  Wetness index : 0.0371
 Proximity to river : 0.0334
 Drainage buffer : 0.0265
   Rainfall : 0.0224
  Landuse/cover : 0.0164
   Population : 0.0160


Consistency ratio = 0.07
Consistency is acceptable.
```

Appendix 6. Questionnaire

Information about the Expert/ ስለ ባለሙያው መረጃ *Date/ቀን:* ____________

Professional title/የባለሙያው ማዕረግ: Senior/intermediate/Junior, _________*Years worked on malaria/ ዓመታት በወባ ጉዳይ ላይ ሠርተዋል።* *Expert designation/የባለሙያ ስያሜ*____________

Questions/ጥያቄዎች

1. Based on the experience that you have obtained from your previous work please give rank (1-13) for malaria-causing factors in Kindo Koysha woreda according to their impact on facilitating the breeding of mosquitoes.

   ካለፈው ሥራ ባገኙት ልምድ መሠረት አባክዎን በኪንዶ ኮይሻ ወረዳ ውስጥ የትንኞች መራባትን ለማመቻቸት በሚኖራቸው ተጽዕኖ መሠረት በማድረግ ወባን ለሚያስከትሉ ምክንያቶች ደረጃ(1-13) ይስጡ።

   a) Geographical or environmental factors/ጂኦግራፊያዊ ወይም አካባቢያዊ ምክንያቶች
      i. Land use land cover /የመሬት አጠቃቀምና የመሬት ሽፋን ☐
      ii. Distance to water bodies/ የውሃ አካላት ርቀት ☐
      iii. Wetness / Relative humidity /የእርጥበት መጠን ☐
      iv. Elevation/ከፍታ ☐
      v. Slope/ተዳፋት ☐
      vi. Aspect/የመሬት ገጽታ ☐
      vii. Drainage buffer/የፍሳሽ ማስወገጃ ቋት ☐
      viii. Rainfall/የዝናብ መጠን ☐
      ix. Temperature/የሙቀት መጠን ☐
   b) Socioeconomic factors/ማህበራዊኢኮኖሚያዊ ምክንያቶች
      i. Population/የህዝብ ብዛት ☐
      ii. Distance to hospital/ከሆስፒታል የለው ርቀት ☐
   c) Epidemiological factors/ኤፒዲሚዮሎጂያዊ ምክንያቶች
      i. Cases of plasmodium falciparum ☐
      ii. Annual Parasite Incidence(API) ☐

2. Please write if there are factors that facilitate the breeding of mosquitoes in the study area that does not mentioned in the above list?

ከላይ በተዘረዘረው ዝርዝር ውስጥ ያልተጠቀሰው በጥናት አካባቢ የትንኞች መራባትን የሚያመቻቹ ነገሮች ካሉ አባክዎን ይፃፉ?____

		A nine point continuous comparison scale						
		less important			More important			
Extremely	very strongly	strongly	Moderately	Equally	Moderately	strongly	very strongly	Extremely
1/9	1/7	1/5	1/3	1	3	5	7	9

	1	2	3	4	5	6	7	8	9	10	11	12	13
1													
2													
3													
4													
5													
6													
7													
8													
9													
10													
11													
12													
13													