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Nanlok Henry Nimlang

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**THÈSE POUR OBTENIR LE GRADE DE DOCTEUR
DE L'INSTITUT MINES-TELECOM (IMT) –
ÉCOLE NATIONALE SUPÉRIEURE DES MINES D'ALÈS (IMT MINES ALÈS)**

**École doctorale Risques et Société
Laboratoire des Science du Risques**

**Diseases risk modelling and prediction using
Remote Sensing and GIS: Application of malaria cases
in Nigeria**

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Le 27 Juin 2024**

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Abstract

Malaria is the most important public health disease, with new cases of the disease being recorded every second. Over a million cases of the disease are recorded annually, primarily in sub-Saharan Africa, where Nigeria is the largest contributor to global cases of the disease. This thesis aims to assess the spatial distribution of malaria transmission risk in the northern zone of Plateau State, Nigeria. This was achieved through an in-depth assessment and modelling of the various risk factors that influence the risk of disease transmission in the study area. An assessment of the World Health Organization's malaria guidelines as a guide for evaluating the activities of the Nigerian malaria elimination programs with the aim of understanding the management of the disease in the study area and Nigeria as a whole. Through this assessment, this research identifies the development of a malaria risk model as an integral factor in providing the necessary framework for effective management of the disease in the study area. To identify the various risk factor parameters influencing malaria transmission risk in the study area, a comprehensive assessment of the study area was carried out in terms of its topography, hydrological composition, geomorphology, anthropogenic activities, climatic, demographic, and infrastructural development. Through this assessment, the risk factors were classified into environmental, climate and socioeconomic risk factors. Based on the vulnerability of different malaria risk factors, the different risk factor parameters identified in the study area were analysed with the following degree of vulnerability: ecological risk factor > climatic risk factor > socioeconomic risk factor. Furthermore, the research employed various experts from different malaria-related institution in the determination of the risk factor's relative importance. The risk factors were further synthesized into a malaria risk model and stratified into different risk levels to represent the corresponding ground conditions as follows: The high-risk area covers 1815.49 km², while the low-risk areas cover 1180.96 km² respectively. The risk model developed in this thesis was validated by performing hotspot and density analysis to determine the disease clusters with a statistical significance confidence level ranging from 90% to 99% for identifying malaria hotspots and coldspots. Additionally, the receiver operating characteristic curve was plotted and the area under the curve was calculated as a means of determining the model performance rate. The model performance rate was calculated to be 98.84%. In conclusion, the malaria risk model is found to be a valuable decision-making tool that can be used by Nigeria's malaria elimination programs in areas such as prudent allocation of scarce resources, effective surveillance and control of malaria initiatives, and entomological surveillance to identify additional vector species etc. to improve vector management practices in the study area and Nigeria.

Keywords: Malaria, transmission risk, prediction, model, decision-making, Multi-Criteria Decision Analysis, Remote Sensing

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Table of Abbreviations

ABBREVIATION	FULL MEANING
AHS	
AIDS	Acquired Immunodeficiency Syndrome
ANP	Analytic Network Process
ARA	Additive Ratio Assessment
ASF	African Spotted Fever
AUC	Area Under the Curve
AVHRR	Advanced Very High-Resolution Radiometer
BT	Blue Tongue
CI	Consistency Index
DEA	Data Envelopment Analysis
DSMW	Digital Soil Map of the World
ELECTREE	Elimination and Choice Translating Reality
ERDAS	Earth Resources Data Analysis System
FPR	False Positive Rate
FST	Fuzzy Set Theory
GAIA	Geometrical Analysis for Interactive Aid
GIS	Geographic Information System
GIS-MCDA	Geographic Information System Multi Criteria Decision Analysis
GPS	Global Position System
HIV	Human Immunodeficiency Virus
IPTp	Intermittent Preventive Treatment in Pregnancy
iRBC	infected Red Blood Cell
IRS	Indoor Residual Spraying
JE	Japanese Encephalitis
LGAs	Local Government Areas
LLTNS	Long Lasting Treated Nets
LSE	Land Surface Emissivity
LST	Land Surface Temperature
LULC	Land Use Land Cover
MACBETH	Measuring Attractiveness by a Categorical Based Evaluation Technique
MAUT	Multi Attribute Utility Theory
MAVT	Measuring Attractiveness by a Categorical Based Evaluation
MCDA	Multi Criteria Decision Analysis
MCDM	Multi Criteria Decision Making
MODM	Multi-Objective Decision-Making
NMEP	National Malaria Elimination Programme
NMIS	National Malaria Indicator Survey
OLI	Operational Land Imager
ORSETE	Outranking Relation Symbolic Evaluation and Translation
PROMETHEE	Preference Ranking Organization Method for Enrichment Evaluation
QGIS	Quantum Geographic Information System
RDTs	Rapid Diagnostic Tests

RH	Relative Humidity
ROC	Receiver Operation Characteristics
RVF	Rift Valley Fever
SMC	Season Malaria Chemoprevention
SMI	Soil Moisture Index
SPHCDA _s	State Primary Health Care Development Agencies
SRTM	Shuttle Radar Thematic Mapper
TIRS	Thermal Infrared Sensor
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
TPR	True Positive Rate
TWI	Topographic Wetness Index
UTA	Utilization to Assess
UTADIS	Utilization of Additive Discordance Indices
VHI	Vegetation Health Index
WHO	World Health Organization
WNF	West Nile Fever
WPM	Weighted Product Model

Résumé de la thèse

Le paludisme est le problème de santé mondial le plus important parmi les maladies à transmission vectorielle en raison de sa répartition géographique, de son impact profond sur les populations humaines et de ses taux élevés de morbidité et de mortalité. Par conséquent, il est essentiel de mener des recherches approfondies sur l'épidémiologie du paludisme pour comprendre l'interrelation intrinsèque entre les habitats de reproduction liés aux vecteurs, le modèle comportemental, la dynamique de transmission, les interactions vecteur-humain, et réussir à gérer et à combattre ce problème de santé publique.

Cette thèse a commencé par évaluer l'impact global des catastrophes biologiques, qui ces dernières années ont été reconnues comme l'une des catastrophes avec des impacts de grande portée sur la santé et le bien-être. L'impact de cette catastrophe, qui se produit généralement sous la forme d'épidémies ou de pandémies, car les épidémies, les maladies transmissibles et les fléaux ont affecté négativement le continent africain, est également examiné. Le fléau des maladies à transmission vectorielle, en particulier le paludisme, est étudié dans cette thèse car il s'agit de la maladie de santé publique la plus importante. 95 % des cas mondiaux surviennent en Afrique subsaharienne, le Nigeria représentant 26,6 % de ces cas, ce qui représente le cas de morbidité le plus élevé. La thèse passe en revue les littératures traitant de l'épidémiologie et de l'écologie vectorielle des maladies à transmission vectorielle pour proposer une compréhension globale des stratégies de prévention et de contrôle. Pour mieux comprendre le cas du Nigeria sur l'élimination du paludisme, la thèse a mené une évaluation approfondie des lignes directrices de l'Organisation Mondiale de la Santé, qui portaient sur des domaines tels que la surveillance, le diagnostic, le traitement et le contrôle des vecteurs. En outre, cette thèse examine également certains pays qui ont réussi à éliminer le paludisme et compare les modèles, programmes et activités d'élimination du paludisme avec le Nigeria dans le seul but d'identifier la zone de besoin. La thèse a examiné la littérature actuellement disponible au Nigeria et dans

l'État du Plateau Jos et a souligné la nécessité d'utiliser la technologie spatiale pour intégrer les différents facteurs de risque associés au paludisme. Elle s'appuie sur les contributions des experts du paludisme pour analyser, modéliser et développer une carte des risques du paludisme qui délimite les zones endémiques du paludisme et guide efficacement les décideurs dans la planification stratégique, la gestion et l'utilisation des ressources rares.

La thèse examine l'influence des intuitions d'experts sur les processus décisionnels à travers une évaluation de l'analyse décisionnelle multicritères. La contribution des experts en épidémiologie du paludisme est considérée comme très cruciale car ces experts sont principalement impliqués dans les processus décisionnels critiques et la mise en œuvre de diverses mesures d'intervention liées à la gestion de la maladie. Les intuitions des experts utilisées dans cette thèse sont basées sur l'identification des facteurs de risque du paludisme, en considérant à la fois l'analyse quantitative et qualitative des différents critères et alternatives. La thèse évalue également comment les différents facteurs de risque du paludisme peuvent être structurés en utilisant différents matériels et logiciels en un seul outil de prise de décision qui peut influencer positivement et améliorer les pratiques de gestion des vecteurs. Ceci est réalisé en structurant le problème de risque de paludisme en définissant d'abord le niveau de risque de paludisme dans la zone d'étude, en identifiant les différents facteurs de risque, en établissant les différents critères de risque et en utilisant l'intuition de l'expert pour déterminer l'importance relative des alternatives. Dans l'ensemble, cette thèse examine également en détail des sujets tels que le concept de prise de décision, les méthodes communes (Multi Criteria Décision Analysés : MCDA), les structures et les propriétés des MCDA, les techniques d'évaluation des poids des critères, et les applications spatiales du MCDA en épidémiologie du paludisme.

Afin de garantir la reproductibilité de cette recherche, la thèse a détaillé et simplifié la méthodologie utilisée pour analyser, cartographier et modéliser la distribution spatiale du risque de transmission du paludisme dans la zone nord de l'État du Plateau au Nigeria. Le manuscrit

décrit les techniques et les processus utilisés dans l'évaluation complète de la prévalence du paludisme, l'identification des différents facteurs de risque, l'incidence et le taux de transmission de la maladie. En outre, la thèse discute également les techniques utilisées pour identifier, traiter et collecter les différents ensembles de données utilisés pour analyser, cartographier et modéliser le risque spatial de la maladie. Ces processus permettent d'évaluer et de modéliser la répartition spatiale du risque de paludisme dans la zone d'étude. Cela s'ajoute à l'orientation des décideurs dans la mise en œuvre de mesures appropriées d'intervention vectorielle et d'autres pratiques de gestion des vecteurs. La thèse discute également les techniques de validation du modèle utilisées pour évaluer la précision du modèle en utilisant des techniques telles que la sensibilité et l'analyse de la densité des cas observés.

En plus de décrire en détail les différentes méthodes utilisées et d'assurer la reproductibilité de cette thèse, le manuscrit évalue l'impact des différents paramètres de facteurs de risque associés au risque de transmission du paludisme dans la zone nord de l'État du Plateau, au Nigeria. L'évaluation évalue la susceptibilité de chaque paramètre, car elle est corrélée aux habitats de reproduction appropriés du vecteur et au risque de transmission du paludisme dans la zone d'étude. La thèse discute également les résultats des différentes analyses paramétriques qui relient les habitats de reproduction adaptés au vecteur et le risque de transmission du paludisme pour estimer le risque global de la maladie dans la zone d'étude. À partir des différentes analyses méthodologiques et des différents facteurs de risque, la thèse aborde le rôle vital de l'élaboration de stratégies efficaces qui délimitent les foyers du paludisme, qui est une étape essentielle dans la lutte contre les défis posés par le paludisme au Nigeria. En identifiant les régions endémiques sujettes au paludisme et en utilisant différents paramètres de facteurs de risque couvrant les différents domaines de la composition sociétale, tels que : Les influences environnementales, climatiques et socio-économiques, cette contribution fournira aux décideurs les outils nécessaires pour planifier et mettre en œuvre des mesures d'intervention ciblées contre le paludisme, en plus d'une surveillance appropriée des

vecteurs. Le fait que cette recherche ait soigneusement identifié divers facteurs de risque et, en outre, fait appel à divers experts de différents domaines liés au paludisme avec des compétences, des qualifications et des années de service différentes pour déterminer leur classement d'importance relative, a assuré une grande précision et une cohérence dans l'évaluation des interrelations complexes entre les divers facteurs de risque.

Sur la base d'une évaluation complète de la topographie, de la composition hydrologique, de la géomorphologie et d'autres activités anthropiques de la zone d'étude, Cette thèse a également soigneusement identifié et classé divers facteurs de risque et paramètres qui influencent l'adéquation des habitats de reproduction des vecteurs et les risques de transmission.

En outre, en examinant le taux de distribution des cas confirmés de paludisme réalisés dans cette thèse, cette étude fournit des lignes directrices utiles pour le Programme National d'élimination du paludisme et les autorités sanitaires locales dans l'attribution des programmes d'intervention aux endroits appropriés en fonction de l'évaluation des besoins urgents de la population.

En outre, parce que cette recherche évalue, analyse, modélise et cartographie de manière globale les points sensibles du risque de paludisme, il peut être utilisé par les décideurs et les différents niveaux de gouvernement pour déterminer la répartition des programmes et des installations de santé nécessaires en fonction de l'analyse des populations locales vulnérables. Étant donné le manque de données entomologiques sur la distribution vectorielle, le modèle de risque peut également aider les autorités à identifier les régions géographiques où les programmes de lutte antivectorielle et la surveillance devraient être concentrés.

De plus, parce que le modèle est spécifique à une région, il peut aider les autorités à évaluer avec précision le risque de transmission locale, ce qui est essentiel pour développer et gérer les programmes de lutte contre le paludisme. Ainsi, ce modèle peut contribuer à une meilleure allocation des ressources et à des interventions ciblées pour lutter contre la

transmission du paludisme.

Chapter 1: Introduction

Malaria is the most important global health problem among vector-borne diseases because of its geographic distribution, profound impact on human populations, and high morbidity and mortality rates. Consequently, conducting comprehensive risk research on the epidemiology of malaria is critical for understanding the intrinsic interrelationship between the vector suitable breeding habitats, behavioural pattern, transmission dynamics, vector-human interactions, and successfully managing and combatting this public health problem. This chapter examines the general overview and impacts of biological disasters, with a focus on vector-borne diseases. This assessment aims to understand the various risk dynamics of vector-borne diseases. The research focus is on the risk dynamics of malaria transmission, vector-host interactions, and suitable breeding habitats.

1.1 Thesis overview

During any disaster outbreak, management activities focus on three main objectives, namely protecting life, property and the environment. Sena & Woldemichael, 2006, broadly classified disasters into 2 types: naturally occurring (e.g., flooding, tornados, hurricanes, ice storms), geological (e.g., earthquakes, volcanic eruptions), biological (e.g., influenza pandemics), and man-made (these disasters result from some human activities, such as explosions, fires, the release of toxic chemicals or radioactive materials, bridge or building collapse, crashes, dam collapse, nuclear reactor accidents, breaks in water, gas, or sewer lines, deforestation, war, etc.). Collaboration between different disciplines, institutions and governments at national and international levels is crucial in dealing with natural or man-made disasters that have both human and environmental dimensions (Sarı & Özer, 2024; Waugh & Streib, 2006). Since disasters (whether natural or man-made) do not respect political boundaries, sound policies must be developed to carry out effective containment, management,

rescue, and response operations or to organize and deliver relief efforts. These policies are typically implemented within politically defined boundaries (Radke et al., 2000). Disaster management activities are categorized into five stages shown in Figure 1.1 Disaster Management Cycle (Coppola, 2011; Radke et al., 2000). as follows: planning, mitigation, preparedness, response, and recovery (Coppola, 2011; Radke et al., 2000).

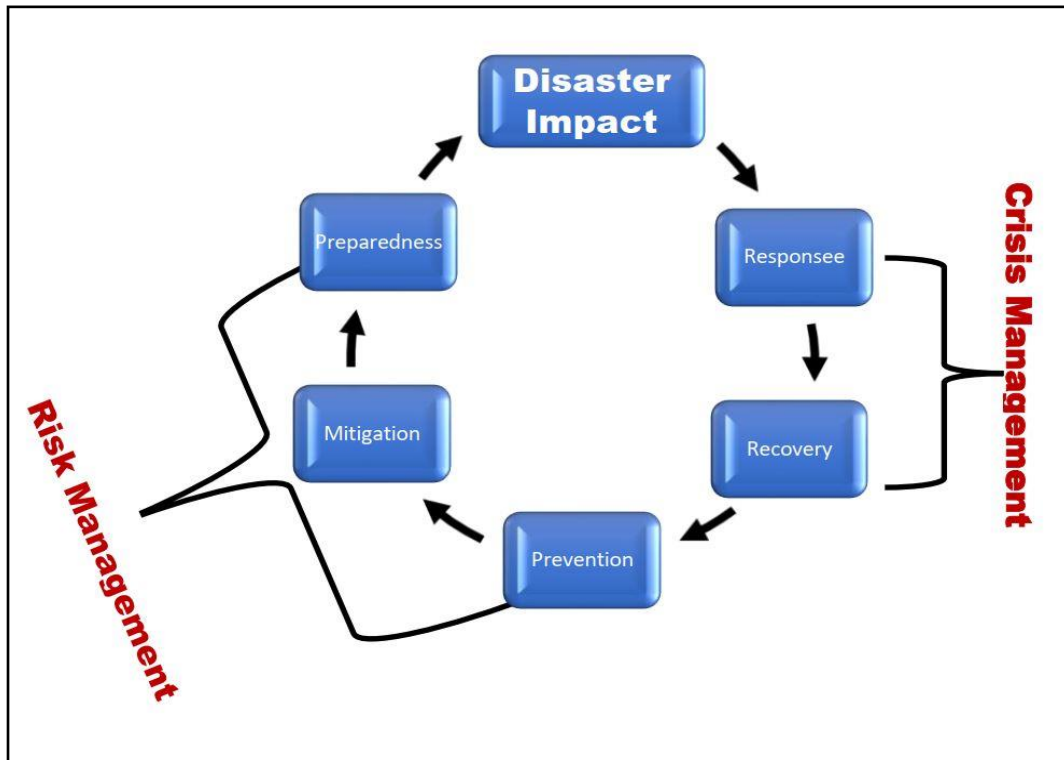


Figure 1.1 Disaster Management Cycle (Coppola, 2011; Radke et al., 2000).

These phases are time and functional, and relate to all types of emergencies and disasters. They are also interrelated, and each require unique management skills. Recently, the integration of geospatial data and its associated advanced technologies such as remote sensing, Geographic Information System, Global Positioning System, RADAR imaging, etc. have proven to be crucial in increasing the effectiveness and efficiency of disaster management efforts (Abid et al., 2021; Mudefi, 2023).

Since time in memorial, humanity has struggled with various forms of biological threats, resulting in various forms of outbreaks, epidemic and pandemics. These disaster events had a

profound impact on humanity, negatively impacting socio-economic, political, demographic and general well-being and resulting in the deaths of millions of people worldwide (ArtiK et al., 2021). However, advances in research, medical sciences, prevention and social medicine have significantly reduced the impact and frequency of biological disasters in most advanced countries (Sharma, 2020). Nevertheless, the effects of the most common epidemics in developing countries are still being felt. Therefore, biological disaster management and mitigation are crucial not only for developing countries but also for developed countries to curb the spread of disasters (Sharma, 2020). To mitigate the effects of most biological disasters, communities and countries must take responsibility for developing emergency response plans, as there are no reliable general plans that address an individual country's specific limitations due to culture, risk, climate, geography, legislation, political structure, and / or location (Geering et al., 1999; Kocik et al., 2004).

Although sub-Saharan Africa is not known to be particularly vulnerable to other types of natural disasters, it is the region most frequently affected by biological disasters such as Ebola, malaria, HIV/AIDS, and other disease epidemics. The scourge of most vector-borne diseases is of particular concern for most diseases afflicting sub-Saharan Africa. Therefore, research is heavily focused on assessing the impact of these disaster events, particularly epidemics and the scourge of vector-borne diseases in the Sub-Saharan Africa region.

Many vector-borne diseases such as African swine fever (ASF), Crimean-Congo hemorrhagic fever, bluetongue fever (BT), West Nile fever (WNF), Rift Valley fever (RVF), and Japanese encephalitis (JE) increased significantly. In the last decade, new vector-borne pathogens such as the Schellenberg virus have also emerged in other regions within the African sub-region (Thompson & Etter, 2015).

According to Thompson & Etter, 2015 these diseases pose a challenge for epidemiologists, who must meet the challenge of developing tools and techniques to better detect, monitor and even predict future changes in pathogen and vector distribution.

According to Thompson & Etter, 2015, a lack of knowledge about vector ecology is one of the most important factors limiting understanding of disease patterns. According to WHO data in 2004, vector-borne diseases have a significant impact on human and animal health and on the global economy, causing millions of dollars in losses. For example, vector-borne diseases account for approximately 17% of the burden of all infectious diseases.

Among other vector-borne diseases, malaria is considered the world's most serious parasitic disease of public health importance (Aribodor et al., 2016). It is observed that at least ten new cases of this disease occur every second. This represents a major public health problem in the tropics, where approximately 40% of the world's population lives (Emmanuel et al., 2017). Malaria is observed to be responsible for more than a million deaths each year, of which approximately 90% occur in sub-Saharan Africa (Aribodor et al., 2016). According to WHO, 2018 reports, approximately 3.4 billion people in approximately 92 countries and territories worldwide are still at risk of a bout of malaria. Malaria is considered the leading cause of death from infectious diseases in Africa after HIV/AIDS and is also the leading cause of death in children under five, accounting for about 20% of deaths (Kweka et al., 2012; Nkumama et al., 2017). According to a 2018 WHO report, Nigeria is the world's largest contributor to malaria cases, accounting for over 25% of the current figure.

1.1.1 Research aim.

The research aims to examine the spatial distribution of vector-borne diseases risk (malaria) within the Northern Zone of Plateau State, Nigeria. This aim will be achieved through an in-depth assessment and modelling of the various risk factors that contribute to the significant burden of disease in the region. To effectively model disease risk using the various

risk factors, the intrinsic relationships between vector transmission dynamics, vector-host interactions, breeding habitats suitable for vectors, and vector behavioural patterns are first examined. Specifically, the research employed advanced spatial techniques such as spatiotemporal predictive modelling as a tool to guide an informed management decision-making. Using remote sensing and geographic information system (GIS) technology, the thesis analyzes malaria endemicity in Nigeria by examining the case study of the northern zone of Plateau State.

1.1.2 Research objectives.

This thesis aims to contribute to the already existing body of knowledge by assessing the intrinsic interrelationship between vector transmission dynamics, vector-suitable breeding habitats, vector-host interactions, and vector behavioural pattern. Furthermore, the dissertation analyzes and models in detail the spatial distribution of malaria in Nigeria using the northern zone of Plateau State as a case study. Attention will be focused on predictive and monitoring modelling of vector-borne diseases (malaria) using veritable tools of Remote Sensing and GIS, adopting geostatistical techniques, and machine learning programming. The research seeks to present a usable and workable model for informed management decision-making in combating the scourge of malaria endemicity in, the Northern Zone of Plateau State and Nigeria at large.

The highlight of the objective of this research includes the following:

Primary Objective: Holistic assessment, evaluation and analysis of the successes, failures, strategies, and research gaps in malaria elimination in Nigeria using the World Health Organization Malaria Elimination Guidelines.

The primary research objective of this thesis is to critically examine, assess, evaluate, and analyze the National Malaria Elimination Programme's strategies, successes, failures, and research gaps. The World Health Organization malaria elimination guidelines regarding vector control, diagnosis and treatment, seasonal malaria chemoprevention, intermittent preventive

treatment in pregnancy, elimination and control strategies, and community engagement solely to identify deficiencies and advances of the National Malaria Elimination programmes.

Through this assessment, the research objective enables us to examine the organizational structure of the National Malaria Elimination Programme, the successes achieved to date and the challenges the programme is currently facing in the fight against malaria in Nigeria. This objective further gives us a comprehensive understanding of the modelling parameters to use, the appropriate tools, and ultimately guides the development of the predictive models.

Secondary Objectives: Spatiotemporal analysis and predictive modelling of malaria endemicity in the northern zone of Plateau State, Nigeria, using ecological, metrological, socioeconomic, and epidemiological data.

The secondary objectives serve as a guide for providing solutions to the primary objective. The objective analyzes and models the spatial spread of the disease and the temporal density of the disease to determine regional spread, temporal concentration of cases and transmission dynamics, and ultimately determine the types of interventions needed to combat the scourge of the disease in the context of the Study should be used area.

Tertiary Objectives: The objective analyzes and models the spatial spread of the disease and the temporal density of the disease to determine regional spread, temporal concentration of cases and transmission dynamics, and ultimately determine the types of interventions needed to combat the scourge of the disease in the context of the study should be used area. Through this analysis and evaluation, the model provides a detailed framework to help facilitate informed management decisions and promote effectiveness, efficiency, and sustainability in combating the scourge of malaria in the study area and Nigeria as a whole.

1.2 Research questions.

The research questions used in this thesis include a series of carefully designed and well-crafted questions that are consistent with the aim and objectives. The subsequent literature review, analysis, methodology, and conclusions serve as integral parts in providing comprehensive solutions to these research questions. The following three specific research questions are addressed in this work:

i. How strictly does Nigeria's Malaria Elimination Programme adhere to the World Health Organization recommended guidelines for effective malaria control and elimination?

This question seeks to examine the strategies, successes, and failures of Nigeria's malaria elimination program in order to provide solutions to malaria elimination efforts. To answer this question, the research examines in detail the World Health Organization's malaria elimination guidelines, policies, and programs in terms of vector control, diagnosis and treatment, seasonal malaria chemoprevention, intermittent preventive treatment in pregnancy, elimination and control strategies, and community engagement and other countries that have successfully eradicated the disease. The strategies, technologies and methods adopted from other countries that have successfully eradicated and eliminated malaria, with the intention of adapting and implementing these strategies, methods and technologies to the malaria elimination campaigns in Nigeria.

ii. To what extent can the developed model help improve management decision making by assessing spatial transmission of disease risk in the Northern Zone of Plateau State, Nigeria?

This research answers this question by examining and analyzing the various risk factors that contribute to the dynamics of malaria transmission in the study area. Furthermore, through an in-depth assessment of the complex and intrinsic interactions between vector transmission dynamics, vector-human interactions, vector-suitable breeding habitats and vector

behavioural patterns, this question is addressed to elucidate human vulnerability to the disease and the associated risk factors.

This assessment aims to understand and identify the various parameters to be used for effective modelling of disease transmission risks, as well as the type of modelling to be developed, and ultimately guide informed decision-making on the type of intervention measures to be implemented to combat the scourge of disease in the northern zone of Plateau State and in Nigeria as a whole. To answer this question, the research modelled the epidemiological malaria data collected by the relevant health facilities, as well as ecological, meteorological, and socio-economic data, using the relevant spatial techniques of Remote Sensing and GIS, geostatistics and machine learning techniques.

iii. *How can these models help in effective management decision making?* This seeks to explore the outcome of the models developed from this thesis. To answer this question, this thesis investigates, analyses, justifies, and develops a realistic model using Remote Sensing and GIS, geostatistical and machine learning techniques to support management decision tools to help eradicate the threat of malaria in the study area. A thorough assessment of ecological, meteorological and socioeconomic risk factors will help in developing spatial distribution and spatiotemporal models that can provide valuable insights into vector transmission dynamics, spatial distribution, vector-host interaction, temporal density and appropriate vector control measures for an effective management of the malaria elimination program will be implemented.

1.2.1 Thesis Contribution Summary

Throughout the thesis, the research aims, objectives and research questions presented are followed by detailed analyses, processes and methods used to achieve these tasks. This takes the form of contributions that aim to answer research questions based on their respective methods and outcomes.

In this thesis, the presented contributions are mainly categorized in to two main areas; the Geostatistical and geospatial Analysis, Justification, and modelling (Ecological, Meteorological, Socio-economic, and epidemiological); and Analysis, Justification, and modelling of hospital prevalence using programming languages. These contributions are illustrated in Figure 1.2. Schematic sketch of the methodology. below.

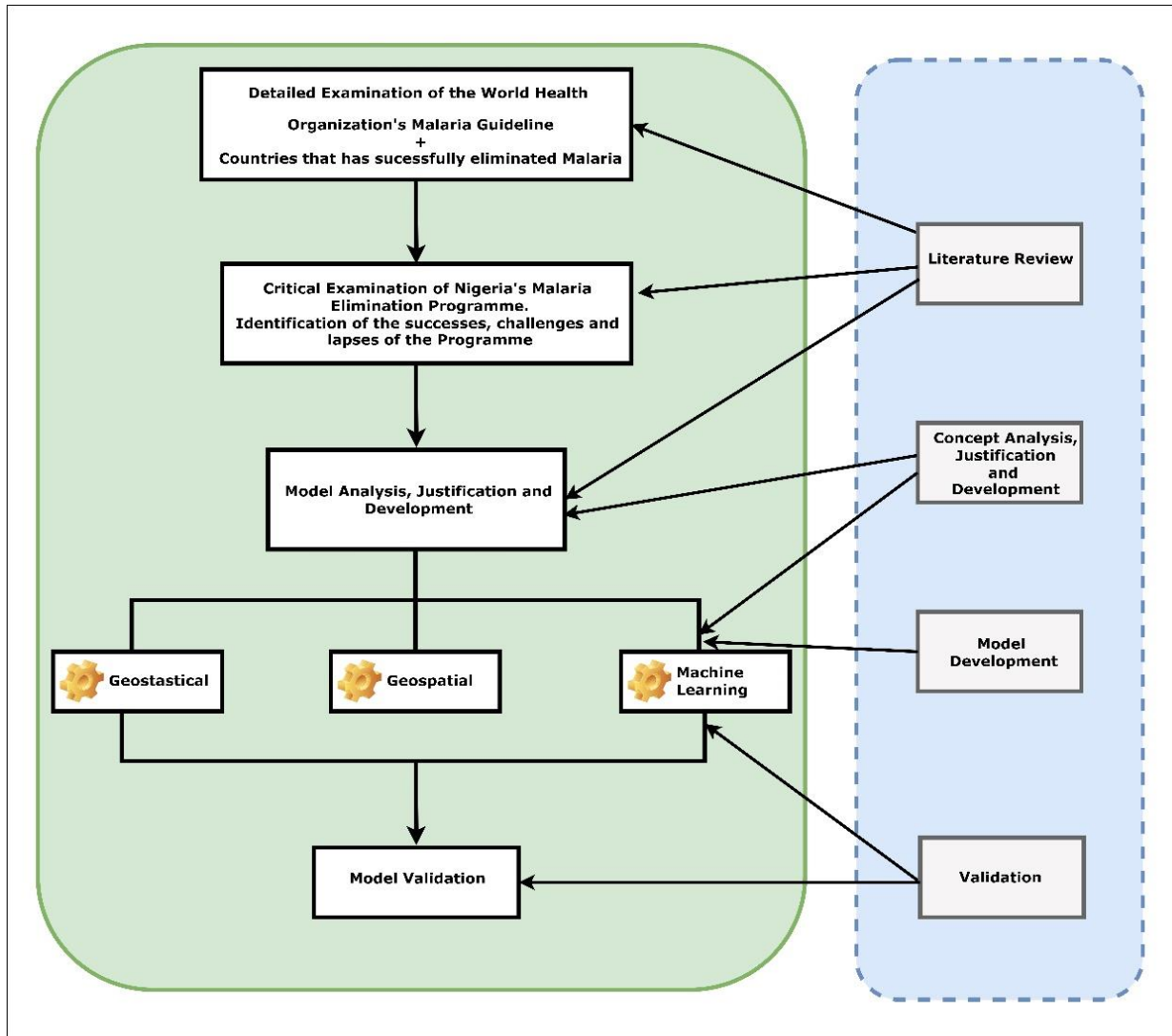


Figure 1.2. Schematic sketch of the methodology.

The main contribution of this thesis is the development of a predictive risk model that uses malaria risk factors such as environmental, meteorological, socioeconomic and epidemiological data to determine malaria hotspots. This model allows the assessment of the spatial distribution of malaria risk within the study area with the aim of developing an effective decision-making tool specifically tailored to an effective management decision within the framework of the introduction of vector control measures and strategies.

This contribution aims to develop a model that can be used to examine the relationship between environmental variables and their causative incidences of the disease. This promotes

understanding of the spatial spread of risk, assesses the dynamics of disease transmission and supports decision-makers in selecting appropriate vector management measures.

1.2.2 Key definition of concepts

Understanding the key aspects of this research focused on biological disaster assessment through an in-depth study of the epidemiology of vector-borne diseases, particularly malaria prediction and surveillance models as part of the disaster preparedness and response phase of disaster management. Therefore, there is a need to properly define and identify certain key concepts. This is done to provide a better understanding of the technical languages, the concept, and its applications in the areas of biological disasters, vector-borne diseases, vector transmission dynamics, vector-human interactions, malaria prediction and surveillance modeling used in the work, to facilitate.

Some of these concepts include an introduction to epidemiology, malaria ecology, malaria risk, malaria risk factors, malaria modeling, geospatial modeling, malaria transmission dynamics, malaria endemicity, and malaria prevalence rate.

1.2.3 Introduction to Epidemiology

Epidemiology is described by many authors as the study of the distribution and determinants of health and disease populations and is primarily used in the control of health problems (Kebede, 2004). The epidemiological study of malaria helps us to comprehensively understand the risk factors and transmission dynamics and to understand the factors that determine the different interventions of the disease. An in-depth assessment of epidemiological trends can be used to analyze reductions in malaria risk, morbidity and mortality by examining incidence, prevalence and mortality rates (Essendi et al., 2019).

1.2.4 Malaria Ecology

This is an in-depth study of all the factors affecting mosquito and parasite life rates, disease transmission dynamics, seasonality and spatial distribution (Castro, 2017). The ecology of malaria is influenced by a variety of factors affecting its spread, relating to humans, vectors and parasite populations, and the environment. The tropical and subtropical regions of Africa, Central and South America, Asia and Oceania are the regions most affected by the scourge of malaria (Oaks, 1991; Bloland & Williams, 2003). Understanding and developing effective prevention measures and control strategies for the disease that contribute to reducing the disease burden can be achieved through an in-depth assessment of malaria ecology (Godfray, 2013).

1.2.5 Malaria Risk

Several factors influence the likelihood of being infected with malaria, and all contribute to the prevalence and risk of infection. Due to the interaction of these factors, the risk of contracting malaria is increased in malaria-endemic areas compared to others (Bloland & Williams, 2003). These factors can range from vector-human interaction to a variety of environmental and socioeconomic factors (Essendi et al., 2019). Certain vulnerable populations, such as pregnant women, infants, children under five, and people migrating from non-malaria regions to malaria-susceptible regions, are at higher risk of contracting the disease (Nyasa et al., 2021).

1.2.6 Malaria Risk factors

These are factors or circumstances that increase the likelihood of malaria infections. These factors cover a wide range of human behavior patterns, physiology, human-vector interaction, vector behavior patterns, environmental, meteorological, socio-economic, etc.(Essendi et al., 2019; Nyasa et al., 2021; West et al., 2013).

1.2.7 Malaria Guidelines

This is a set of comprehensive guidelines, guidelines and recommendations for the assessment, diagnosis, prevention, and treatment of malaria. These policies, guidelines and recommendations are usually formulated by the World Health Organization, other related international organizations and agencies, and national and local malaria control authorities of the affected countries(Oaks, 1991; WHO, 2015).

1.2.8 Malaria Modelling

These are models that involve the use of mathematical and geospatial tools to simulate malaria transmission dynamics. They provide an in-depth understanding of disease transmission dynamics achieved by analyzing the disease pattern with respect to humans and the vector host. The models serve as valuable tools in the development and implementation of strategies and intervention programs necessary to combat the scourge of disease. In addition, these models can also be crucial in analyzing the epidemiology, transmission dynamics, and other aspects of the disease (Mandal et al., 2011; T. A. Smith et al., 2017).

1.2.9 Malaria Risk Model

These are mathematical, statistical, or geospatially explicit approaches that assess or estimate the risk of malaria transmission in a specific geographical region or population by considering various factors that influence transmission of the disease, such as: ecological, socioeconomic, mosquito breeding habitats and vectors-human interactions etc. (Aguilar & Gutierrez, 2020). These models play a crucial role in predicting the spatial evolution of the disease and provide valuable information to various authorities about the effective and necessary intervention measures that need to be implemented. They serve as useful tools for decision-making and influencing appropriate measures to combat the disease.

1.2.10 Multi-Criteria Decision Analysis (MCDA)

This is a structured process of evaluating alternatives/options based on different and contradictory criteria and selecting the best alternative among them (Zhao et al., 2020). It allows for the examination of multiple qualitative and quantitative criteria, leveraging both data-driven and qualitative indicators from stakeholder input. MCDA is a component of a broad class of operations research models suitable for dealing with complex problems with high uncertainty, competing goals, multiple interests and viewpoints, and different types of data and information (Wang et al., 2009).

1.2.11 Spatial-Multi-Criteria Decision Analysis (Spatial-MCDA)

Spatial-MCDA, also known as GIS-MCDA, is a combination of geographic information systems and MCDA that can be used to better understand how planning, land use, and demographics influence program management in public health and other sectors (Zhao et al., 2020). GIS combines spatial datasets with quantitative and qualitative databases and supports Multi-Criteria Decision Analysis (MCDA), which can transform and integrate geographical data and expert knowledge to generate relevant information for decision-making (Eastman *et al.*, 1995).

1.2.12 Malaria Endemicity

This is the complexity of the problems related to the factors affecting the host, vector, parasite and environment of the disease (Autino et al., 2012). An assessment of malaria endemicity provides information about disease prevalence. This is because regions with similar endemicity usually share the same characteristics.

1.2.13 Malaria Cycle

This is the study of the complicated life cycle of malaria, which includes the two host phases of humans and female *Anopheles* mosquitoes (Tyler, 2006). The two main phases of the disease include parasitic infection of the vertebrate host and transmission of the disease from the infected vertebrate host to another by an infected female *Anopheles* mosquito.

1.2.14 Malaria Distribution Rate

This is a study of the incidence and prevalence of malaria in specific demographic or geographic regions (Khagayi et al., 2019). To determine the rate of spread, the number of malaria cases per 1,000, 10,000, 100,000 or 1000,000 vulnerable populations is typically measured (De Oliveira Padilha et al., 2019).

1.2.15 Malaria Transmission Dynamics

These are the interrelated factors that influence the transmission of malaria from an infected person to an uninfected person (Kar et al., 2014). A wide range of factors that influence the complexity of malaria transmission range from natural environmental conditions to human behavior to the various intervention measures used to control the disease (Savi, 2022). Most commonly, malaria transmission is influenced by complex human-vector-parasite-environmental interactions (Agusto et al., 2019).

1.3 Manuscript organization

The thesis manuscript is structured into separate chapters, each of which contains detailed explanations, annotations, and clarification of the contents, and technical aspects of the entire research. The organization of the manuscript is as follows.

Chapter two provides a comprehensive overview of the current state of the art, focusing in particular on existing knowledge in the literature in various areas such as epidemiology,

malaria ecology, malaria modelling, geospatial and geostatistical malaria modelling, malaria risk and transmission dynamics. In addition, the relevant definitions, processes, and methods from various literature research were examined and explained in the chapter. These serves as the basis for the activities in the subsequent chapters. This chapter also focuses on the World Health Organization (WHO) malaria guidelines and other regions with particular emphasis on the fundamental principles on which the guidelines are based. The aim is to assess the performance of Nigeria's malaria elimination programme against these guidelines and identify areas that require further improvement.

In addition, this chapter examines the malaria programs of other countries that have successfully achieved malaria elimination status with the aim of identifying areas where national malaria elimination programme can be strengthened and providing valuable lessons from the successful experiences of these countries. The final section of the chapter focuses on the analysis of the topographical, hydrological, geomorphological composition and anthropogenic activities related to malaria transmission in the study area as a guide for identifying the relevant factors contributing to malaria transmission risk.

Chapter three evaluates the contributions of malaria experts to assess the relative importance of each pair of factors. The chapter examined the various methods for Multi-Criteria Decision Analysis (MCDA) as well as the various techniques for calculating criteria weights. This chapter also discusses the criteria for selecting the desired MCDA method and the criteria to be implemented. Application of the criteria and MCDA techniques to assess the relative importance of malaria risk is carried out in chapter four.

Chapter four focuses on spatiotemporal predictive modelling of malaria risk using various risk factors to develop a model that identifies areas within the study area that are vulnerable to malaria endemicity. Building on the state-of-the-art elements discussed in the previous chapter, this chapter introduces the methods and establishes the primary framework

for the work. It includes the necessary model requirements, model development processes and validation procedures. This chapter, guides the development of the model, reviews the key components of the vector life cycle, the parasite life cycle, the behavioural patterns of the parasite, factors affecting vector transmission dynamics, and the use of remote sensing and geographic information systems in modelling malaria risk.

It also deals with the collection of necessary data sets related to the modelling process, data preparation and analysis of the various parameters related to the three main risk factors: environmental, meteorological, and socio-economic factors. The chapter also utilizes spatial multi-criteria decision analysis by synthesizing expert opinions in deciding the relative importance of the various factors responsible for malaria transmission using a pairwise comparison matrix of the analytical hierarchy process.

Chapter five discusses the results, analysis, and interpretation of the various risk models, as well as the validations in chapter four.

The objective is to conduct a spatiotemporal assessment of the disease risk as a vital resource tool for effective management decisions. In addition, the chapter also examines the impact of the composition of different experts from different malaria-related fields in determining the relative importance of the risk factor parameters. Finally, this chapter assesses the susceptibility of the various risk factor parameters in relation to suitable vector breeding habitats, vector-human interactions, and disease transmission dynamics.

Chapter six discusses the key findings and also examines the practical application of our model as a valuable contribution to malaria elimination efforts in Nigeria. In addition, recommendations and suggestions for future research are presented to further advance the field of malaria research and contribute to ongoing efforts to eliminate malaria. Finally, chapter six highlights the important applications of the risk model developed in this research as an important decision-making tool in areas such as judicious allocation of scarce resources,

effective surveillance and control of malaria initiatives, entomological surveillance to identify additional vector species, etc. as a guide for improving vector management practices in the study area and in Nigeria.

Conclusion

This introductory chapter establishes the foundation for the research by providing a thorough and comprehensive overview of the key concepts used in this thesis. It lays the foundation for the sound understanding of the key elements that will be explored throughout the study. The chapter improves the understanding of the thesis by providing a clearer insight of its basic structure and scope. This includes a detailed presentation of the research aim, primary and secondary objective, and key questions guiding the research. These elements will subsequently function as roadmaps during the research process and guide the acquisition, analysis, and interpretation of the required datasets to effectively address the research objectives and questions. The chapter also introduced and defined key concepts used during the research process to facilitate the achievement of the outlined aims and objectives of this thesis.

Lastly, this chapter makes the connection between malaria modelling and the key concepts in malaria elimination strategies by identifying, analysing and modelling the associated risk of the disease. The research methodology described in this chapter provides a clear roadmap of the research process, from the introduction and input to the conclusion.

Chapter 2: State of the art

This chapter examines the global impact of biological disasters, which in recent years have been recognized as one of the most neglected disasters with far-reaching impacts on global health and well-being. The impact of this disaster, which usually occurs in the form of epidemics or pandemics as outbreaks, communicable diseases and plagues have negatively affected the African continent, is also examined. The scourge of vector-borne diseases, particularly malaria, is of interest to this research because it is the most important public health disease. 95% of global cases occur in sub-Saharan Africa, with Nigeria accounting for 26.6% of the global cases, representing the highest burden of disease. This chapter further review literatures dealing with the epidemiology and vector ecology of vector-borne diseases to gain a comprehensive understanding of prevention and control strategies. The chapter assessed World Health Organization guidelines, which focused on areas such as malaria surveillance, diagnosis, treatment, and vector control. In addition, this chapter also examines some countries that have successfully eliminated malaria and compares the malaria elimination models, programs and activities with Nigeria with the sole aim of identifying the areas of needs.

Finally, this chapter reviewed the literature currently available in Nigeria and Plateau State and highlighted the need to utilize spatial technology to integrate the various risk factors associated with malaria. It leverages the contributions of malaria experts to analyse, model and develop a malaria risk map/model that delineates malaria endemic areas and effectively guides policymakers in strategic planning, management, and use of scarce resources.

2.1 Biological disasters

Biological disasters are known to pose a major economic threat as well as public health concerns, as human health and safety are most affected during these events. Biological disasters

also impose a heavy financial and social burden on affected communities, countries and the global health system (Aminizadeh et al., 2022). It is important to fully understand the concept of biological disasters to minimize their devastating consequences and financial impact (Rebmann et al., 2009).

Kumar, 2020 defines biological disaster as “scenarios involving widespread disease, disability, or death of humans, animals, and plants as a result of toxins or diseases caused by living organisms or their products”. Kumar, 2020, noted that these events could be caused by epidemics, the accidental release of virulent microorganisms, or in some cases malicious act (bioterrorism) using biological warfare agents such as anthrax, smallpox, and others. According to Sharma, 2020 biological disasters in most cases could lead to mass illness and death among humans, animals, and plants if they encounter biological hazards in the form of living organisms such as bacteria, viruses, fungi, etc. This can be due to natural, accidental or intentional causes (Sharma, 2020). Regardless of the cause, these events can lead to large-scale epidemics. Natural disasters such as floods, wildlife, earthquakes, etc. can reduce the resilience of the ecosystem. For example, the flood in Pakistan in 2022 led to a five-fold increase in the number of cases of malaria in the country. On the other hand, human factors such as environmental pollution and genetic modification can also increase the rate and frequency of biological disasters (Service, 2019). Biological disasters mostly occur in the form of epidemics or pandemics as outbreaks, communicable diseases, and plagues with certain common characteristics, such as: periodicity, suddenness, short life cycle, high rates of productivity, high rate of variability and difficulty in monitoring and control, high rate of migration and finally high rate of ecosystem disruption (Service, 2019)

Vulnerability which is the tendency or predisposition of a system to be influenced by unfavorable external factors without being able to adapt (Song et al., 2020). Vulnerability to

biological disasters is often determined by various factors such as living conditions, quality of healthcare and community awareness (Kumar, 2020; Song et al., 2020).

The major factors responsible for this determinant are factors such as population growth, poverty, lack of rapid response in epidemic control and containment mechanisms, lack of public awareness, poor health status and malnutrition, poor healthcare systems, urban congestion, bioterrorism and modern mode of transportation (Kumar, 2020). Although these disaster events could have devastated impacts impact on human existence. Kumar, 2020 describes the following as steps that can be used to prevent, mitigate, and protect against the effects of biological disasters:

- i. Legal access to critical research and clinical materials must be maintained.
- ii. Preventing the unauthorized entry or removal of biological materials using suitable detection techniques, such as x-rays and other scanning methods, to identify microorganisms, plant pathogens, and toxins at international airports, seaports, and land borders.
- iii. Training and evaluation of pathogen protection procedures for personnel and security authorities.
- iv. Regular review of risk and threat assessments.
- v. Strict biosafety and biosecurity compliance measures at all levels.
- vi. There must be an inventory control system in laboratories that deal with bacteria, viruses, or toxins.
- vii. Specific information about organisms and toxins handled in various laboratories must be documented by the laboratories/organizations in question.
- viii. When not in use in the laboratory, dangerous pathogens must be stored in secure incubators, refrigerators, or storage cabinets.
- ix. Controlling and restricting access to laboratories to authorized users only.
- x. The public should be educated about the threats and risks associated with it.

- xi. Only boiled/chlorinated/filtered water and cooked food should be consumed.
- xii. Control measures against insects and rodents must be implemented immediately. Suspected and confirmed cases must be clinically isolated.
- xiii. The key to managing biological warfare casualties is early and accurate diagnosis.
- xiv. The existing disease surveillance system and vector control measures need to be promoted with greater zeal.
- xv. The mass immunization programme in the suspected area has been more closely monitored.
- xvi. Improving clinicians' knowledge and skills is critical to mitigating the effects of the attack.
- xvii. In any case, the basic public health procedures, and medical protocols for dealing with biological agents are the same as for any infectious disease.

2.2 Epidemiology of vector borne diseases

While the world is dealing with a variety of man-made and natural disasters, sub-Saharan Africa is more often affected by biological disasters like HIV/AIDS, malaria, Ebola, and other disease epidemics. (Farah et al., 2023; Suhr & Steinert, 2022). The scourge of vector-borne diseases such as African spotted fever (ASF), Crimean-Congo hemorrhagic fever, bluetongue (BT), West Nile fever (WNF), Rift Valley fever (RVF) and Japanese encephalitis (JE) are of widespread particular importance as the most important public health disease in sub-Saharan Africa, as these diseases are observed to have increased significantly in this region in the last decade (Thompson & Etter, 2015). These diseases pose a challenge for epidemiologists, who must address the challenge of developing tools and techniques to better detect, monitor, and even predict changes in the spatial distribution of pathogens and vectors in the near future (Thompson & Etter, 2015). According to the World Health Organization (WHO) report in 2004, vector-borne diseases have a significant impact on human and animal health and on the global economy, causing millions of dollars in losses.

Additionally, the report states that the disease accounts for about 17% of the burden of all infectious diseases worldwide (WHO, 2004). According to Yang et al., 2010, infectious diseases caused by viruses, bacteria, protozoa or bacteria, which are typically transmitted by disease-carrying biological agents called vectors and usually transmit the disease without becoming infected, are called vector-borne diseases described. These diseases, particularly mosquito-borne diseases such as malaria, dengue fever and West Nile fever, are usually transmitted to humans by blood-sucking mosquitoes and are known to be a major public health problem worldwide (Yang et al., 2010). Recently, environmental and climate changes, increasing international trade, increasing and faster global transport, human and animal population dynamics, and emerging drug resistance in both vectors and pathogens have been described as key factors driving the global spread of most vector-borne pathogens transmitted diseases (Knols & Takken, 2007; Rocklöv & Dubrow, 2020). Although the prevalence of most vector-borne diseases has been drastically reduced in the last century through the implementation of various vector control strategies, it is observed that these diseases have re-emerged in most developed countries, resulting in significant deaths and raising concerns worldwide (Chala & Hamde, 2021). A number of complex factors, including insecticide and drug resistance, changes in public health policies, prevention programs, demographic and societal changes, climate and genetic changes in pathogens, are observed to be responsible for the re-emergence of vector-borne diseases (Gubler, 1998; WHO, 2023). In most developing countries, factors such as astronomical population growth due to rural urban migration, unplanned and uncontrolled urbanization, inadequate housing, deteriorating water usage and storage, and waste management are observed as key factors in the spatial distribution of vector-borne diseases (Gubler, 1998). In general, several factors contribute to the complexity of the high prevalence of vector-borne diseases, such as: human conflicts, the effects of climate change, demography, deforestation, agriculture, urbanization, biodiversity, alien species, water

bodies and the interaction between vectors and pathogens. The progression of vector-borne diseases shown in

Table 2.1. Vector-borne diseases transmitted to humans (source: WHO, 2020) are as a result of some of these factors (Kamareddine, 2019): early detection, case management, spatial monitoring of pathogen circulation, monitoring of health indicators, spatial modelling and mapping, and finally the identification of new pathogens are crucial for a comprehensive understanding of vector ecology (Thompson & Etter, 2015).

Table 2.1. Vector-borne diseases transmitted to humans (source: WHO, 2020)

Vector	Parasite	Disease caused	Type of pathogen
Mosquito	Aedes	Chikungunya	Virus
		Denge	Virus
		Lymphatic filariasis	Parasite
		Rift Valley fever	Virus
		Yellow fever	Virus
	Anopheles	Zika	Virus
		Lymphatic filariasis	Parasite
		Malaria	Parasite
	Culex	Japanese encephalitis	Virus
		Lymphatic filariasis	Parasite
West Nile fever		Virus	
Aquatic snail		Schistosomiasis (bilharziasis)	Parasite
Blackflies		Onchocerciasis (river blindness)	Parasite
Fleas		Plague (transmitted from rats to humans)	Bacteria
		Tungiasis	Ectoparasite
Lice		Typhus	Bacteria
		Louse-borne relapsing fever	Bacteria
Sandflies		Leishmaniasis	Parasite
		Sandfly fever (phlebotomus fever)	Virus
Ticks		Crimean-Congo haemorrhagic fever	Virus
		Lyme disease	Bacteria
		Relapsing fever (borreliosis)	Bacteria
		Rickettsial disease (eg: spotted fever and Q fever)	Bacteria
		Tick-borne encephalitis	Virus
		Tularaemia	Bacteria
Triatome bugs		Chagas disease (American trypanomiasis)	Parasite
		Sleeping sickness (African trypanomiasis)	Parasite
Tsetse flies			

Among vector-borne diseases, malaria is considered the most important due to its global distribution, the number of people affected and the large number of deaths. Therefore, studying its epidemiology is crucial (Kalluri et al., 2007). Five genera of Plasmodium namely *Plasmodium falciparum*, *P.vivax*, *P.ovale*, *P.marariae* and *P.kowlseli* are primarily known for transmitting of malaria infections through the bites of Anopheles mosquitoes (Kasetsirikul et al., 2016). As of 2022, approximately 249 million cases of the disease were recorded

worldwide, resulting in the death of 608,000 people. The number of infected people in 2022 has increased by 5 million compared to the previous year as shown in Figure 2. 1: The global trends in incidence of malaria infection in 204 countries and territories. (A) The malaria ASRs in 2019; (B) changes in malaria episodes between 1990 and 2019; (C) the EAPCs of malaria ASRs from 1990 to 2019 (Liu et al., 2021).

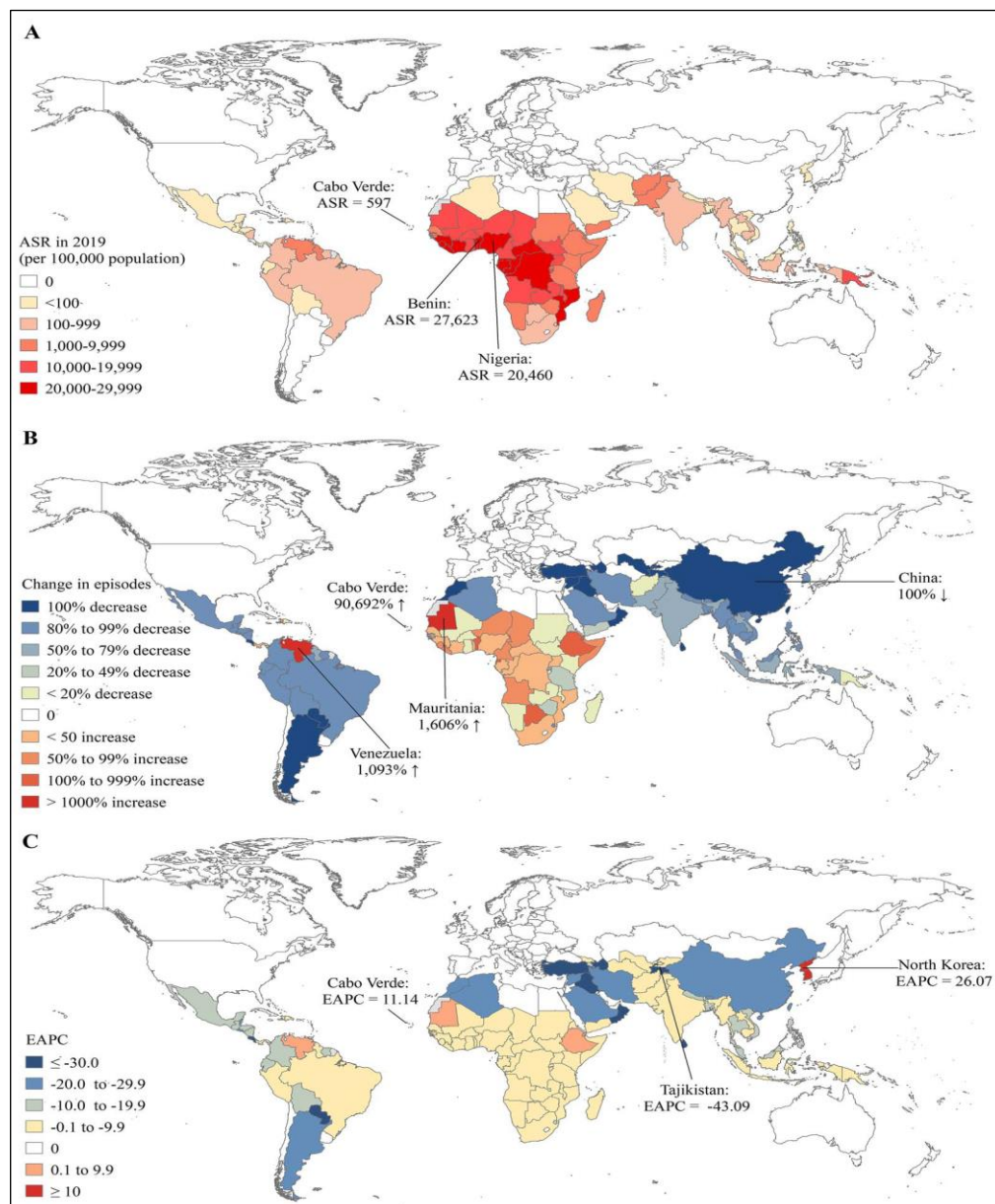


Figure 2. 1: The global trends in incidence of malaria infection in 204 countries and territories. (A) The malaria ASRs in 2019; (B) changes in malaria episodes between 1990 and 2019; (C) the EAPCs of malaria ASRs from 1990 to 2019 (Liu et al., 2021).

Unfortunately, 76% of these were children under 5 years old (WHO, 2022). The 2020 WHO report stated that Nigeria accounts for a significant 26.8% of global deaths, with an incidence of 306 cases per 1000 vulnerable population. According to the report, only fifteen countries in India and Sub-Saharan Africa account for 80% of the world's malaria cases. Five countries - Nigeria (25 percent), the Democratic Republic of Congo (11 percent), Mozambique (5 percent), India (4 %) and Uganda (4 %) - account for almost half of all malaria cases worldwide, the report says.

2.3 Malaria vector ecology

There are approximately 460 Anopheles mosquito species worldwide, of which over 100 species can transmit malaria to humans and other animals (Afrane et al., 2012). *Plasmodium falciparum* (95%) is the most common parasite specie in Nigeria and the most pathogenic of the five human malaria parasites (NMIS, 2021). Other non-falciparum parasites found were *Plasmodium malariae* (9.8%) and *Plasmodium ovale* (5.8%), as well as mixed infections (10.4%). Plasmodium parasites, which are found in female Anopheles mosquitoes and bite infected people, transmit malaria. The *P. falciparum* parasite's complicated life cycle makes it difficult for humans to deal with and also makes it difficult for scientists to develop vaccines to combat this disease. One of the major factors that has made *P. falciparum* a difficult parasite for humans to handle and a daunting challenge in developing its vaccine is the complicated life cycle of all Plasmodium species, which includes both a vertebrate host and an insect vector (Votýpka et al., 2017).

When a female Anopheles mosquito bites an infected human as shwon in Figure 2. 2: Life cycle of Plasmodium falciparum (source: Rowe et al., 2009) consumes infected red blood cells (iRBCs), which contain gametocytes (Engwerda et al., 2005; Yamauchi et al., 2007; Cowman et al., 2016). When male and female gametocytes combine in the mosquito's gut, they

form a zygote, which then develops into an ookinete and migrates through the mosquito midgut epithelium to form an oocyst before developing into sporozoites via asexual sporogonic replication (Greenwood et al., 1991).

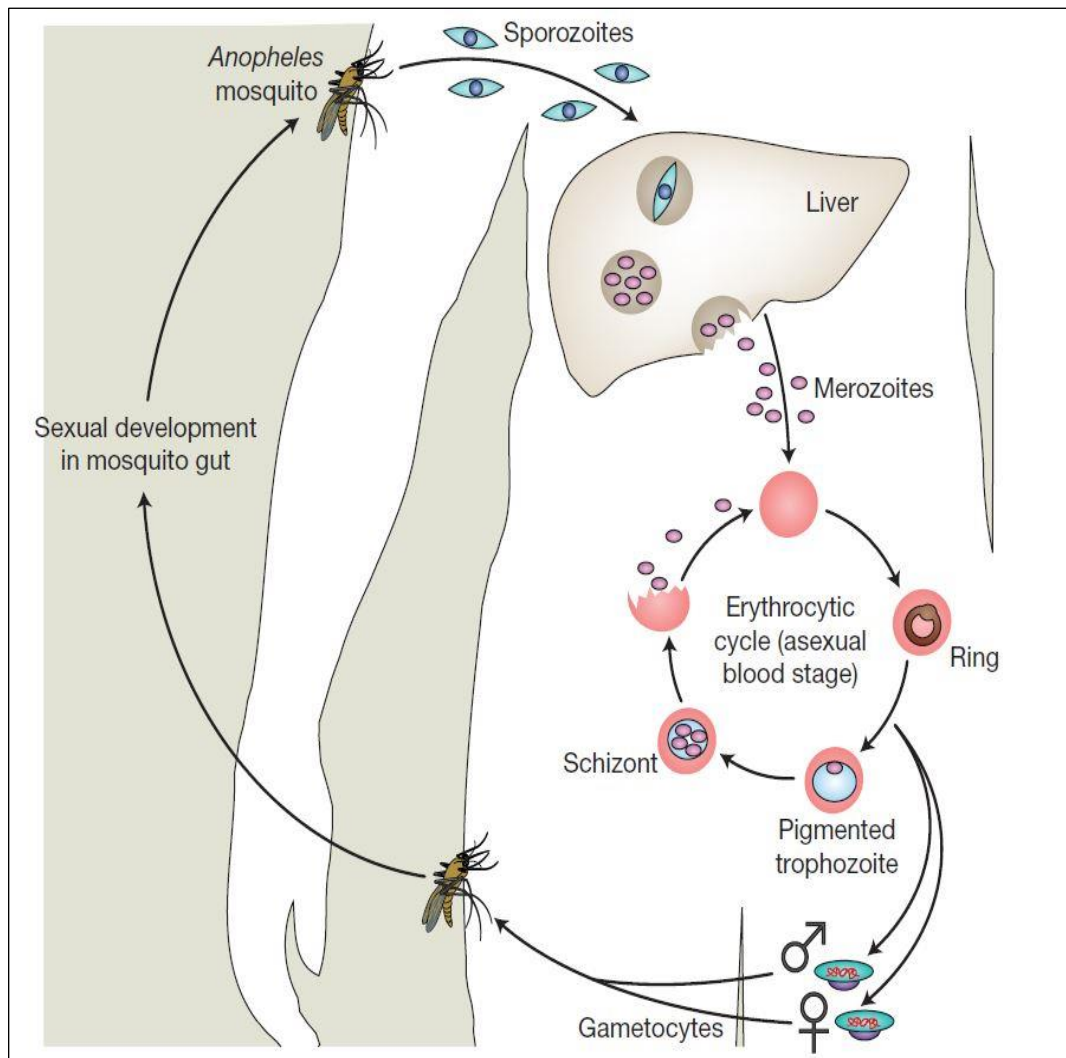


Figure 2. 2: Life cycle of *Plasmodium falciparum* (source: Rowe et al., 2009)

When an infected mosquito has its next meal, sporozoites travel to the vector's salivary glands and are injected into the skin of the person bitten by the mosquito through the mosquito's saliva, and the sporozoites can remain under the skin for up to six hours before entering the person's bloodstream, according to Yamauchi et al., 2007. Although fewer than 100 sporozoites are injected per mosquito bite, only a third of them reach the human liver (Amino et al., 2006).

According to Greenwood et al., 1991, the number of sporozoites injected has no influence on the course of the disease, but does have an influence on the time until malaria symptoms appear.

Sporozoites infect the liver cells of the person bitten by the mosquito and, after two to thirty minutes, multiply into merozoites (Yamauchi et al., 2007). Given that a single sporozoite can eventually reproduce asexually to form up to 40,000 merozoites, the immune system of infected persons' immune system must be strong enough to deal with this phase of the life cycle as quickly as possible in order to avoid serious complications caused by the merozoites. The liver stage lasts two to ten days. Afterwards, infected liver cells release large numbers of merozoites that infect red blood cells (Engwerda et al., 2005).

The stage in the parasite's life cycle in which hepatocytes allow their asexual reproduction is called schizogony (Yamauchi et al., 2007; Schofield et al., 2005; Prudêncio et al., 2006). Merozoites that enter the bloodstream and infect liver cells develop into trophozoites and eventually schizonts (each schizont can contain up to 36 merozoites), which rupture and release more merozoites that attack uninfected red blood cells (Schofield et al., 2005). The erythrocyte cycle is believed to last 48 hours. At this point, the infected person begins to show signs of malaria, such as periodic fever during the red blood cell exit phase, which releases the merozoites. According to Langhorne et al., 2008, during the parasitic proliferation phase in the red blood cells, the fever decreases, giving the patient the impression that he is feeling better. The sexual stage of the parasite cycle is the third stage of the parasite cycle. After several cycles of intraerythrocytic dissemination, some merozoite-infected red blood cells cease asexual reproduction and instead differentiate into sexual forms of the parasite, either as male or female gametocytes, a process known as gametocytogenesis (Cowman et al., 2016; Josling et al., 2015; Bancells et al., 2019). The parasite cycle is then reactivated as gametocytes hibernate and develop in the bone marrow before entering the peripheral circulation and being ingested during a blood meal by an *Anopheles* mosquito (Yamauchi et al., 2007; Cowman et al., 2016;

Greenwood et al., 1991). Hibernation of gametocytes in the bone marrow is an immune evasion mechanism used by the parasite to prevent clearance from the spleen during parasite development and represents another potential source of disruption in the parasite's life cycle (Schofield et al., 2005 ; Prudêncio et al., 2006). Adult survival and fecundity, as well as immature development time and survival are all dependent on mosquito density (Mordecai et al., 2013).

2.4 Guidelines for malaria control and elimination

A comprehensive review of the World Health Organization's guidelines on malaria control/elimination provides a better understanding of malaria control/elimination activities and programs in Nigeria. In this section, a thorough assessment of Nigeria's malaria elimination programs and activities is carried out by carefully evaluating the successes of other countries in eradicating the disease. Through this comprehensive assessment, this research identifies areas of improvement, strategies, and best practices that the National Malaria Elimination Programme (NMEP) must implement for effective management of the disease.

2.4.1 World Health Organization's malaria recommended guidelines.

Comprehensive malaria guidelines are developed with the sole aim of preventing, diagnosing and treating the disease in most endemic and other regions of the world (WHO, 2022). These guidelines are intended to guide countries where malaria is endemic in the fight against the scourge of the disease. The WHO malaria guidelines are divided into seven subdivisions as follows.

- i. ***Vector control/management***: the guidelines place greater emphasis on the use of long-lasting insecticide-treated nets (LLTNs) and indoor residual spraying (IRS) as a key measure to control, manage and prevent malaria transmission in endemic regions and countries. The

control measures target the vector that transmits the malaria parasite and are aimed exclusively at reducing the vector population and human-vector contacts.

- ii. ***Case diagnosis and management/treatment:*** the guidelines recognize that accurate case diagnosis and rapid treatment/management of the disease are critical to reducing the incidence and prevalence of the disease. The guidelines recommend the use of quality-assured diagnostic tests such as microscopy and Rapid Diagnostic Tests (RDTs) to confirm malaria cases. The choice of malaria treatment to administer should depend on the type of malaria and localized drug resistance patterns.
- iii. ***Antimalaria drug resistance:*** due to the emergence and spread of malaria strains that are often resistant to drugs, posing a significant challenge to the disease's elimination campaigns, WHO guidelines recommend comprehensive surveillance and monitoring of anti-malarial drug resistance and ensuring effective treatment to manage such cases in such regions to effectively combat resistance.
- iv. ***Seasonal Malaria Chemoprevention (SMC):*** in regions with high seasonal malaria transmission, the guidelines recommend the use of SMC as one of the prevention strategies for children between 3 and 59 months. The guidelines also recommend administering antimalarial drugs at monthly intervals during the peak of the disease transmission season.
- v. ***Intermittent Preventive Treatment in Pregnancy (IPTp):*** the guidelines recognize that malaria infections during pregnancy pose a major risk to both the mother and the unborn child. The guidelines recommend IPTp in pregnancy with sulfadoxine-pyrimethane (sp) for pregnant women in malaria-endemic regions to prevent maternal anemia, low birth weight and other associated complications.
- vi. ***Malaria elimination and control strategies:*** according to the WHO malaria guidelines, malaria-endemic regions or countries seeking to eliminate the disease should focus their elimination policies on implementing comprehensive strategies that include vector control,

case management, vector surveillance and community engagement. The sole goal of these programs is to achieve a significant disruption in vector transmission while ceasing to cause domestic cases of the disease.

- vii. ***Community Engagement:*** the guidelines also recognize the importance of community engagement as critical to the success of malaria control/elimination programs. The WHO malaria guidelines advocate effective community participation, education, and empowerment to locate and implement preventive measures, prompt action in seeking treatment and other necessary control/management activities.

2.4.2 An assessment of Nigeria malaria control/elimination programme.

The Nigerian malaria control programme is considered the oldest vector control program in the country, having been established in 1948. The program has undergone several transitions, resulting in a change in nomenclature from the National Malaria Service to the National Malaria Control Programme in 1986 and finally to National Malaria Elimination Programme in 2013, reflecting the country's desire for complete malaria eradication. According to Maduka, 2018, the National Malaria Programmes and their state elimination programs are all overseen by the Federal Ministry of Health and are charged with functions such as regulations, oversight and program management for malaria control and elimination.

Since the roll-back Malaria Programme was launched in 1998, Nigeria secure funding from a variety of partners, including the Global Fund for AIDS, Tuberculosis, and Malaria (GFATM), the world banks and the Presidential Malaria Initiative (PMI-USAID). The United Kingdom Department for International Development (DFID), United Nations agencies (WHO and UNICEF), and others, to combat this disease (National Malaria Elimination Programme [NMEP], 2015). To effectively implement malaria control programs in Nigeria, the National Malaria Strategic Plans (NMSP) was tasked with developing a strategic malaria control plan

with specific objectives designed every six years over the years Nigeria Malaria Indicator Survey [NMIS], 2015).

2.4.3 Organisational structural model of the Nigerian malaria control/elimination programme

Nigeria has structured its malaria elimination programme model to reflect the country's political structure, which consists of a federal entity with 36 states and 774 local government areas (Ukoha et al., 2016). According to Nigeria Malaria Indicator Survey (NMIS, 2015), the federal government is responsible for the Nigerian health sector, which is shared between states and local government areas. However, some exceptional services are only available to the federal government. The public health system in Nigeria is divided into three tiers, which correspond to the administrative levels of government. According to a 2010 report by the Federal Ministry of Health, the federal government is responsible for the tertiary health system and formulates its policies through the Federal Ministry of Health. Specialized services are provided at this level by teaching hospitals, federal medical centers, specialty hospitals and medical research institutes. The state government, on the other hand, oversees secondary health care through state-run general hospitals, while Local Government Areas (LGAs) oversee primary health care, which is typically designed to serve populations between 0 and 30,000 people. The federal government provides health care funding to both state and local governments. The federal government oversees the private health sector, non-governmental organizations that provide health services, and local communities that are also involved in health care (NMIS, 2015). Nigeria's National Malaria Elimination Programme (NMEP) is tasked with developing policies, developing strategies, and coordinating all malaria control/elimination efforts in the country (NMIS, 2015).

Malaria elimination programs and activities are led by governors at the state level, while primary health care departments are responsible at the local level (NMIS, 2021). Typically,

NMEP coordinates and develops frameworks to provide guidelines for these activities at the state and local government levels. According to Ukoha et al., 2016, at the state level, state governments have significant autonomy and independence in terms of planning and implementing health care programmes. To improve Nigeria's healthcare delivery systems, the government recently implemented structural reforms that have changed the administrative structure of the state health system. In 2011, this reform led to the creation of State Primary Health Care Development Agencies (SPHCDA), which changed the degree of variation in the administrative organization or models of state malaria governance architecture (Ukoha et al., 2016). Based on the administrative location of malaria programmes at the States and LGAs, Ukoha et al., 2016 identified three types of organizational structures or models, namely: State malaria control programs are located within the state Department of Health, which reports to the state Department of Health. The state malaria elimination program is integrated into the state primary health care development agencies. State malaria control programs run parallel to the Ministry of Health and state primary health care development agencies and are led by a political appointee (special adviser), usually appointed by and reporting directly to governors. According to Ukoha et al., 2016, state models for malaria administration can be switched to any of the three options at the discretion of state governors.

National malaria elimination programmes and activities. To effectively manage and eliminate the burden of malaria in Nigeria, the Federal Government through the Federal Ministry of Health and National Malaria Elimination Programme has initiated some programs and activities to advance the malaria campaign in the country (NMIS, 2021). These programmes and activities are summarized as follows:

- i. ***The development of malaria elimination strategic plans:*** every six years, the Federal Ministry of Health develops a strategic plan as part of the national malaria elimination programme, which serves as a blueprint for guidelines for malaria control and elimination.

These include malaria prevention through a strong integrated vector management strategy, accurate diagnosis of all malaria cases at all levels and timely availability of all malaria elimination products and services. These strategic plans resulted in a huge increase in resources through partnership with the relevant non-governmental organizations and relevant national and international malaria partners but faced some formidable challenges due to poor infrastructure development and poor accessibility to health facilities in the rural areas.

ii. ***Disease surveillance, case management and follow-up:*** National malaria transmission studies conducted across Nigeria showed that *Plasmodium falciparum* (95%) is the dominant parasite species in the country and the most pathogenic of the five malaria parasites (NMIS, 2021). Entomological studies also suggest that the major vectors with wide geographical distribution in Nigeria are the *Anopheles gambiae* complex and the *Anopheles imetus* group. The national malaria transmission studies also found different infection rates for different mosquito species in different regions, with the entomological inoculation rate (EIR) ranging from 18 to 145 infectious bites per man per year. *gambiae* in the north central region to 0-12.4 infectious bites per man per year for *An. arabiensis* in the southwest (NMIS, 2021).

iii. ***Malaria case management in Nigeria:*** programmes have been introduced to ensure that only recommended antimalarial drugs are administered in both public and private health facilities, with a focus on improving parasitological diagnosis of malaria in such facilities (NMIS, 2021). The program adopted artemisinin-based combination therapy as the recommended drug for treatment. In addition, strategic malaria control interventions including intermittent patent treatment (IPT) and immediate treatment of confirmed cases at all levels across Nigeria were also implemented as part of case management. In addition, IPT with sulfadoxine-pyrimethamine, proper use of LLINs, and prompt treatment of all confirmed malaria cases have also been adopted as core strategies to combat malaria in pregnancy (NMIS, 2021).

2.4.4 Identifiable lapses of the National Malaria Elimination Programme

A close examination of Nigeria's malaria elimination activities, strategies and programs compared to the malaria elimination programs of other countries such as Algeria, Cape Verde and especially Sri Lanka's structural malaria elimination strategies and programs revealed the following areas of needs (Abeyasinghe et al., 2012; Cotter et al., 2013; de Pina et al., 2019; DePina et al., 2018; Dhiman, 2019; Lindblade et al., 2021; WHO, 2019, 2021):

- i. It was noted that the Nigerian elimination programme is based on the foundation of good malaria control, particularly with the establishment of the National Malaria Elimination Program in 2013 under the political leadership of the National Malaria Control Strategic Plan, which established strategic guidelines for the elimination program every six years. Because the national program does not have complete control over its activities, the specific goals and objectives are often unclear.
- ii. The Nigerian National Malaria Elimination Programme has failed to fully adopt and implement the policies and strategies recommended by the World Health Organization. Over the years, the elimination program has placed greater emphasis on vector management, such as distributing long-lasting insecticide-treated nets and spraying indoor areas with residue, rather than on elimination itself.
- iii. The Nigerian National Malaria Elimination Programme did not include personnel with extensive experience in geospatial technology, geography, and epidemiology in terms of area coverage to implement and monitor an evidence-based malaria elimination program. The program appeared to rely primarily on rural health workers who were unfamiliar with risk areas, population groups and their migration (movement) rates, and potential vector breeding sites.
- iv. Another shortcoming of the programme is its inability to effectively deploy malaria specialists to rural areas and introduce mobile malaria clinics to existing rural health

- facilities in high-risk areas due to vector prevalence, poor access to diagnosis or other local events or occurrences supplementing increased the risk of malaria transmission.
- v. Nigeria's National Malaria Elimination Program is developing and implementing a six-year strategic plan and strategies under its National Malaria Strategic Plans (NMSP), which appear to be insufficient to effectively coordinate, monitor and eliminate malaria in the shortest possible time.
 - vi. Another factor preventing malaria elimination is the poor state of health infrastructure in Nigeria, particularly in rural areas where malaria is most common, as well as the country's high illiteracy rate.
 - vii. Another factor hindering the eradication of malaria in Nigeria is the inability of the National Malaria Elimination Programme to effectively monitor, control and distribute most malaria products and services.
 - viii. A key component that has not been leveraged to accelerate the elimination program in Nigeria is the program's ability to conduct proactive and reactive case detection in malaria endemic areas and seasons.
 - ix. To effectively eliminate malaria in Nigeria, the National Malaria Elimination Programme can enlist the support of most non-governmental organizations and international organizations that operate in crisis areas and can act as facilitators in the distribution of antimalarial drugs and other services throughout the country.
 - x. The National Malaria Elimination Programme in Nigeria needs to improve its entomological surveillance program, with a focus on highly endemic regions of the country.
 - xi. Nigeria's national malaria elimination programme needs to improve its integrated vector management practices, moving away from relying on the distribution of long-

lasting insecticide-treated nets and indoor residue spraying and instead incorporating other techniques such as breeding.

- xii. Collaboration between other ministries such as environment, agriculture, education, and organizations with technical expertise in larval source management should be strengthened. This can help strengthen the policies, strategic framework, and implementation of the National Malaria Elimination Programme Action Plan.

2.5 Research gap.

This section aims to review the literature that has already been written about the epidemiology of malaria in Plateau State and Nigeria to gain important insights into the disease's current spatial distribution and risk vulnerability. By reviewing the existing literature in the study area, we were able to gain valuable insights into the epidemiology of malaria, identify gaps in knowledge, identify research needs and highlight the areas requiring further investigation in the northern zone of Plateau State.

2.5.1 Statement of problem

Though there has been a positive decline in malaria infections in recent years, increased funding, and the provision of critical preventive measures to endemic populations are responsible for the enormous gains witnessed. These measures have led to a reduction in the global burden of malaria, and several countries with malaria incidence are currently experiencing declining trends and are moving toward eventual malaria elimination (Dhiman, 2019). Furthermore, the global decline in malaria cases as shown in Figure 2. 3: Global distribution of malaria endemicity (WHO, 2018) is due to elimination strategies that focus on aggressive malaria control in high-endemic countries using improved and sustainable intervention tools that are accessible to most at-risk areas (Coll-Seck et al., 2008; Hemingway et al., 2016; Nkumama et al., 2017; RBM, 2015; Tanner et al., 2015).

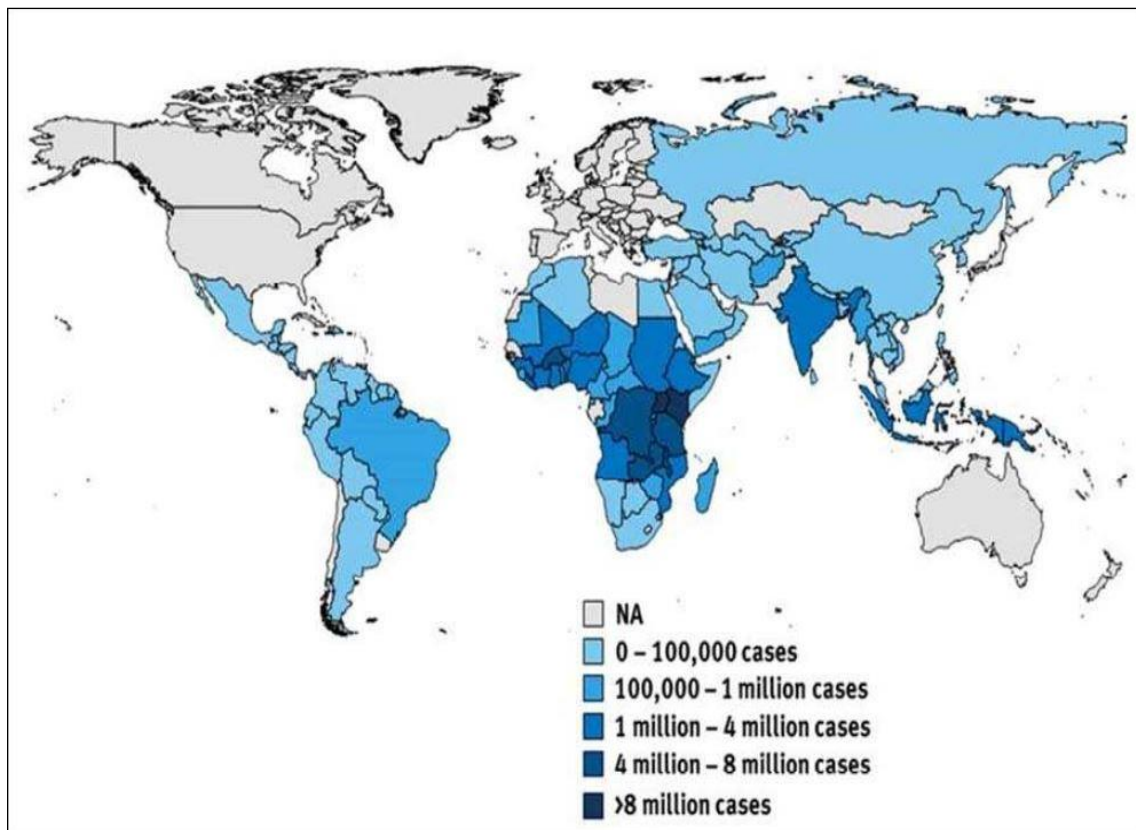


Figure 2. 3: Global distribution of malaria endemicity (WHO, 2018)

Despite this massive improvement in the fight against the disease, malaria still remains a significant public health concern globally, leading to high morbidity and mortality rates particularly in sub Saharan Africa where it is the leading cause of child mortality and a major contributor to morbidity (Acheson et al., 2015; Binka et al., 2007; Dewald et al., 2016; Kleinschmidt et al., 2001). It is observed that many developing countries where malaria is endemic continue to bear its economic and health burden (Alimi et al., 2016).

Nigeria, in particular, had the highest burden of disease, accounting for 26.6% of all malaria cases and 31.1% of global deaths (WHO, 2022). This makes the country the country with the highest prevalence of malaria infections, with 97% of the country's population at risk of transmitting the disease. According to the report, one in four people in Nigeria is infected with malaria and one in four deaths is due to malaria infection. The infection rate is reported to be around 306 cases per 1,000 people at risk, with malaria-related deaths at 0.91 per 1,000

people. There are marked differences in malaria prevalence across the country as shown in Figure 2. 4: Spatial distribution of malaria endemicity in Nigeria (Emmanuel et al., 2017). with the southern and southeastern regions of the country having 16%, while the northern region of Nigeria has a higher prevalence at 34%. (NMIS, 2021).

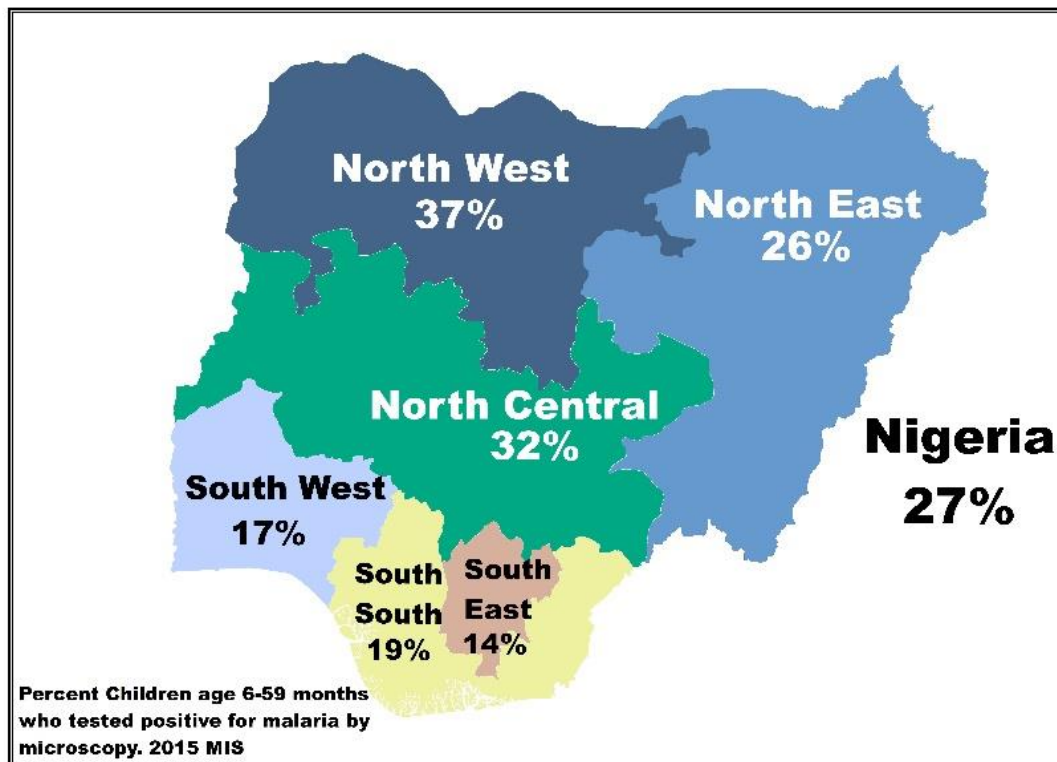


Figure 2. 4: Spatial distribution of malaria endemicity in Nigeria (Emmanuel et al., 2017).

In Plateau State in north-central Nigeria, where the study area is located, the disease is reported to have a consistently high prevalence despite spatial and seasonal variations with notable differences in the ecological conditions of the different zones (Nanvyat et al., 2017). Therefore, there is a need to analyze, model and map the spatial distribution of the disease risk to determine the areas that require immediate intervention and the type of vector control measures that need to be implemented in these areas.

Malaria transmission processes are multifactorial and dynamic and are largely influenced by various interrelated factors such as environmental, climate, socioeconomic and anthropogenic factors (Gonzalez Daza et al., 2023; Shah et al., 2022; Kar et al., 2014). It also

is governed by a wide range of variables associated to the parasite, the vector, and the host (Bhatt et al., 2014). These factors determine the relationship between vectors and the host population and have been described as extremely complex. However, they can be measured by studying vector or human infection relationships (Omumbo et al., 1998). The human-parasite-vector triangular interaction provides an empirical approach to malaria control or eradication. However, this may be hampered by a lack of information on the relationship between parasite exposure and the clinical outcome of the disease, which has recently become a barrier to successful malaria treatment (Omumbo et al., 1998). Furthermore, the lack of reliable and precise epidemiological data in heavily affected countries poses a significant challenge in researching the macroeconomic impact of the disease and allocating public health resources to combat it (Gallup et al., 2001; Bhatt et al., 2014).

2.5.2 Spatial technology in malaria epidemiology

By using spatial technology, it is possible to easily assess malaria endemic areas. Integration of these technologies with prevalence and incidence data from various healthcare facilities leads to accurate predictions of disease distribution in regions that lack baseline data, reliable population risk estimates, and appropriate guidance on necessary intervention strategies and responsible use of limited resources (Kassaw et al., 2020). Additionally, the spatial patterns of malaria risk may be revealed at a remarkably fine spatial resolution through the integration of malaria risk factors with Geographic Information System (GIS) decision-support algorithms. This is important for figuring out where malaria is most likely to spread in endemic areas and helpful for giving policymakers the direction they need to implement efficient plans, manage limited resources, and develop strategies. (Alimi et al., 2016; Gwitira et al., 2018; Kassaw et al., 2020; Youssefi et al., 2022). The advent of high-resolution, publicly available satellite data and effective decision-making tools such as Multi-Criteria Decision Analysis (MCDA) has opened up enormous opportunities for analyzing, mapping, modelling

and predicting malaria transmission risk at low cost, efficiently and accurately (Alimi et al., 2016; Ahmad et al., 2017; Kassaw et al., 2020; McMahon et al., 2021). Spatial MCDA, a valuable tool that combines statistical techniques and expert participation to understand the nonlinear relationship between malaria risk factors. This leads to the spatial incidence and distribution of the disease, is widely used in malaria risk mapping and modelling. Through transformation and geospatial data integration, data is used to create spatial malaria risk models that are helpful in prioritizing areas requiring intervention, monitoring and surveillance, and making informed decisions (Sarkar et al., 2019; Zhao et al., 2020; McMahon et al., 2021; Mihiretie, 2022).

2.6 Gap in literature

The evolution and trend of research interests related to malaria in Nigeria include vector biology, immunology, drug discovery and development, vaccine development, immunology, public health policy, etc. Through systematic literature searches in databases such as Scopus and Web of Science as shown in Figure 2.5 in Nigeria, it was found that malaria research has gained momentum in the last two decades due to growing global concern over the endemicity of malaria.

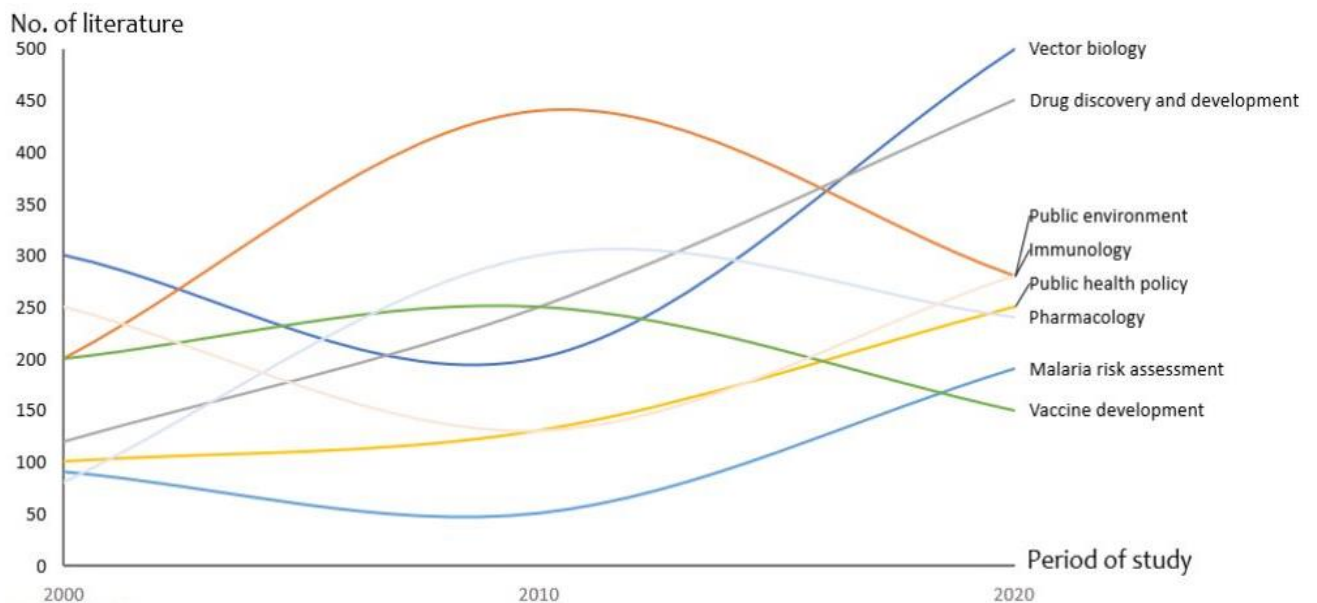


Figure 2. 5: Illustrates the trends of malaria related research in Nigeria between 2000-2023

However, there is a notable research gap in the use of spatial technology in analyzing and modeling various risk factors, ranging from the use of environmental, climate and socio-economic factors to predicting the spatial variation in disease vulnerability risk in Plateau State. While the existing literature sheds light on malaria research interests such as prevalence, ecology, vector biology, vaccine development and parasitemia in Plateau State and Nigeria, a systematic literature review analysis conducted using Web of Science via Boolean '(((("Malaria") AND (Spatial) Risk* OR Modeling)) AND (Plateau State))' suggested that there is still a significant gap in the literature regarding the application of spatial analysis techniques and multi-criteria spatial decision algorithms. This is critical to understanding the comprehensive relationship between malaria transmission dynamics and suitable breeding habitats, human vector interactions and the various risk factors that influence disease risk in Plateau State. The systematic literature review over a period of over 20 years (see Figure 2.6 below) shows that no study has been conducted to comprehensively assess the spatial distribution of the malaria hotspot in the study area.

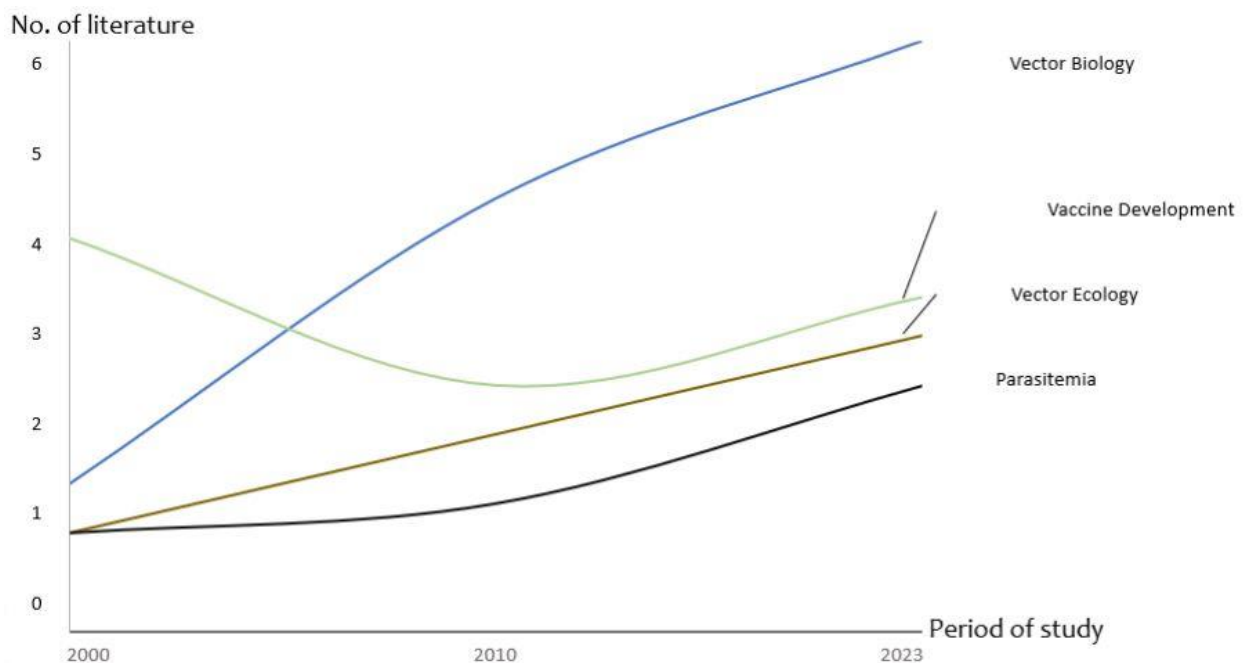


Figure 2. 6: Illustrates the trends of malaria related research in Plateau State between 2000-2024

To address this research gap, it is critical to conduct a thorough analysis, assessment, and modeling of the various malaria risks into a comprehensive risk map and model that illustrate the spatial distribution of malaria vulnerability risk. This is crucial as Plateau State and the study area are known to have unique environmental characteristics, including varying topography, land use practices, climatic conditions, settlement patterns and socioeconomic activities, which influence the dynamics of malaria transmission.

Furthermore, most of the literature lacks the integration of expert knowledge valuable in understanding disease transmission dynamics using spatial multi criteria decision analysis techniques in analyzing, assessing, mapping, and modeling malaria risk in Plateau State. This technique often provides a systematic framework for analyzing, assessing, and prioritizing the various risk factors that influence malaria transmission risk, such as: environmental, socio-economic, climatic and health-related factors by involving malaria experts in the decision-making process by determining the relative importance of the factors. The gap in the literature in the analysis of spatial granularity and the failure to identify the local variations in malaria transmission risk are addressed by examining the spatial distribution of the disease and its changes over time through the comprehensive assessment, analysis and modelling of the various risk factors fixed impact on malaria transmission dynamics in this study. Understanding malaria transmission dynamics, vector-host interactions, suitable breeding habitats for vectors, and vector behavior patterns is made possible by the thorough assessment, analysis, and modelling of the various risk factors influencing malaria vulnerability risk in the northern zone of Plateau State. This study will help policymakers make informed decisions, use scarce resources prudently, implement appropriate vector control measures, and understand the level of malaria vulnerability in the region. In addition, this study aims to provide the necessary guidelines for implementing practices that reduce the burden of disease by promoting cross-sector collaboration in addressing the problem.

In summary, the identified gaps in the literature for this area of study underline the importance of conducting a thorough assessment, analysis and modeling of the various malaria risk factors using spatial technologies. A thorough understanding of malaria transmission dynamics, vector-host interactions, vector behavioral patterns, and appropriate vector breeding habitats will be possible through the integration of spatial decision algorithms to delineate malaria risk foci in this study. This approach provides a comprehensive understanding of required intervention strategies, resource allocation, and guidance for public health efforts to reduce the burden of disease in the study area.

Chapter 3: Multi-Criteria Decision Analysis

This chapter examines the influence of expert intuitions on decision-making processes through an assessment of multi-criteria decision analysis. The contribution of experts in malaria epidemiology is crucial as these experts are mostly involved in critical decision-making processes and implementation of various intervention measures related to disease management. The experts' intuitions used in this chapter are based on identifying malaria risk factors, considering both quantitative and qualitative analysis of the various criteria and alternatives. The chapter also evaluates how the various malaria risk factors can be structured using different hardware and software into a single decision-making tool that can positively influence and improve vector management practices. This is achieved by structuring the malaria risk problem by first defining the level of malaria risk in the study area, identifying the various risk factors, establishing the various risk criteria, and using the expert's intuition to determine the relative importance of alternatives. Overall, this chapter examines in detail topics such as the concept of decision making, common MCDA methods, structures, and properties of MCDAs, methods and processes for solving MCDA problems, techniques for evaluating criteria weights, and spatial applications of MCDA in malaria epidemiology.

3.1 The concept of Decision-making Processes.

Daily decision-making problems, ranging from personal and professional decisions to national and international policies, are often based on choosing between different alternatives (Cinelli et al., 2020). The inexhaustible list of alternatives that we encounter in everyday decision-making arises from the fact that most decisions require a comparative evaluation of alternatives to select one or a subset of a larger pool of such alternatives (Cinelli et al., 2020). For a decision maker to make a particular decision, various alternatives must be properly evaluated in terms of one or more evaluation criteria, often referred to as performance

measures, variables, or indicators. Therefore, no decision can be adequately addressed without resorting to a structural framework such as these evaluation criteria (Cinelli et al., 2020 ; Taherdoost & Madanchian, 2023). Decision making is a cognitive process that involves a variety of factors and aims to achieve definite results for solving problems. This process can be classified as rational or irrational and can utilize implicit or explicit assumptions influenced by a variety of factors such as physiological, biological, cultural, social and other factors (Taherdoost & Madanchian, 2023). Multi-Criteria Decision Analysis (MCDA) is a field developed within the operational research and decision engineering discipline to facilitate the evaluation of various alternatives considering multiple criteria (Cinelli et al., 2020). The best tools for analysing multiple alternatives are said to be MCDA methods, particularly when there are many options for a single problem. These decision-making techniques are crucial for identifying the most suitable alternative with the best cost criteria, the lowest environmental impact and good energy efficiency (Zlaugotne et al., 2020). These decision-making tools are considered the most accurate decision-making methods, and their effectiveness is proven by their successful application in a wide range of solved problems, including medicine, engineering, economics, resource management, epidemiology, etc. (Velasquez & Hester, 2013 ; Cinelli et al., 2020 ; Taherdoost & Madanchian, 2023).

MCDA is most effective in complex scenarios where multiple facets and alternatives are involved, and decision-making processes are required. These processes are known to facilitate the resolution of multidisciplinary and multidimensional analyses, thereby providing guidance to decision makers in their decisions (Guarini et al., 2018). Although MCDA is still relevant in daily life, complex decision-making problems can be solved by using mathematical equations, diverse statistics, mathematics, economic theories, and computer-based software to automatically calculate and estimate solutions to improve decision-making problems (Taherdoost & Madanchian, 2023). In practice, MCDA is applied by using different experts to

give different weights to the criteria, reflecting their relative importance in particular cases. The aim of this process is to determine the optimal solutions, taking both qualitative and quantitative criteria into account (Taherdoost & Madanchian, 2023). To achieve this, decision-making must be based on appropriate structuring and clear evaluation of each individual criterion using the necessary hardware and software.

The best use of MCDA techniques are achieved by clearly defining the problem in question, identifying the available alternatives and establishing the various criteria that may vary costs, social and environmental impact indicators, energy efficiency, quality and other specific criteria relevant for the problem (Taherdoost & Madanchian, 2023). It is worth noting that there are many MCDA methods and each of these methods has a unique definition of the best alternative. Furthermore, the main goal of these techniques is to create a preference ranking between different decision options based on their performance against a variety of criteria by selecting between a limited number of alternatives to select the best option (Steele et al., 2009; Tzeng & Huang, 2013).

MCDA is described as a comprehensive procedure that uses a variety of techniques to organize and evaluate decision-making processes in a clear and coherent manner (Langemeyer et al., 2016). It can also be described as a complex mental process that involves a problem-solving program that attempts to determine a favourable outcome by considering various factors (Taherdoost et al., 2023). The selection of the appropriate MCDA technique is based not only on the properties and requirements, but also on the type and characteristics of the data used in the decision-making process (Hafezalkotob et al., 2016 ; Zlaugotne et al., 2020).

The inherent ability of these techniques to evaluate numerous alternatives based on various criteria to determine the optimal options makes them indispensable for solving complex problems in various research areas (Ardielli, 2016). Before employing MCDA techniques, it is important to define the problem, quantify the alternatives, and evaluate the different criteria

(Zlaugotne et al., 2020). This is particularly crucial when there are several possible alternatives to a given problem, as the goal is to select the best one among the other alternatives (Arabameri et al., 2018).

3.2 Types of MCDA methods

Many authors have developed or improved various types of MCDA techniques over the past decades. The complexity of algorithms, criteria weighting methods, representation of preference evaluation criteria, handling of uncertain data, and data aggregation type are the key distinguishing features of MCDA techniques (Bączkiewicz et al., 2021; Taherdoost & Madanchian, 2023). In addition to the type of decision problem to be solved, when considering the type of MCDA techniques to use, decision makers should select the techniques that best fit their decision-making context, their technical knowledge, and their level of involvement.

Although examining different MCDA methods is critical to improving decision quality, it is important to note that no single method is superior to others in all situations (Vassoney et al., 2021; Taherdoost & Madanchian, 2023). Criteria for selecting MCDA methods includes its requirements and properties.

There are currently more than 100 different MCDA methods available. However, some of the most commonly used and implemented MCDA methods are: Analytic Hierarchy Process (AHP), Fuzzy Set Theory (FST), Multi-Attribute Value Theory (MAVT), Measuring Attractiveness by a Categorical Based Evaluation (MAVBETH), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), KOMPROMISNO RANGIRANJE, d. H. multi-criteria optimization and compromise ranking (VIKOR), Elimination Et Choix Tradusiant la, d. H. Elimination and Choice Translating Reality (ELECTRE III), Preference Ranking Organization Method for the Enrichment of Evaluations (PROMETHEE), The Analytic Network Process (ANP), Data Envelopment Analysis (DEA), Simple Additive Weighting

(SAW), Weighted Product Model (WPM), etc. (Saaty, 2013; Guarini et al., 2018). Selecting the MCDA method most appropriate for the specific objective of the decision problem has a significant impact on the overall efficiency of the decision process (Guarini et al., 2018). Based on their relative importance, the alternatives are evaluated and arranged in descending order, with the best option being the most desirable and the worst option being the least desirable.

These steps are commonly included in almost all MCDA techniques. (Pramanik et al., 2021).

- i. Selection and identification of relevant resource attributes as decision criteria.
- ii. Assign weights to the properties of the resources.
- iii. Using MCDA techniques to determine the order of preference for available resources.

MCDA is defined as a multi-step process consisting of a set of structured methods that evaluate various alternatives by analysing and evaluating criteria, capturing the preferences of experts, and using this preference data to create a preference model that evaluates the various alternatives and several criteria consolidated across the board (Langemeyer et al., 2016; Cinelli et al., 2020 ; Zlaugotne et al., 2020). Most MCDA model allow comparing alternatives through techniques such as ranking, sorting, classification, comparison, etc., thereby facilitating the decision-making process (Garg & Jain, 2017 ; Sennaroglu & Varlik Celebi, 2018; Cinelli et al., 2020; Zlaugotne et al., 2020).

3.3 Elements of Multi-Criteria Decision Analysis

There are common elements and concepts for the various MCDA methods based on natural decision problems (Zlaugotne et al., 2020). The main elements and concepts common to all MCDA methods are as follows:

- i. *Alternatives* are referred to as the different courses of actions available for consideration.
- i. *Attribute* is referred as a measurable or quantifiable characteristic of an alternative under consideration.

- ii. *Aggregation* refers to the process of assessing the performance of an alternative based on specific criteria as a means of making an informed decision regarding the alternative.
- iii. *Decision variables* are referred to as components of alternative's vectors.
- iv. *Decision space* is referred to as "feasible alternatives" within a decision process.
- v. *Elements* that are utilized to quantify an alternative to its attribute by assigning to the attribute numbers or symbols are referred to as *measures*.
- vi. *Criteria* are referred as "tools used for evaluating and comparing the different alternatives, considering the implications of their selection".
- vii. *Preferences* are referred to as "the extent to which an alternative fulfils the requirements of a decision-maker concerning a particular attribute".

3.4 Composition of MCDA Decision Makers

The quality of stakeholders involved in a decision-making process depends on the various assessment questions the MCDA needs to address and the decision-maker's intention to initiate the participatory process (Guarini et al., 2017). It is important to consider whether the decision-making process is a participatory process, a participatory process activated with a limited and specialized number of stakeholders, or a participatory process activated with a significant number activated by interest groups, preferably organized categories (Guarini et al., 2017). According to Guarini et al., 2017, the stakeholders that need to be included in the decision-making process can be classified:

- i. *Standard stakeholders*: these are stakeholders that have the required expertise to participate a decision-making process (Lahdelma et al., 2000).
- ii. *Interest groups*: these are stakeholders that encompass various groups, ranging from local or professional representatives, leaders of Non-Governmental Organizations (NGO), public sectors, etc (Guarini et al., 2017).

Both decision makers, whether standard or interest groups, have their own motives in evaluating the possible alternatives and often maintain different preference systems. Based on the nature of the variables involved, decision problems can be divided into three main groups (Guarini et al., 2017). These includes:

- i. *Descriptive problems* have the primary objective to distinguish between the distinctive features feature from a group of alternatives.
- i. *Sorting problems* defines similar alternatives based on their characteristics.
- ii. *Ranking choice problems* ranks alternatives into hierarchy ranging from the best to the worst.

It is worth noting that when evaluating the alternatives involved in a decision-making process, each stakeholder or interest group has its own driving factor or motivation that influences their rational systems of preference (Guarini et al., 2017).

According to Guarini et al., 2017 the expected solution to the decision problems can be divided into three categories depending on the specific information needs identified in the evaluation process:

- i. The closest alternative to the set objective.
- ii. The valid alternative based on the defined objective.
- iii. The best alternative based on the set objective.

3.5 Structure and properties of MCDA.

Regardless of the MCDA methods used to solve the decision-making process, certain properties are inherent in all methods (Taherdoost & Madanchian, 2023). Mathematically, MCDA problems are expressed as follows equation 3.1 and 3.2 :

$$A = \{A_i | i = 1, 2, \dots, m\} \tag{3.1}$$

Where A is a distinct and finite set of alternatives, and m represents the number of them.

$$C = \{C_i | i = 1, 2, \dots, n\} \tag{3.2}$$

where C is a set of certain criteria that are used to evaluate A , and n is the number of them.

Although the alternatives typically exhibit homogeneity, these characteristics are not necessarily the same for the criteria (Taherdoost & Madanchian, 2023). In most cases, alternatives tend to have similarities, while the criteria may differ from the characteristics of the alternatives. In other words, criteria can have different entities without any interrelationships and include conflicting objectives with both minimizing and maximizing objectives in equation 3.3.

$$W = \{W_i | i = 1, 2, \dots, n\} \tag{3.3}$$

where W is a set of normalized weights assigning to each criterion based on their importance. The MCDA problem can be convincingly expressed as a matrix in

Table 3.1: Structure and properties of MCDA methods with the alternatives represented by rows and the criteria represented by columns (Vassoney et al., 2021).

Table 3.1: Structure and properties of MCDA methods

MCDA Matrix	C_1	C_2	...	C_n
A_1	x_{11}	x_{12}	...	x_{1n}
A_2	x_{21}	x_{22}	...	x_{2n}
...	x_{ij}	...
A_m	x_{m1}	x_{m2}	...	x_{mn}

In the matrix above, x_{ij} represents the value of A_i to relate to C_i , and the matrix (M) and the weights' vector ($W = \{w_1, w_2, \dots, w_n\}$) are the basic inputs for the MCDA problems.

It is worth noting that in any matrix, the columns and rows can be reorganized based on the MCDA method for simplification (Taherdoost & Madanchian, 2023). Typically, MCDA assigns a score to each alternative and arranges them in order of best to worst. In general,

MCDA is divided into two smaller phases: compilation and construction. This phase refers to the assessment of the problem in question. These consist of different alternatives and their performance across different criteria and sub-criteria as well as their respective weighting and evaluation indicators (Guarini et al., 2018). In the second phase, the data contained in the evaluation matrix is processed with the aim of evaluating the alternatives in accordance with the defined goals. This phase includes data processing, which depends on a variety of different procedures depending on the method used (Battisti & Guarini, 2017).

3.6 Procedures of solving MCDA problems

There are different interpretations to solve an MCDA problem. However, the main goal is to rank the options based on their overall performance value. This is achieved by creating a preference ranking by combining their scores with appropriate weights. In general, an MCDA problem can be solved in four steps (Németh et al., 2019; Bączkiewicz et al., 2021; Taherdoost & Madanchian, 2023), these are:

- i. Choosing between alternatives: Analytic Hierarchy Process (AHP), Analytic Network Process (ANP), Multi-Attribute Utility Theory (MAUT), Utility Theory Application (UTA), Measuring Attractiveness by a Categorical Based Evaluation Technique (MACBETH), Preference Ranking Organization METHod Enrichment Evaluations (PROMETHEE), Elimination Et Choix Traduisan la REalite I (ELECTRE I), Technique for Order Preferences by Similarity to Ideal Solution (TOPSIS), etc.
- ii. Classifying alternatives: Analytic Hierarchy Sorting (AHSSort), UTilities Additives DIScriminantes (UTADIS), etc.
- iii. Identifying alternatives: Graphical Analysis for Interactive Aid (GAIA) and Feature Selection- Graphical Analysis for Interactive Aid (FS- GAIA).

- iv. Rating alternatives: Analytic Hierarchy Process Sensitivity (AHS), Aggregation of Assessment (AAS), Multi-Attribute Utility Theory (MAUT), Utility Theory Application (UTA), Measuring Attractiveness by a Categorical Based Evaluation Technique (MACBETH), Preference Ranking Organization METHod Enrichment Evaluations (PROMETHEE), Elimination Et Choix Traduisan la REalite I (ELECTRE III), Technique for Order Preferences by Similarity to Ideal Solution (TOPSIS), etc.

The complexity of MCDA problem solving and the decision-making process can be influenced by a variety of factors such as expertise, authority, risk level and other related aspects (Vassoney et al., 2021; Taherdoost & Madanchian, 2023).

3.7 Methods of calculating criteria weights

One of the most important indicators of the relative importance of each criterion in MCDA methods is the weighting of the criteria (Rădulescu et al., 2019). Measuring the weight of criteria is considered one of the biggest challenges in MCDA. This is reflected in the fact that the weighting of the criteria has a significant influence on the outcome of the decision-making process. Therefore, it is important to pay special attention to objectivity factors when determining criteria weight (Odu, 2019; Wątróbski et al., 2019). In most instances, according to Zanakis et al., 1998 ; Özcan et al., 2011, several contributing factors are responsible for the variations in results when applying different methods of calculating criteria weight:

- i. The different criteria weight estimation techniques use weights differently in the calculations.
- ii. The algorithms used to estimate the different criteria weights differ in their approach to selecting the “best solutions”.
- iii. Various algorithms attempt to normalize the goals and thus influence the criteria weights that already exist.

- iv. Certain algorithms are known to have additional parameters that influence the final decision recommendations.

Below are some of the inexhaustible techniques used to calculate criteria weights.

3.7.1 The point allocation method

This technique of determining weight is considered one of the simplest methods based on the priority of criteria. In this technique, a decision maker assigns a specific point to each criterion. The more points a criterion receives, the higher its relative importance (Gołaszewski & de Visser, 2012). The total number of points that a decision-maker awards for the criteria considered is 100 points. The sum of all criteria weights must be 100. It is imperative that the cumulative criteria weights of all criteria considered are 100. Normalizing criteria weights using this technique is quite simple. However, the weights determined using these methods are usually not very accurate. Furthermore, the application of the technique becomes increasingly difficult as the number of criteria increases beyond six (Odu, 2019).

3.7.2 The direct Rating method

The decision-maker first classifies all the criteria considered according to their relative importance. This method is also considered very easy to use, since it is possible to change one criterion independently without adjusting the weighting of another (Arbel, 1989). In this method, the estimation of the criteria weights is done simply by asking the involved stakeholders to assign numerical values to the different criteria, without having to make any compromises (Ribeiro et al., 2013).

3.7.3 The pairwise comparisons

This technique is used to analyse multiple populations in pairs to determine the extent to which they have statistically significant differences. Here, decision makers systematically compare each criterion with others and explain the degree of preference for each pair of such

criteria (Odu, 2019). The method uses a scale from 1 to 9 to determine the preference values of each criterion compared to another. For its application, the ANP is one of the most commonly used methods based on pairwise comparisons. The number of pairwise comparisons is determined by the formula in equation 3.4:

$$c_p = n(n - 1)/2 \quad 3.4$$

Where:

C_p is the number of comparisons.

n is the number of criteria.

Determining criteria weights based on the paired comparison method involves three steps:

- i. Matrix development by comparing the different criteria.
- ii. Weight calculation to get the priority value or the principal eigenvector.
- iii. Estimation of the consistency which involves conducting a sensitivity analysis or the consistency ratio.

In the AHP assessment, the decision problem is usually analysed in a hierarchical, multi-level structure with the aim of ultimately making a decision at the highest hierarchical level (Nemeth et al., 2019).

3.7.4 Ranking method

The ranking method is considered one of the simplest criteria weight estimation techniques, where the criteria are ranked from most important to worst (Odu, 2019). This method uses three methods to calculate the criteria weight, namely rank sum, rank exponent, and rank reciprocal, respectively.

Rank sum: In the rank sum method, criteria weights are determined by calculating individual ranks and then normalized by dividing the sum of those ranks (Uniwersytet & Roszkowska, 2013). Rank sum can be expressed in equation 3.5.

$$W_sRS = \frac{n - p_j}{\sum_{k=1}^n n - p_{k+1}} \quad 3.5$$

Where p_j is the rank of the j -th criterion, $j = 1, 2, \dots, n$

The rank exponent weight (RE) method: It has similarities to the rank sum method except that the calculated value is subjected to exponentiation by a parameter “ p ”, which is usually estimated by a decision maker based on the important criterion (Uniwersytet & Roszkowska, 2013). The rank exponent weight is express as shown in equation 3.6.

$$W_sRS = \frac{(n - P_j)^2}{(\sum_{k=1}^n n - p_{k+1})^p} \quad 3.6$$

where p_j is the rank of the j -th criterion, and p is the parameter describing the weights, $j = 1, 2, \dots, n$

The reciprocal (or inverse) weights (RR) method: This method uses the normalized reciprocal of the criterion rank (Uniwersytet & Roszkowska, 2013). it is expressed as shown in equation 3.7.

$$W_j(RS) = \frac{1/P_j}{\sum_{k=1}^n (1/p_k)} \quad 3.7$$

Where p_j is the rank of the j -th criterion, $j = 1, 2, 3, \dots, n$.

It should be noted that this method is not suitable for many criteria due to its ability to perform direct ranking. Most often, these techniques are considered methods for approximating criteria weights due to their simplicity and ease of checking criteria weights (Uniwersytet w Białymstoku & Roszkowska, 2013).

3.7.5 Ratio weighting method

This technique requires decision makers to rank relevant criteria based on their relative importance (Odu, 2019). Here, the criterion that is least important is assigned a value of 10, while the other criteria are assigned values that are multiples of 10. Finally, the estimated weights are normalized to ensure that their cumulative sum is equal to 1.

3.7.6 Swing weighting method.

In this method, the task of the decision maker is to identify the alternative with the worst outcome. The idea is to select the criteria where performance is most likely to change or fluctuate, moving from worst to best (Odu, 2019). The criterion with the best swing or change is often given the highest weight. Next, the decision maker strategically identifies the criteria whose performance wants to change from the worst to the best level. Values between 0 and 100 are assigned to indicate relative importance. The average normalized weight and the normalized weight intervals are determined (Parnell & Trainor, 2009). The consistency rule for the swing weight method is very important to ensure uniformity and reliability in weighting individual cells within the matrix. The following relationship is strictly adhered to ensure consistency between non-normalized swing weights is maintained (Odu, 2019).

- i. $C_R > C_i$ for all value of I in all other cell
- ii. $C_u > C_x, C_v, C_y, C_w, C_z$
- iii. $C_s > C_v, C_t, C_y, C_w, C_z$
- iv. $C_x > C_y, C_z$
- v. $C_v > C_y, C_w, C_z$
- vi. $C_t > C_w, C_z$

When assigning swing weights, stakeholders are required to strike a balance between the degree of importance and the variability of the measurement scale (Odu, 2019). This is done to allow stakeholders to assign a random weight to the top left side of the matrix. The normalized swing value for the i th value is expressed using the following equation 3.8.

$$W_i = \frac{C_i}{\sum_{i=1}^n C_i} \quad 3.8$$

Where C_i is the unnormalized swing weight.

Criteria levels are considered when calculating criteria weighting in the swing weighting technique. Stakeholders begin the decision-making process by imagining a hypothetical worst-case scenario in which all criteria considered are set to the worst possible level (Odu, 2019). The decision makers then identify the most important criterion by selecting the criterion whose expansion would lead to a significant improvement in the overall situation.

3.7.7 Nominal Group Technique (NGT)

It is a structured brainstorming technique for calculating criteria weights that is used to generate a significant number of ideas on a specific topic while ensuring that all participants are equally represented (Odu, 2019). In addition to the technique's ability to generate a significant number of ideas, it also serves the purpose of facilitating prioritization, with the ideas receiving the most selected votes (Abdullah & Islam, 2011). According to Odu, 2019, The following procedures are used to calculate criteria weights using experts with at least seven members:

Step 1: Generating ideas silently through writing: All participants have 10 minutes to articulate as many ideas as possible silently and independently on the respective topic.

Step 2: Round-robin recording of ideas on a flip pad: In this step, each participant is asked to submit the best idea from the list of ideas created in the first step. The different ideas are written on a flip pad or marker board. This process is repeated in a round-robin fashion, ensuring that all participants contribute until all ideas on the list have been exhausted.

Step 3: Idea discussion for clarification: Here all the ideas listed are discussed for clarification. The moderator first goes through the master list again and asks participants for feedback on the clarity of the meaning of the list presented. If an item on the list is not clear to participants, it is imperative that the person suggesting it, or another participant provides the necessary clarification.

Step 4: Voting to select the most important ideas: In this step, participants are tasked with selecting the five most important ideas from the master list provided and rating them on a scale of 1 to 5 representing their level of importance. The most important idea is assigned a score of 5, while the least important is given a score of 1. This evaluation is carried out by the different participants and the overall vote is calculated.

3.7.8 Simple Multi-Attribute Rating Technique (SMART)

This is a compensatory technique of multi-criteria decision making. Here experts are required to rank the criteria from worst to best in terms of their relative importance. This method uses a graded point system in which the most significant criterion receives 100 points, and the least important criterion receives 10. The remaining criteria are assigned an increasing number of points according to their relative importance. The criterion weight is then calculated by normalizing the sum of the points to one (Odu, 2019; Edwards, 1977).

3.7.9 Objective weighting methods

These techniques leverage information collected from each criterion by using mathematical functions to calculate the weights of the criteria without involving different decision makers (Odu, 2019). Examples of these methods are the entropy method, the mean weight, the standard deviation, the statistical variance method, and the criterion importance by intercriteria (CRITIC).

3.7.10 Entropy Method

This method is used to evaluate specific problems where the decision matrix contains certain amounts of information for a set of candidate materials (Odu, 2019). This technique is based on a predetermined decision matrix and is suitable for evaluating the relative importance of criteria using material data associated with each criterion. The set of normalized results of the j th criterion is given by the expression in equation 3.9.

$$E_j = -\frac{[\sum_{i=1}^m P_{ij} \ln(P_{ij})]}{\ln(m)}; j = 1, 2, \dots, n \text{ and } i = 1, 2, \dots, m \quad 3.9$$

where P_{ij} is gotten from the normalised decision matrix and is given by the expression in equation 3.10

$$P_{ij} = \frac{r_{ij}}{\sum_{i=1}^m r_{ij}}; i = 1, 2, \dots, \text{ and } j = 1, 2, \dots, n \quad 3.10$$

Where r_{ij} is an element of the decision matrix, k is a constant of the entropy equation and E_j as the information entropy value for j th criteria. Thus, the criteria weights, W_j is gotten using the expression equation 3.11.

$$W_j = \frac{r_{ij}}{\sum_{j=1}^n (1 - E_j)}; j = 1, 2, \dots, n \quad 3.11$$

where $(1-E_j)$ is the degree of diversity of the information involved in the outcome of the j th criterion.

3.8 Classification of MCDA

There are numerous MCDA methods available for quantifying, ranking, and sorting options. The criteria, alternatives, and solution set characteristics found in the decision problem structure influence which MCDA methods should be applied (Arslan, 2018).

The MCDA techniques can be broadly divided into two main classes based on their purpose and data organization: examples of multi-purpose decision making (MPDM), vector optimization objective programming, de novo programming, data envelopment analysis, and examples of multi-quality decision making (MQDM). Examples include: AHP, ANP, TOPSIS, ELECTRE, PROMETHEE, “VIKtor Kriterijumska Optimizacija I Kompromisno Resenja” translated to “VIKtor Criterion Optimization and Compromise Solution” (VIKTOR), Decision Making Trial and Evaluation Laboratory (DEMATEL) (Arslan, 2018)I.

According to Hodgett, 2016, MCDA methods can also be classified into two types based on attributes: multi-attribute (MA) methods and outranking methods. The MA methods aggregate a decision problem and provide a numerical result for each alternative that can be maximized (AHP, ANP, weighted sum, TOPSIS, etc.), while the outranking methods sort or rank alternatives by giving pairwise outranking scores of each determine pairs of alternatives (ELECTRE, PROMETHEE) (Arslan, 2018). The type of approach can be used to evaluate problems with a predefined number of available choices.

Arslan, 2018 categorized MCDA problems according to the type of data involved, which includes deterministic, stochastic and fuzzy data. Taherdoost et al., 2023 classified MCDAs into three methods based on the feasibility of negative criteria for attributes and the degree of compensation: compensatory (e.g. SAW, AHP), non-compensatory (e.g. ELECTRE III, Lexicographic, Aspect Elimination, Sat elimination by aspect, satisticing), and partially compensatory (weighted sum model, TOPSIS). Sabaei et al., 2015, on the other hand, classified MCDA techniques based on the number of decision makers involved, as either an individual (TOPSIS, Simple Additive Weighing) or a group decision-making approach (AHP, Evaluation Based on Distance Average (EDAS)). Taherdoost et al., 2023 further classified MCDA techniques into tradeoff-based and non-tradeoff-based methods. According to Arslan, 2018 MCDA techniques can also be grouped based on the quantity of decision makers as; Elementary

(Dominance, Maximin, Lexicographic, Conjunctive, Elimination by aspects, Linear assignment, Additive Weighting, Weighted Product), Unique Synthesis Criterion (MAVT, MAUT, Utility theory additive, AHP, TOPSIS, SMART, Fuzzy Weighted System, Fuzzy Maximum, Grey Relational Analysis, etc.), and Outranking (ELECTRE I, IS, ELECTRE II, ELECTRE III, IV, TRI, PROMETHEE I, II, ORSETE). MCDA methods are classified based on factors such as data, criteria, alternatives, or the number of decision makers as; Basic Methods (Graphical Methods, Simplex Method, Linear Programming, Integer Programming, Goal Programming), Single Analytical Methods (AHP, ANP, MAUT, SMART, TOPSIS, Data Envelopment Analysis, Grey Relational Analysis, etc.) and Hybrid Methods. The Hybrid methods can be further classified as follows; This method, when combined with other techniques, considers criteria, and involves a single analysis example are AHP and VKTOR. Methods that use both single analysis and fuzzy logic simultaneously example Fuzzy logic TOPSIS. Methods that use a single analysis as well as other optimization techniques at the same time example AHP, genetic algorithm (Arslan, 2018). Outranking relations (ELECTRE, PROMETHEE), utility function; Additive Ratio Assessment (ARA), discriminant function, and function-free models (AHP, ELECTRE) are some of the aggregation methods used by MCDM (Taherdoost & Madanchian, 2023). Lastly, based on attributes and objective, Tzeng et al., 2013 categorized MCDA techniques into multi-attribute decision making (MADM) and multi-objective decision making (MODM).

3.9 MCDA in epidemiology

Zhao et al., 2020 observed that MCDA has been used in a variety of fields, including public health, agriculture, transportation, and urban planning. Multi-criteria decision-making considers the nonlinear relationships that are typical between disease organisms and the

environment and employs statistical techniques and human intuition. It also allows for expert engagement (Zhao et al., 2020; Tavana et al., 2010; Gigović et al., 2019; Marsh et al., 2018).

Multi-attribute decision-making techniques are designed for choosing discrete options, whereas multi-objective decision-making techniques are better suited for handling multi-objective planning issues, which have a theoretically unlimited number of continuous alternatives determined by a set of constraints on a vector of decision variables (Opricovic et al., 2004). Multi-criteria decision analysis also enables the use of decision rules derived from existing knowledge or speculated understanding of the factors leading to disease occurrence in estimating disease risk (Zhao et al., 2020).

Tsoutsos et al., 2009; Pohekar et al., 2004, theorized that there are many justifications for adopting multi-criteria decision-making processes in any field of research:

- i. It enables the analysis and incorporation of the interests and objectives of many variables.
- ii. It manages the complexity of the multi-actor scenario.
- iii. It's user-friendliness because the suggested criteria are estimated and assigned values that are consistent and comparable with the supplied data.
- iv. The outcomes are pertinent and readily applicable for the relevant stakeholders due to the output format.
- v. It is a popular and widely used evaluation approach that also contains several iterations of the method created and investigated for certain issues and/or circumstances.
- vi. It is a technique that provides for objectivity and inclusivity of various perceptions and interests of the experts without requiring a lot of time and money.
- vii. The techniques can offer alternatives to management issues that are becoming more complex.

- viii. They let participants play a more active role in decision-making procedures, promote consensus, and group decisions, and offer an excellent platform for studying models' and analysts' perceptions of reality in a practical setting.
- ix. It provides higher decision-quality outcomes by making decisions clearer, logical, and effective.
- x. It's easier to negotiate, evaluate, and communicate the priorities.
- xi. There are limitations to each technique. According to Kangas et al., 2002 some of the limitations are enumerates as follow:
- xii. Primarily due to model assumptions.
- xiii. The formulations of the decision problems do not equate to the same decision patterns.
- xiv. Different approaches have different ways of processing preference data.
- xv. Different methods use different interpretations of the criterion weights.

In its most basic form, MCE is a structured tool that allows for the evaluation of alternatives based on multiple, possibly conflicting, or even incommensurate criteria in a decision problem.

3.10 Spatial-MCDA

Spatial MCDA, also known as GIS-MCDA, is a combination of geographic information systems and MCDA that can be used to better understand how planning, land use, and demographics influence program management in public health and other sectors (Zhao et al., 2020). GIS-MCDA is beneficial because it is an evidentiary reasoning technique that reduces the unstructured nature of the problem and provides a structured framework for information interaction between the various stakeholders. It can also be used to streamline and optimize the decision-making process (Zhao et al., 2020). In recent years, risk modelling/mapping for vector-borne diseases has found wide application of GIS-MCDA (Bhatt et al., 2014).

According to Tavana et al., 2010, spatial-MCDA makes malaria hazard and risk modelling/mapping more efficient, methodical and thorough. The design and implementation of prevention and control strategies can be directly influenced by socio-environmental and environmental factors, local malaria transmission patterns, and spatially accurate and fine-grained risk maps, which can assist in planning, decision-making, and prioritization of areas for targeted control interventions (Sturrock et al., 2016).

There are five phases in evaluating spatial MCDA. These include the following: identification of risk factors, determining the relative importance of the risk factors, standardizing the risk factors, evaluating multiple criteria, and assessing accuracy. These stages will be discussed in detail in chapter four.

Chapter 4: Methodology

In order to guarantee the reproducibility of this research, the methodology used in analysing, mapping, and modelling the spatial distribution of malaria transmission risk in the Northern Zone of Nigeria's Plateau State is covered in chapter four. This chapter also provides a comprehensive assessment of malaria prevalence, identification of the various risk factors, incidence, and transmission rate of the disease. In addition, the chapter discusses the techniques used to identify, process, and collect the various datasets used in analysing, mapping, and modelling the spatial risk of the disease. Furthermore, the chapter discusses the integration of expert intuition and the analysed spatial dataset through spatial MCDA in evaluating the various risk factors and determining their relative importance. These processes help assess and model the spatial distribution of malaria risk in the study area. This is in addition to guiding decision-makers in implementing appropriate vector intervention measures and other vector management practices. Finally, the chapter discusses model validation techniques used in evaluating the accuracy of the model using techniques to perform sensitivity and hotspot/density analysis of the risk model.

4.1 Study area.

The research is conducted in the Northern Zone of Plateau State Nigeria and the dataset were collected over a period of five years, from 2017 to 2021. As shown in the Figure 4 1: **Map of Nigeria showing the study area.** below, the area comprises six Local Government Areas (L.G.As): Bassa L.G.A, Jos North L.G.A, Jos South L.G.A, Jos East L.G.A, Barkin Ladi L.G.A and Riyom L.G.A.

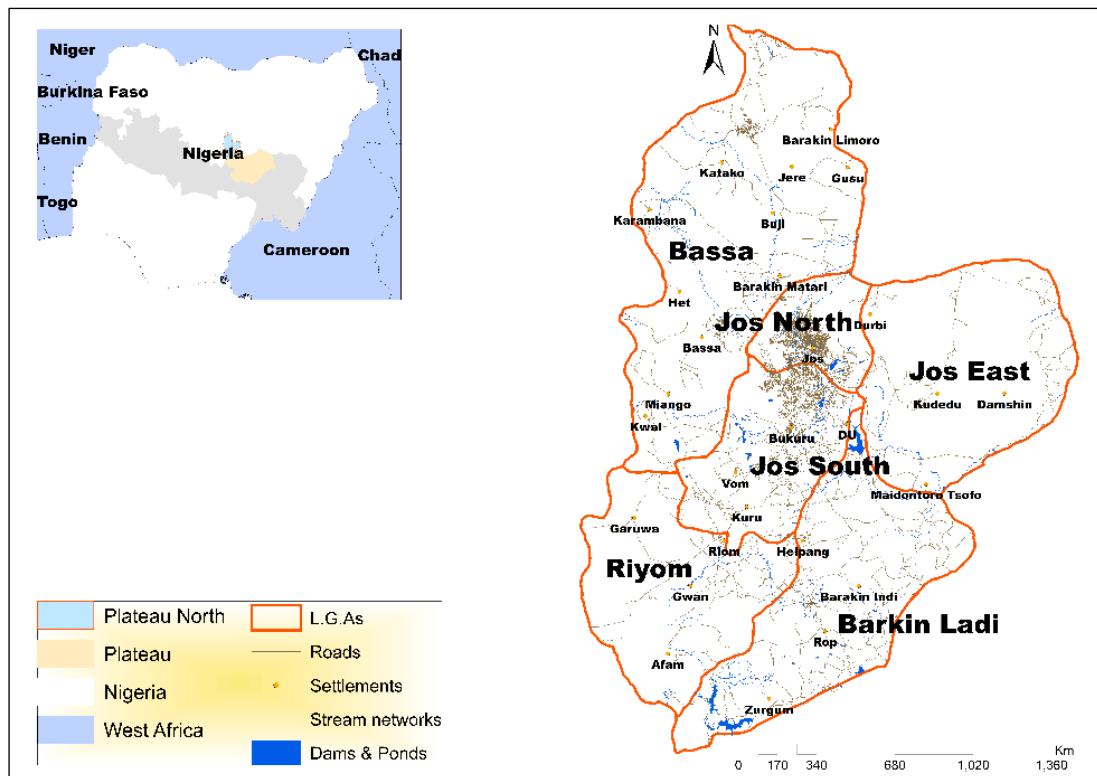


Figure 4 1: Map of Nigeria showing the study area.

The study area is located in Plateau State, North Central Nigeria and occupies an estimated area of 4,777.89 km². It lies between latitude 9' and 10' N; and longitude 8' and 9' E with an elevation of 1280 meters above sea level. It is surrounded by granitic hills and other rock outcrops with an elevation of about 300 metres. The research area is located on the peak of the Plateau which gradually slopes towards the north-eastern, and north-western sides. The area has an abrupt 600m escarpment runs along the southern side of the plateau. Lee, 1972 described the vegetation as northern Guinea savanna, which mostly consists of a wide grassland and farms, with occasional punctuations of rocky hills and small patches of indigenous arboreal vegetation and reforested zones. Within the study area, there are a few abandoned mining ponds that could serve as mosquito breeding grounds.

The study area's climate is divided into two seasons: the dry season, which lasts from November to April, and the wet season, which lasts from May to October. An annual monthly temperature range of 22.8-36.1 C and 10.2-20.8 C, respectively. Most agricultural practises in

the study area are peasant farming of cereals (sorghum, maize, and guinea corn). Coco yams, cassava, vegetables, and Irish potatoes are examples of root crops that are grown commercially.

4.2 Data requirements

An assessment of malaria prevalence was conducted in the study area through disease vulnerability assessment. This was done through an assessment of the topography, geomorphology, anthropogenic activities, climatic variations, demographics, and infrastructural structure of the study area. This helped in identifying the various risk factors and understanding the incidence and transmission rate of the disease as shown in Figure 4.2:

Malaria susceptibility assessment and risk classification. below.

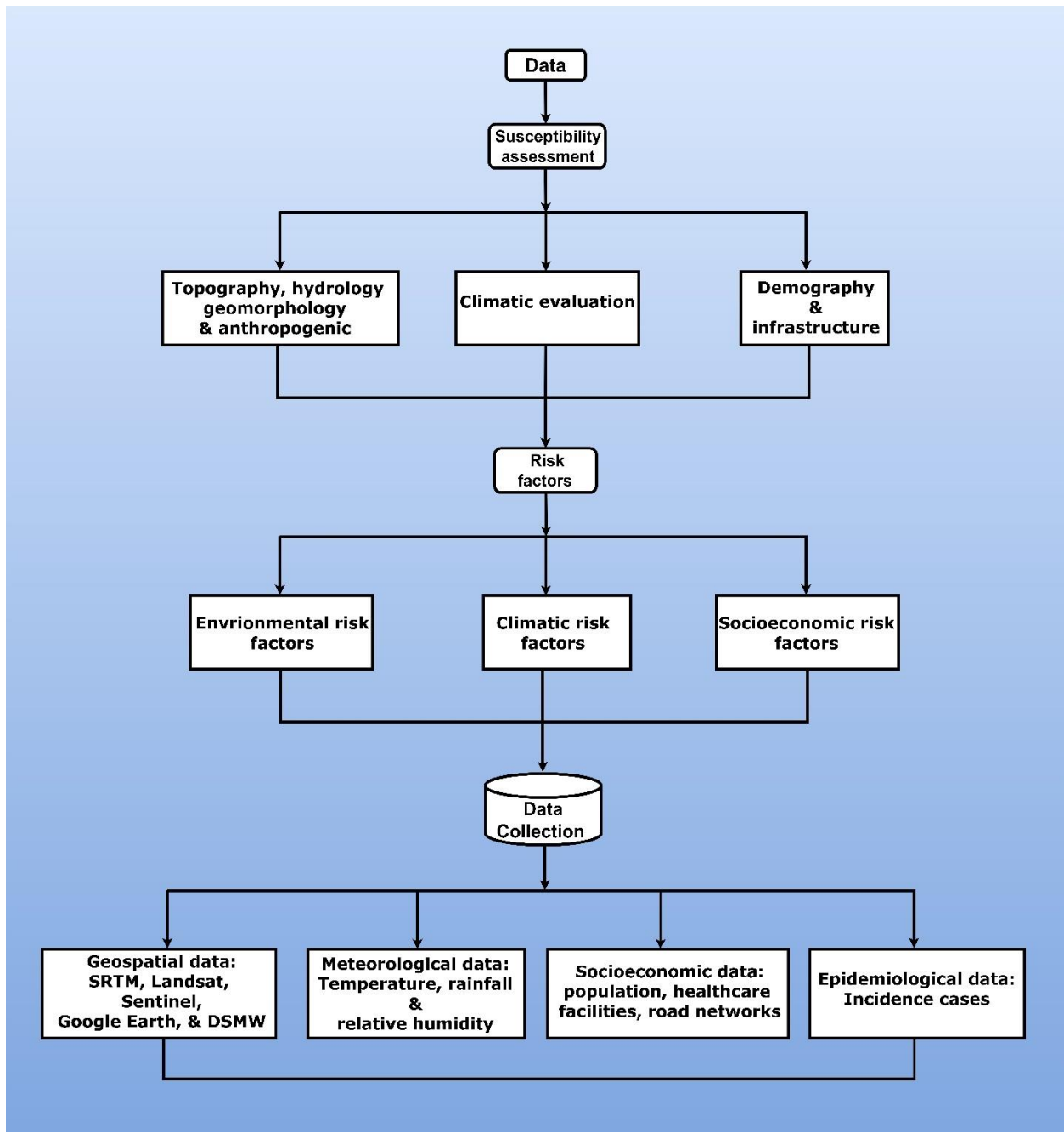


Figure 4.2: Malaria susceptibility assessment and risk classification.

Finally, the study analysed, mapped, and modelled the spatial distribution of the disease risk in the study area. The data requirements for this thesis were therefore identified and classified as follows:

4.2.1 Epidemiological data

Monthly malaria incidence data were collected from Nigeria's National Malaria Elimination Program, the Centre for Disease Control, and various health facilities, including public hospitals, private hospitals, local clinics, rural health centres, and state and national ministries of health for a five-year period spanning 2017-2021. The data was recorded as persons with fever, persons tested positive for fever by RDT, persons tested positive for fever by microscopy, persons with confirmed uncomplicated malaria, persons with severe malaria and clinically diagnosed malaria. In addition, the type and category of the health facility, their spatial reference locations, and the L.G.As. recorded in detail.

4.2.2 Environmental data

Based on an in-depth assessment of the study area in terms of its topography, hydrology, geomorphology and anthropogenic activities, the environmental risk factors were identified, and necessary data were collected on their propensity for malaria transmission. These include aspect, elevation, topographic wetness index, soil moisture index, soil types, land use/land cover, land surface temperature, water bodies and vegetation health index.

4.2.3 Socioeconomic data

The propensity of socio-economic factor to malaria transmission risk was equally assessed using parameters such as infrastructural composition, demographics, etc. and the required data set collected. These includes the following: population density, population of the most vulnerable age group (children under 5years), distance to health facilities and distances from settlements to road networks as risk factors influencing mosquito breeding habitats and malaria transmission in the study area.

The population density for the general population and the vulnerable age group population are estimated from the 2006 National Population Commission census projections and the data were correlated to the neighbourhood administrative units. Furthermore, the

different road networks and the distances to settlements within the study area were delineated from 0.5 metres-resolution Google Earth image within the ArcGIS 10.8 extension.

4.2.4 Climatic/meteorological data

In this thesis, ambient temperature, precipitation, and relative humidity were identified as key meteorological risk parameters influencing mosquito breeding habitats and malaria transmission in the northern zone of Plateau State, Nigeria. These climate datasets were collected from the Jos weather station of the Nigerian Meteorological Agency.

4.2.5 Software packages

Different software packages and programming languages such as Arc GIS 10.8, Quantum GIS, ERDAS Imagine, E-View software, RStudio and Python programming languages were used to analyse the different dataset. Table 4.1: Data requirements below summarizes the datasets requirements for analysis, mapping and modelling of malaria vector suitable breeding habitats and transmission risks in the Northern Zone of Plateau State Nigeria.

Table 4.1: Data requirements

S/No	Data	Spatial Resolution	Model Analysis	Acquisition Sites
1	Shuttle Radar Thematic Mapper	30*30m	Topographic Wetness Index, Aspect and Elevation	https://earthexplorer.usgs.gov/
2	Sentinel 2	10*10m	Landuse/landcover Land Surface Temperature, Soil Moisture Index,	https://scihub.copernicus.eu/dhus/#/home
3	Landsat 8 OLR/TIR	30*30m	Vegetation Health Index, and Normalized Difference Vegetation Index	https://earthexplorer.usgs.gov/
4	Google Earth Image	0.5m	Roads, Stream, Ponds, and Dams	QGIS Tiles-Plugin Extension
5	Digital Soil Map of the World	5*5 arc minutes	Soil Type Classification	http://www.fao.org/geonetwork/srv/en/...
6	Temperature, Relative Humidity & Rainfall		Temperature, Relative Humidity & Rainfall	https://power.larc.nasa.gov/data-access-viewer/
7	Population Density		Population, Population of vulnerable group	National Population Commission Nigeria
8	Distance to Hospital		Distance to nearest hospital	https://hfr.health.gov.ng/facilities/hospitals-list

4.3 Data cleaning and processing.

Malaria risk analysis, mapping and modelling requires careful collection, cleaning, and processing of various datasets to ensure the accuracy and completeness of both primary and secondary data as shown in Figure 4.3: Schematic representation of the methodology below.

The data preparation processes that include cleaning and processing are discussed and classified as follows:

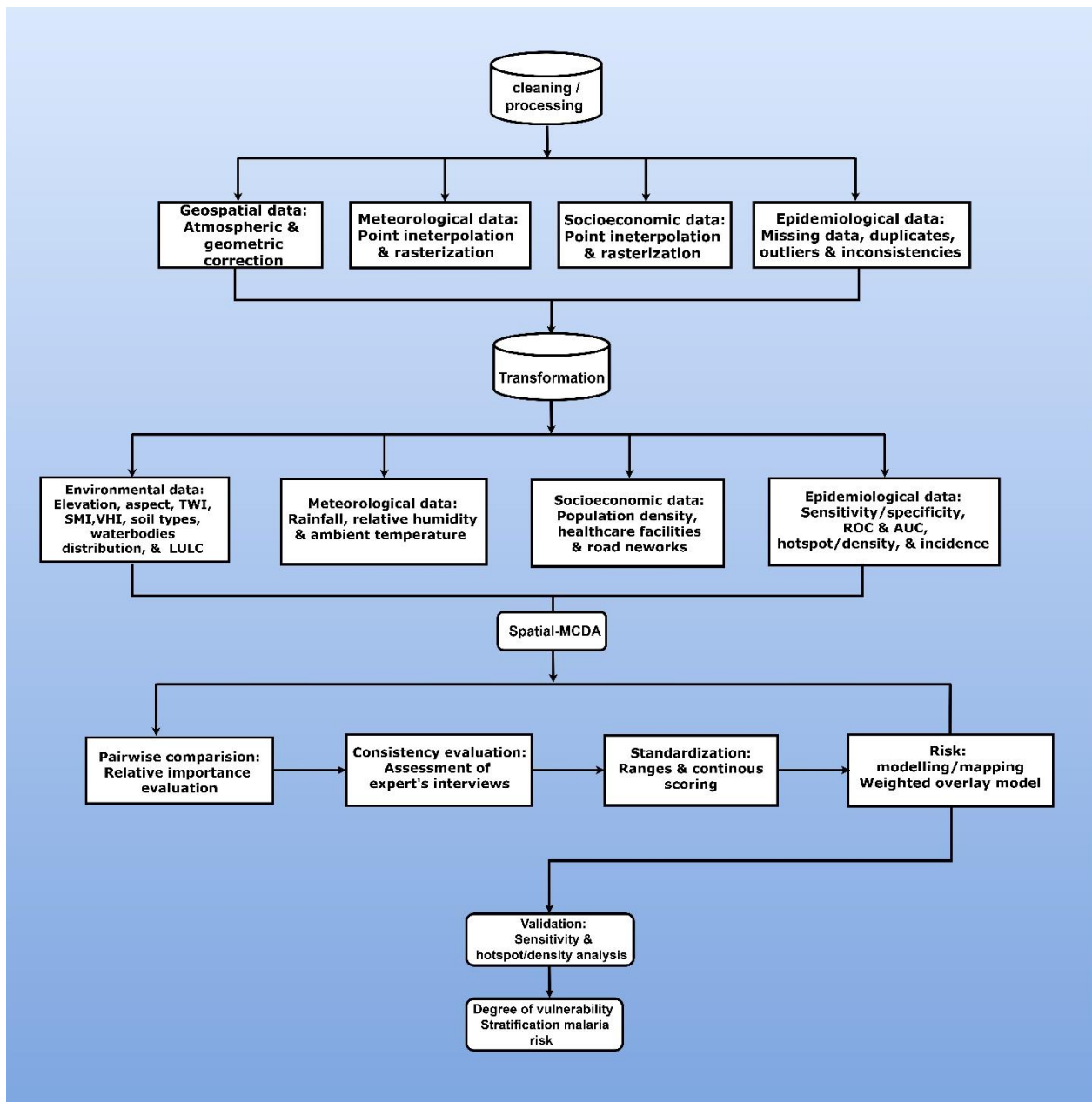


Figure 4.3: Schematic representation of the methodology

4.3.1 Epidemiological data

The epidemiological data collected from various data sources in the study area were checked for completeness and data integrity was also checked. Data cleaning processes include checking for missing data, duplicates, outliers, and inconsistencies in the various variables analysed. The imputation technique analysed in the Rstudio environment was used to resolve missing values, assigning plausible values based on observed patterns in the existing dataset. In addition, data cleansing processes were carried out, which included identifying and correcting errors/inconsistencies by cross-checking the data with known sources to ensure accuracy. Finally, these data sets were organized into formats that can be easily analysed statistically.

4.3.2 Satellite image processing

The various spatial data collected for the study area were analysed and processed to eliminate the influence of external elements and other disturbances such as scattering, absorption and instrument calibration that may occur during the data collection process. This is done in order to obtain an accurate representation of the features and phenomena of the Earth from the various analyses carried out. Some of the processing carried out on the geospatial data are listed below.

Atmospheric Correction: According to Vermote et al., 1997, the presence of other elements in the atmosphere has a strong influence on most satellite images of land surface in the visible and near infrared ranges. Atmospheric correction is defined as the recovery of reflected spectra from measured radiance. It is calculated using the formula in equation 4.1:

$$\text{Atmospheric correction} = \text{Landsat band } x / \sin(\text{sun elevation}) \quad 4.1$$

When performing multi-temporal and/or multi-sensor analyses such as the Normalized Difference Vegetation Index (NDVI), Normalized Difference Built-Up Index (NDBI),

Normalized Difference Water Index (NDWI), Land Surface Temperature (LST), and so on, atmospheric correction is necessary (Rozenstein et al., 2014).

Radiometric correction: Scattering and atmospheric absorption, the geometry of sensor target illumination, sensor calibration, and image processing processes all impact Landsat images (Rozenstein et al., 2014). These factors may influence image quality over time. To detect landscape changes in surface reflectance, multi-dated satellite images must be radiometrically corrected (Rozenstein et al., 2014). In the ArcGIS software environment, the following algorithm is used to perform radiometric correction in equation 4.2

$$\begin{aligned}
 & \text{Digital Number (DN) Value to Top of Atmosphere Reflectance} && 4.2 \\
 & = \text{Band Specific Mult_Band X} * \text{DN Values} \\
 & + \text{Reflectance Band X}
 \end{aligned}$$

Band rationing: Band rationing is a technique that is commonly used to remove shadows from satellite images, resulting in a true reflectance of the surface.

Normalized Difference Vegetation Index (NDVI): This calculates the thickness of vegetative cover in a specific location using two bands of satellite imagery. It uses the Near Infrared band and the Red Band, which corresponds to Landsat Band 4 and 5 in Landsat image 8 respectively. This assumes that vegetation's chlorophyll content is typically absorbed strongly by the red wavelength and reflected by the Near Infrared wavelength. NDVI is calculated as in equation 4.3.

$$NDVI = \frac{NIR - RED}{NIR + RED} \quad 4.3$$

Where:

NIR = Near Infrared = Landsat Band 5

RED = Red = Landsat Band 4.

The possible of NDVI values ranges between -1 and +1. Values tending towards -1 indicates that the vegetation is less green (not healthy or no vegetative cover/bare surfaces) whereas, values tending towards +1 shows that the vegetation cover are much healthier.

Conversion of digital number to top of atmosphere radiance: According to Esri, 2014, Landsat8 imagery can be converted to Top of Atmosphere spectral Radiance using the radiance scaling factor gotten from the metadata files shown in equation 4.4.

$$L\lambda = M_L * Q_{cal} + A_L \tag{4.4}$$

Where:

$L\lambda$ = Top of Atmosphere Spectral Radiance (watts/cm² * Srad * μm)

M_L = Band-specific multiplicative rescaling factor from the metadata (RADIANCE_MULT_BAND_x, where x is the band number).

Q_{cal} = corresponds to band 10.

A_L = Band-specific additive rescaling factor from the metadata (RADIANCE_ADD_BAND_x, where x is the band number).

Q_{cal} = Quantized and calibrated standard product pixel value (Digital Number)

Converting radiance to at-satellite brightness: The band data from thermal infrared sensors can be converted from spectral radiance to brightness temperature using the thermal constant provided in the metadata file shown in equation 4.5

$$T(^{\circ}C) = \frac{K_2}{\ln\left(\frac{K_1}{L\lambda} + 1\right)} - 272.15 \tag{4.5}$$

Where:

T = At-satellite brightness temperature (K)

$L\lambda$ = Top of Atmosphere Spectral Radiance (watts/cm² * Srad * μm)

K_1 = Band Specific thermal conversion constant from the metadata
($K_1_constant_BandX$)

K_2 = Band Specific thermal conversion constant from the metadata
($K_2_constant_BandX$)

Where, X = Thermal Band number.

-272.15 is the conversion constant from Kelvin to degree centigrade.

4.4 Data analysis

Various analyses of the different datasets were carried out using GIS software packages such as ERDAS Imagine, ArcGIS, QGIS, and programming languages such as Rstudio and Python. These various variable analyses are mainly used as predictors/indicators for the malaria incidence/prevalence model. The following will be included in their analyses:

4.4.1 Epidemiological data analysis

Sensitivity analysis: Receiver Operation Characteristics (ROC) and Area Under the Curve (AUC) were calculated using RStudio to validate the predictability and accuracy of the malaria model in the northern zone of Plateau State, Nigeria. To validate the accuracy of the developed model, the performance of the model was compared with epidemiological datasets. According to Zhao et al., 2020, the AUC of a model reflects the suitability of the risk model for malaria transmission. In any quantitative validation of a risk model, an AUC with a relatively high predictive power is considered useful for prediction. According to Swets, 1988; Manel et al., 2001, an AUC of 50-70% indicates low accuracy, 70-90% indicates useful applications, and >90% indicates very high accuracy.

This study involves determining the average risk in the study area and then using the fuzzy membership function to derive the predicted values from the suitability model. According

to Zhao et al., 2020, since the scale information differs in the spatial parameter layers, a fuzzy membership function is used to standardize the different layers to a common scale range, which is necessary to facilitate model integration. This uses control points determined by correlating the layer with malaria vectors to assess the degree of membership of data cells within a layer.

Density and hotspot analysis: Kernel Density determines the concentration of points in the area surrounding each raster cell in the final output (Ozdarici-Ok et al., 2022). This study uses kernel density analysis to determine the density distribution of malaria cases in the study area to provide a more comprehensive understanding of the spatial distribution and density of confirmed malaria cases compared to malaria risk factor model analysis. The kernel density analysis values for the study area are divided into seven classes based on the Jenk classification of natural fractures, with or without major consideration of confirmed malaria cases.

While kernel density can provide information about clusters of points at a particular location, it does not provide any indication of the statistical significance of the clusters (Ozdarici-Ok et al., 2022). This limitation is overcome by hot spot analysis, which locates clusters and evaluates their statistical significance. The Ord-Gi statistic for each feature in a point dataset can be calculated using hot spot analysis by considering each feature in the context of neighboring features. The returned Gi statistic represents a Z-score for each feature in the data set. Using the Getis Ord Gi statistic, the hot spot analysis produced a map that indicated statistically significant hot and cold spots (Ozdarici-Ok et al., 2022). A larger Z-score with statistically significant positive Z-scores indicates a more intense accumulation of high values (hot spot). A smaller Z-score, on the other hand, indicates a more intense accumulation of low values for statistically significant negative Z-scores (cold spot).

Finally, malaria Incidence data for the study area is calculated using the malaria incidence per 1000 people formula in equation 4.6.

Malaria incidence per 1000 persons

4.6

$$= \frac{\text{No. of suspected malaria patients}}{\text{Total Population}} \times 1000$$

4.4.2 Environmental data analysis

After carrying out the necessary spatial data processing, corrections, and conversion of the digital number to reflectivity, the following analysis was carried out to determine the relationship between environmental parameters, their stability and accessibility of mosquito breeding sites and the risk of malaria transmission. These include the following.

Shuttle Radar Topographic Mission (SRTM): The SRTM data using the shapefile of the northern zone of Plateau State, Nigeria with a spatial resolution of 30 meters is processed by filling in the void spaces. The filled SRTM is then used to perform various topographical analyses which includes the following.

Elevation: Elevation values are defined by elevation profiles across the entire area of a map or scene (Esri, 2021). Using the filled SRTM, the elevation of the study area based on its propensity for malaria transmission is analyzed. A Digital Elevation Model (DEM) was constructed using the SRTM of the study area to determine the relationship between topography and terrain, as well as the suitability and accessibility of mosquito breeding sites and malaria transmission using a 30 m SRTM shown in Figure 4.4: Environmental risk factors(H).

Aspect: Aspect describes the slope and direction of a continuous surface, such as the terrain seen in a DEM (Buckley, 2019). Aspect has been identified as a key component in malaria transmission. Due to the lack of direct sunlight, higher moisture content and denser vegetation than other aspects, the northern aspects covering the area from NW340 to NE70 are also known as shadow areas (Atieli et al., 2011; Ahmad et al., 2017). The aspect of the study area was examined based on its susceptibility to malaria transmission shown in Figure 4.4: Environmental risk factors(E).

Topographic wetness index: The primary method for measuring topographic control over hydrological processes is the topographic wetness index (Sørensen et al., 2006). The slope and the upstream contributing area per unit width orthogonal to the flow direction determine the topographic wetness index. The topographic make-up of an area in terms of its ability to collect and pool water can be identified using hydrologic techniques, that help model how water moves over a given surface (Sørensen et al., 2006). The topographic wetness index of the study area was analyzed on the bases of its susceptibility to malaria transmission shown in Figure 4.4(G).

Land surface temperature estimation: Climate change, urban climate, the hydrological cycle, and vegetation monitoring are just some of the uses for land surface temperature estimation (Rozenstein et al., 2014). Depending on the type of analysis, different techniques such as split-window algorithm, single-mono-window algorithm and others can be used to estimate land surface temperature. However, the split window algorithm uses a variation in the atmospheric absorption of two adjacent long-wave infrared (LWIR) bands to accurately determine surface temperatures (Rozenstein et al., 2014). According to Rajeshwari et al., 2014, when predicting land surface temperature using Landsat 8 data, the single window algorithm is known to perform better. The single-window algorithm has been used for several operations of various sensors, including the Moderate Resolution Imaging Spectrometer, the Advanced Along-Track Scanning Radiometer, and the Advanced Very High-Resolution Radiometer (AVHRR), among others. The single-window algorithm was chosen for this study due to its accuracy when using the Landsat-8 dataset. After converting Radiance to At-Satellite Brightness, the average of the two thermal bands (Bands 10 and 11) is calculated. The Land Surface Emissivity is then calculated to determine the proportion of vegetation used in calculating the Land Surface Temperature.

Land Surface Emissivity is calculated by the algorithm in equation 4.7 below.

$$PV = \text{square}\left(\frac{NDVI - NDVI_{min}}{NDVI_{max} + NDVI_{min}}\right) \quad 4.7$$

Where:

PV = Proportion of Vegetation.

Emissivity:

$$e = 0.004PV + 0.986$$

Where:

e = emissivity.

After getting all the variables, the Land Surface Temperature is calculated using the algorithm in equation 4.8 below.

$$LST = \frac{BT}{1 + W} * \left(\frac{BT}{p}\right) * \ln(e) \quad 4.8$$

Where:

BT = At-Satellite Temperature

W = Wavelength of emitted radiance (11.5 μ m) which corresponds to Landsat Band 10 without any correction.

$$P = h * c / s \quad (1.438 * 10^{-2} \text{ mk})$$

Where:

h = Planck's constant (6.626 * 10⁻³⁴ Js)

s = Boltzman constant (1.38 * 10⁻²³ J/K)

C = Velocity of light (2.998 * 10⁸ m/s)

The value of p is estimated to be 14380.

The land surface temperature estimates of the study area shown in Figure 4.4: Environmental risk factors (J)below.

Soil moisture index: According to Magagi et al., 2022, soil moisture retention capacities, or permeabilities, are essential components for malaria vector reproduction. soil moisture

retention capacities have been identified as one of the most important elements that influences the development of water-logged areas. After performing all necessary Band corrections and calculating the Land Surface Temperature, the Soil Moisture Index using the algorithm in equation 4.9 below.

$$\text{Soil Moisture Index} = \frac{(\text{Land Surface Temperature max} - \text{Land Surface Temperature})}{(\text{Land Surface Temperature max} - \text{Land Surface Temperature min})} \quad 4.9$$

The study area soil moisture index estimate presented below as shown in Figure 4.4: Environmental risk factors Figure 4.4: Environmental risk factors(B)

Vegetation health indices: Rahman et al., 2010, identified a correlation between malaria transmission and vegetation density distribution. They stipulate that mosquito activity decreases in the cooler months of the year, when vegetation is less healthy, and fewer malaria cases are recorded during this period. As the number of cases increased, a greater association was observed between the annual variation in malaria incidence and the temperature condition index than with the Vegetation Health Index (VHI).

Using Landsat 8 Band 4 visible red and Band 5 near infrared images with wavelengths of 0.630 to 0.680 m and 0.845 to 0.445 m, respectively, the vegetation health index was calculated for the study region. The indices, which include the Vegetation Condition Index (VCI) for moisture conditions, the Temperature Condition Index (TCI) for thermal conditions, and the Vegetation Health Index (VHI), were calculated using the Normalized Difference Vegetation Index (NDVI) and the Brightness Temperature (BT) from Landsat8 image.

NDVI and BT were used to calculate the Vegetation Condition Index (VCI) in equation 4.11, which represents the moisture conditions, the Temperature Condition Index (TCI) in equation 4.12, which represents the thermal conditions, and finally the Vegetation Health Index (VHI) in equation 4.10 and Figure 4.4: **Environmental risk factors (A)**.

$$VHI = a * VCI + (1 - a) * TCI \quad 4.10$$

$$VCI = 100[(NDVI - NDVI_{min})/(NDVI_{max} - NDVI_{min})] \quad 4.11$$

$$TCI = (BT_{max} - BT)/(BT_{max} - BT_{min}) \quad 4.12$$

Where:

VCI is the Vegetation Condition Index

TCI is the Temperature Condition Index, and BT is the red band count (Band 4) that has been converted to Brightness Temperature. a = coefficient of the quantifying share of the VCI versus TCI contribution to vegetation Health. The shares values are usually not known for specific locations; thus, it is assumed to be equal. $a = 0.5$.

The three indicators range from 0 to 100 as shown in Figure 4.4: Environmental risk factors (A), with 100 reflecting very favorable vegetation conditions, high NDVI and cool BT and 0 reflecting heavily stressed vegetation, very low NDVI and hot BT.

Soil type: Soils with finer grains have lower permeability, resulting in waterlogged areas, while soils with coarser grains allow water to seep through due to their porosity (Bhatt et al., 2014). Additionally, Bhatt et al., 2014 theorized that the poorly drained, fine-grained soil promotes water retention, which facilitates the reproduction of malaria vectors. In contrast, coarse-grained soils are well drained and do not allow water accumulation, making them unsuitable for vector breeding. The different soil classes analyzed for the study area shown in Figure 4.4: Environmental risk factors (F) below are as follows: loamy, loamy-sand, sandy clay-loam, and sandy loam.

Landuse and Landcover activities: Land use and land cover activities have been observed to play a key role in the occurrence of malaria and in the transmission and distribution of the disease (Kumi-Boateng et al., 2015). The majority of malaria cases in most urban areas are attributed to human-induced activities changes in land use and land cover activities, which create favourable conditions for the reproduction of malaria vectors in the region (Bindu et al., 2009).

A supervised classification method using the maximum likelihood classification technique was used to classify the satellite image into eight land use and land cover classes based on the propensity of the different classes to transmit malaria as shown in Figure 4.4: Environmental risk factors (I). The topographic map of the study area served as a guide for the classification processes.

Ponds, Dams and Stream Network Distribution: The presence of water bodies in any location such as streams, rivers, dams, ponds, etc. is considered to be one of the most visible and significant variables in the spread and transmission of malaria (Eniyew, 2018). Suitable habitats for mosquitoes are intermittent rivers and streams, pond environments, swampy and swampy areas, etc. Therefore, there is a significant risk of malaria transmission associated with land use and settlement activities near water bodies (Eniyew, 2018). In most areas, bodies of water are largely responsible for the spread and transmission of malaria; Consequently, locating and mapping these waters is a direct indicator of malaria risk areas (Chikodzi, 2013).

Distances to waterbodies such as streams, dams, and ponds that serve as suitable breeding sites were delineated and classified using the Euclidean Distance Tool. The estimated Euclidean distance from bodies of water such as dams and abundant mining ponds see Figure 4.4: Environmental risk factors (D) below. Likewise, the estimated Euclidean distances for most river networks in the study area as shown in Figure 4.4: Environmental risk factors (C).

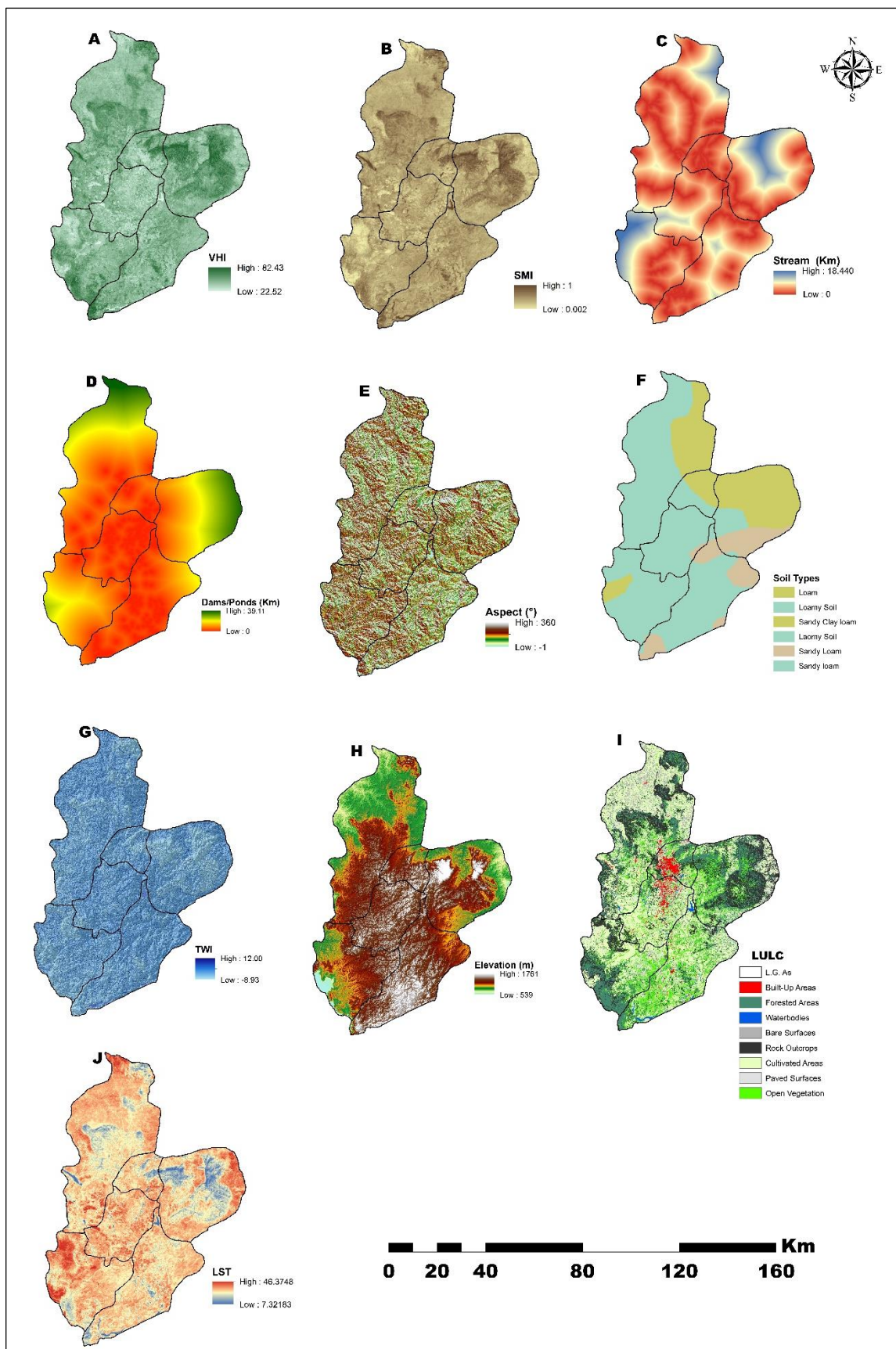


Figure 4.4: Environmental risk factors

4.4.3 Climatic/Meteorological Data Analysis

Ambient temperature: Given that climate change has a fundamental impact on critical malaria transmission rates, it is important to understand how temperature affects malaria transmission (Mordecai et al., 2013). Given that temperature influences mosquito population, breeding and malaria transmission, temperature changes have been found to significantly affect mosquito development and survival (Depinay et al., 2004; Kassaw et al., 2020). The study area's temperature range, according to the analysis of the data shown in Figure 4 5: Climatic factors (A).

Relative humidity: The ability of mosquitoes to complete their life cycle is known to be affected by climatic variables such as relative humidity (Mazher et al., 2018). A mosquito's lifespan is also influenced by relative humidity and a saturation deficit, which can extend the duration of transmission (Ovadge et al., 2019; Mazher et al., 2018). The study area's relative humidity shown in Figure 4 5: Climatic factors (C).

Rainfall: Rainfall is regarded to be the primary cause of malaria, and differences in rainfall throughout space show a strong positive correlation with malaria incidence (Ra et al., 2012). Because rainfall limits the availability of aquatic environments necessary for vector mosquito reproduction, rainfall has a significant impact on malaria transmission (Smith et al., 2013). The study area's rainfall range shown in Figure 4 5: Climatic factors (B)

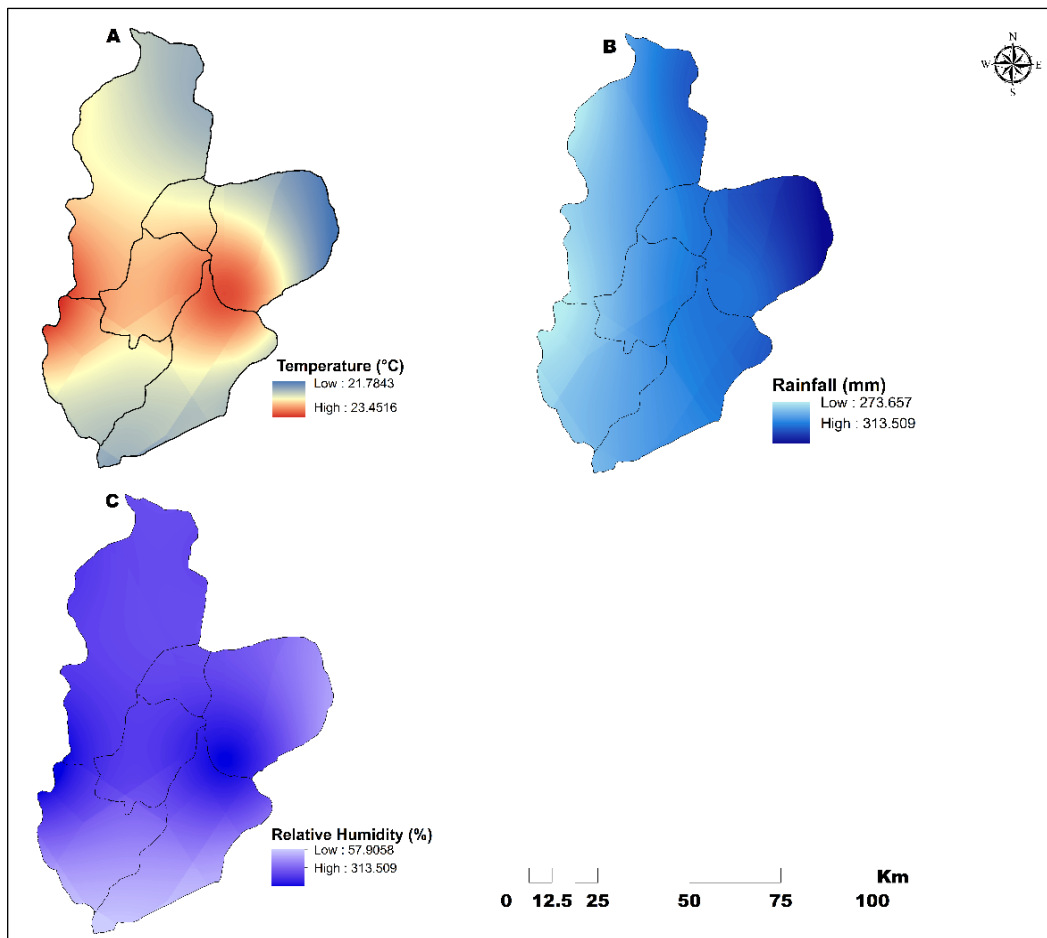


Figure 4 5: Climatic factors

4.4.4 Socio-economic Data Analysis

Population density: Population density has been shown to be a key indicator of malaria risk because it explains risk patterns in the most densely populated urban areas (Zhao et al., 2020). This is because increased density of *Anopheles spp.* have been associated with higher resident densities, potentially making an area more attractive to these mosquitoes (Beier et al., 1999). An analysis of the study area's population density is shown in Figure 4 6: Socioeconomic factors (A).

Vulnerable age groups (children under 5 years): Children under five are believed to be the age group at highest risk of malaria and experience a disproportionate share of malaria-related morbidity and mortality. Malaria has an impact on the prenatal development of the vast majority

of children (Sachs et al., 2002). An analysis of the study area's vulnerable age group (children under five years of age) shown in Figure 4 6: Socioeconomic factors (B).

Distance to roads: The accessibility of a location and/or the effectiveness of intervention measures needed to reduce the risk of malaria infection could be influenced by the distance of a location from the road network, which is known to be a risk factor (Degarege et al., 2019). Infrastructure, particularly roads, may be associated with a higher risk of malaria, according to Ovadje et al., 2019.

The Spatial Analyst tool was used to delineate the roads in the study area and estimate the Euclidean distance. This gives us a better understanding of the composition of the road network and distances to settlements within the study area (see Figure 4 6: Socioeconomic factors C).

Distance to healthcare facilities: The distance between the patient's home and the nearest health facility is a risk factor for malaria as it reflects the rapid and efficient delivery of malaria control and treatment (Zhao et al., 2020). Access to healthcare, as a particular variable solely related to the host, may be another risk factor for disease transmission(Lambin et al., 2010).

The Spatial Analyst tool in the ArcGIS environment was used to delineate the healthcare facilities and estimate the Euclidean distance in the study area as shown in Figure 4 6: Socioeconomic factors (D) below.

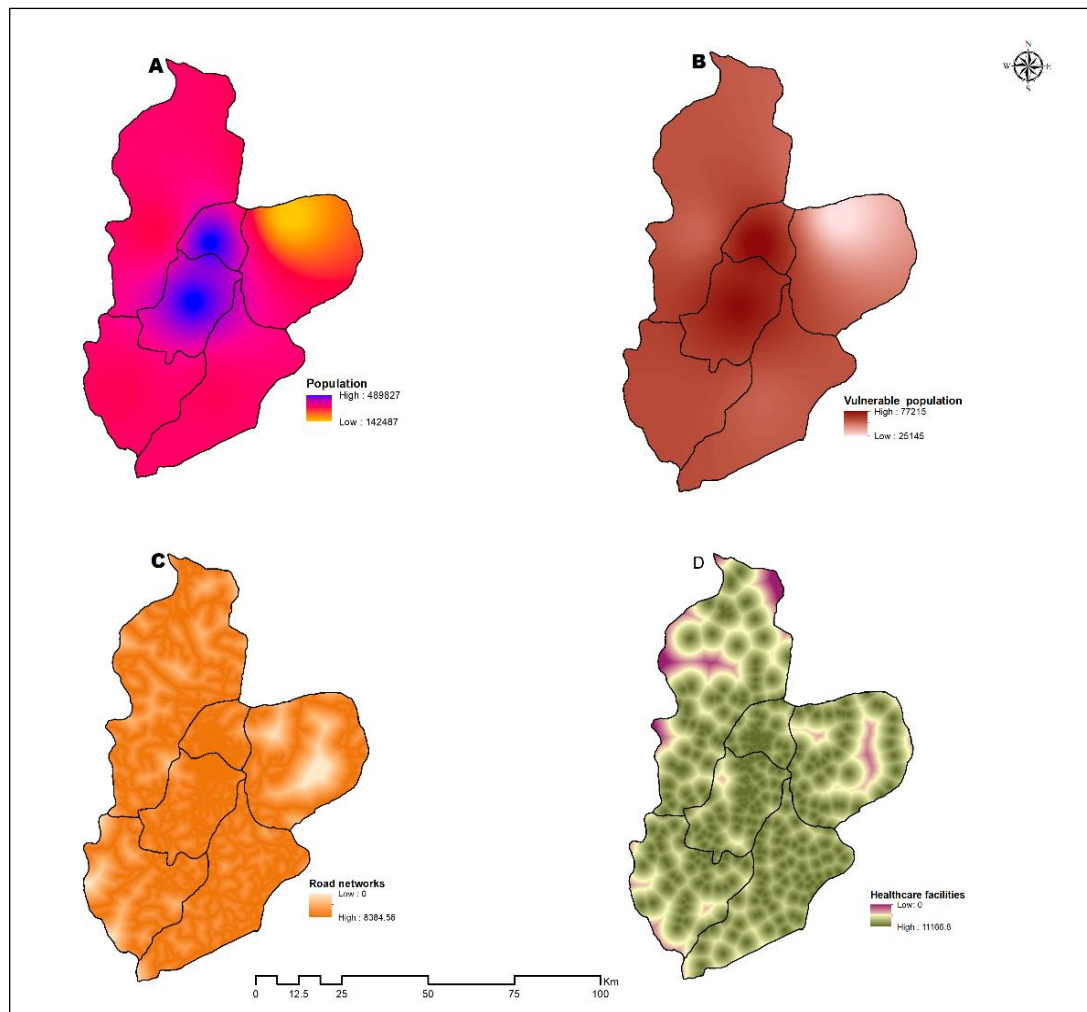


Figure 4 6: Socioeconomic factors

4.5 Spatial-Multi-Criteria Decision Analysis (MCDA)

The application of spatial MCDA in analyzing, mapping, and modelling malaria transmission risk in Plateau State, Nigeria can help identify high-risk areas, increase the efficiency of prevention efforts, support vector management practices, and predict malaria outbreaks, guiding effective elimination campaigns.

4.5.1 Stages of Spatial-MCDA

The spatial MCDA model employed in this study included five stages namely:

Risk factors identification: Interactions between hosts, vectors, pathogens, and the environment often result in risk factors for malaria transmission that evolve over time and space

(Zhao et al., 2020). In developing the malaria risk model, extensive literature reviews and professional expert opinions were used to identify and quantify these risk factors. In addition, the development of our malaria risk model utilized 45 experts from various institutions with varying expertise in malaria control (health practitioner/case management), field experience (field worker/vector management), educators (advocacy), and project management (administrator). Factors influencing vector breeding and malaria transmission risk in the study area were identified as three main risk factors. They include ecological factors (aspect, topographic moisture index, elevation, soil types, vegetation health index, stream, dams and ponds, land use/land cover and land surface temperature), climatic factors (air temperature, precipitation, and relative humidity), and social-economic factors (population density, Distance to health facilities, proximity to road networks and population of children under five) risk factors.

Identify the relative importance of each risk factor: 45 experts with at least five years of experience in the various malaria-related fields were interviewed using a 9-degree pairwise comparison matrix. During the interview process, the various experts evaluated the risk factors, made a list, and brainstormed about them based on their relative importance. The experts then evaluate and rank the seventeen parameters based on their relative importance in relation to vector breeding and malaria transmission risk in the study area. They used a 9-degree Thomas-Saaty paired comparison matrix, which is shown in the Table 4.2: Thomas Saaty Pair-Wise Comparison matrix below.

Table 4.2: Thomas Saaty Pair-Wise Comparison matrix

of Importance	Intensity	Definition	Explanation
	1	Equal Importance	Two criteria contribute equally to the objective
	3	Moderate Importance of one over another	Experience and judgment slightly favour one criterion over another
	5	Essential or Strong Importance	Experience and judgment strongly favour one criterion over another
	7	Very Strong or demonstrated Importance	A criterion is favoured very strongly over another; its dominance demonstrated in practice
	9	Extremely Importance	The evidence favouring one criterion over another is of the highest possible order of affirmation
2, 4, 6, 8		Intermediate values between the adjacent scale values (when compromise is needed)	
Reciprocals		If criteria i has one of the above numbers assigned to it when compared with criteria j, then j has the reciprocal value when compared with i	

According to Tables 4.2,3, 4 and 5, the value assigned to each parameter reflects the relative importance of each factor relative to the other in a pair and would range from 1 to 9, with 9 indicating extremely greater relevance. The consistency of the pairwise matrix is then tested using the following criteria:

Consistency ratio: This consistency test was used to determine the degree of accuracy or consistency with which the matrix derivation procedure was performed. The consistency ratio compares the consistency index with the random consistency index, which is represented in equation 4.13 and 4.14 as follows.

$$CR = CI/RI \quad 4.13$$

The consistency Index (CI) is given by.

$$CI = \frac{\lambda_{\max} - n}{n - 1} \quad 4.14$$

Where n is the comparison matrix's dimension and λ_{\max} is the comparison matrix's maximum Eigen value.

The Random Index (RI) is a theoretical shown in Table 4.3: Random Index below.

Table 4.3: Random Index

	3	4	5	6	7	8	9	10	11	12	13	14	15
RCI	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.48	1.56	1.57	1.59

CR is typically referred to as an indication of the consistency of an assessment. In most cases, an acceptable consistency ratio (CR) is 0.1 or less. Any value greater than 0.1 indicates that there was an inconsistency in the development of the comparison matrix and the judgment should therefore be reconsidered.

Table 4 4: Consistency tests

Risk Factor	Eigen value (λ_{\max})	Consistency Index (CI)	Random Index (RI)	Degree of Consistency (DC)
Ecological	11.24	0.138	1.49	0.093
Climatic	3.04	0.019	0.58	0.033
Socio-economic	4.14	0.047	0.9	0.052

According to Saaty, 1994, the inconsistency of the matrix is considered acceptable if the consistency ratio is less than or equal to 10% as shown in Table 4 4: Consistency tests above. If the consistency ratio is greater than 10%, the subjective decision must be reconsidered.

Degree of consistency: The consistency level is the ratio of the consistency index to the random index shown in equation 17, which is usually given as a theoretical value, as shown in Table 4.7 above.

$$\text{Degree of Consistency} = \frac{\text{Consistency Index}}{\text{Random Consistency Index}} \quad 4.15$$

The environmental, climatic, and socioeconomic risk factors in this study are compared using a 10 x 10 matrix, a 3 x 3 matrix, and a 4 x 4 matrix, respectively. Consequently, 1.49, 0.58, and 0.90 represent the Random Index for each of these risk factors.

The RI of the comparison matrix is accurate and can be used for further analysis because the consistency level is below 0.1. On the other hand, if the consistency level is greater than 0.1, it is probably unreliable and should not be used for future research when determining the comparison matrix's weight. The degree of consistency was assessed as 0.093, 0.033 and 0.052 for the environmental, meteorological, and socioeconomic risk factors, respectively. This implies that the weight of the comparison matrix is trustworthy.

Standardize the factors for comparability: In this study, malaria hazard or risk maps were created by estimating relative weights and overlaying ecological, climatic, and socioeconomic variables in the study area. The weighted overlay model was used in this research to develop predictive modeling of malaria transmission risk. The spatial datasets for the various risk factors were analyzed, and because each dataset had a distinct size and unit, we scored them all on the same scale. The dataset's propensity for mosquito breeding was used as the basis for this scoring. Depending on the type of data being scored, a variety of scoring methods can be applied to different spatial data. There are three types of scoring: discrete (binary, yes/no, and 1/0), ranges (rating spatial datasets into ranges), and continuous (used for spatial datasets that are linearly increasing, decreasing etc.). The following scoring methods were performed in this research.

Range scoring: Using the reclassification tool in the Spatial Analyst tool, continuous and discrete data sets were reclassified into different classes. Land use/land cover and soil types

used were assessed using this assessment method, while all remaining parameters for the three main risk factors were assessed using the continuous assessment method.

Continuous scoring: We scored our spatial data using a mathematical function below to provide homogeneity and uniformity.

$$\frac{X_i - X_{min}}{X_{max} - X_{min}}$$

Where X is the spatial data being analyzed.

When applying the weighted overlay model, it is important that all criteria or parameters be scored on the same scale.

Perform multi-criteria evaluation (MCE): The weighted overlay model method was used to integrate the malaria risk factor parameter weighting layers into create the composite risk map in the study area. The model shown in Figure 4.7: Correlation matrix of malaria risk model to produce the malaria risk map formula in equation 4.196, 4.197 and 4.198 as follows:

$$\begin{aligned} \text{Ecological risk factor} = & [(Dams*0.24 + (streams*0.22) + & 4.16 \\ & (elevation*0.17) + (LandUse/LandCover*0.11) + (Soil Moisture Index*0.09) \\ & + (Vegetation Health Index*0.07) + (Topographic Wetness Index*0.05) + \\ & (Aspect*0.03) + (Soil Types*0.02) +(Land Surface Temperature*0.01)] \end{aligned}$$

$$\begin{aligned} \text{Climatic/Meteorological risk factor} = & [(Temperature*0.106) + & 4.17 \\ & (Rainfall*0.633) + (Relative Humidity*0.260)] \end{aligned}$$

$$\begin{aligned} \text{Socio-economic risk factor} = & [(Population Density*0.330) + (Distance to & 4.18 \\ & Roads*0.070) +(Distance to Hospitals*0.091) + (Population Children under \\ & 5years*0.509)] \end{aligned}$$

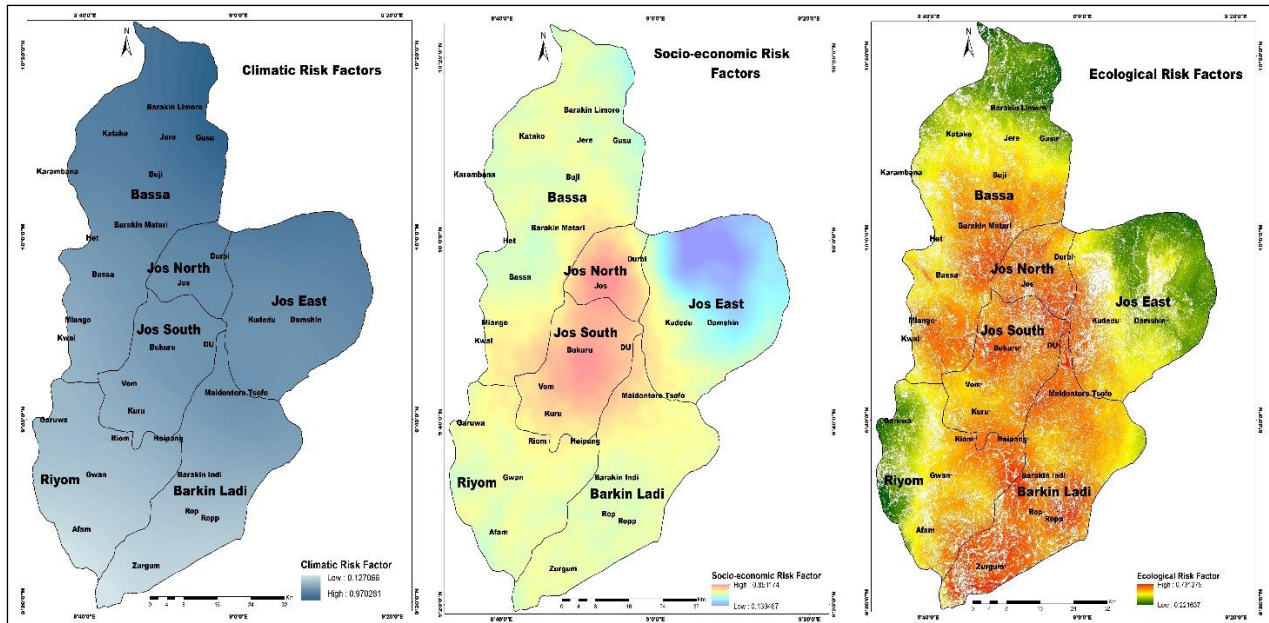


Figure 4.7: Correlation matrix of malaria risk model

The weights of the ecological, climatic, and socio-economic risk factors listed in and Figure 4.7: Correlation matrix of malaria risk model were determined and compared by 45 experts using a correlation matrix shown in Table 4. 5: Risk factors correlation matrix.

Malaria Risk	Meteorological Risk Factors	Ecological Risk Factors	Socio-economic Risk Factors	Criteria Weight
A1	1	0.25	0.333	0.115
A2	5	1	3	0.626
A3	3	0.333	1	0.258
Total	9	1.583	4.333	1

Using the raster calculator function, the risk factors and corresponding weights were integrated to create the malaria risk maps for the study area using the formula in equation 4.19 as follows:

$$\text{Malaria risk map} = [(\text{Meteorological Risk Factors} * 0.115) + (\text{Ecological Risk Factors} * 0.626) + (\text{Socioeconomic Risk Factors} * 0.258)] \quad 4.19$$

The different layers of risk factors shown in Figure 4.8: Malaria Risk Model were reclassified based on their risk level using the reclassification tools as Very High Risk, High Risk, Moderate, Low Risk, and Very Low Risk.

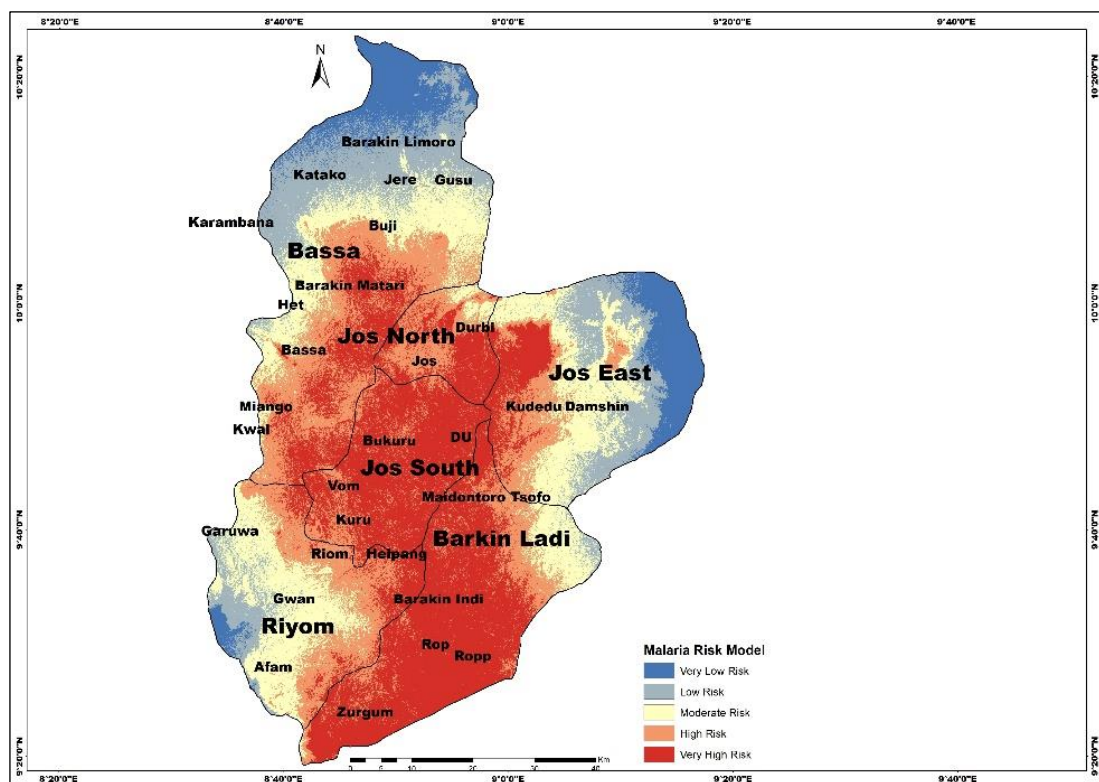


Figure 4.8: Malaria Risk Model

Validate the model (accuracy assessment): The sensitivity and specificity of the model were calculated using the optimal cut-off of the malaria risk map. The model was validated using the following datasets.

Estimated hospital-level parasite index of the general population. This aids in assessing the frequency of hospitalizations due to the disease. Estimated parasite index for the most vulnerable age group (children under five years). Reported cases of malaria in the study area and binary data generated from Fuzzy membership function in ArcGIS environment.

The nnet package was used to create a logistic regression model from the datasets. Next, an analysis of the confusion matrix and misclassification error for the model is performed after running the logistic regression model.

To evaluate the performance of our model, the ROCR package was used to make predictions using the logistic regression model and our binary data, using a probabilistic prediction for our values. The different cut-off value ranges are used in a plot of the model analysis evaluation using the True Positive Rate (TPR) and False Positive Rate (FPR).

A plot of ROC using TPR versus FPR shown in Figure 4.9: Receiver Operation Characteristics /Area Under Curve. shows the performance of various limits. The performance of the model was then recorded by plotting an intercept of 0 and a slope of 1. The area under the curve (AUC), is mainly calculated to show the performance rate of the model.

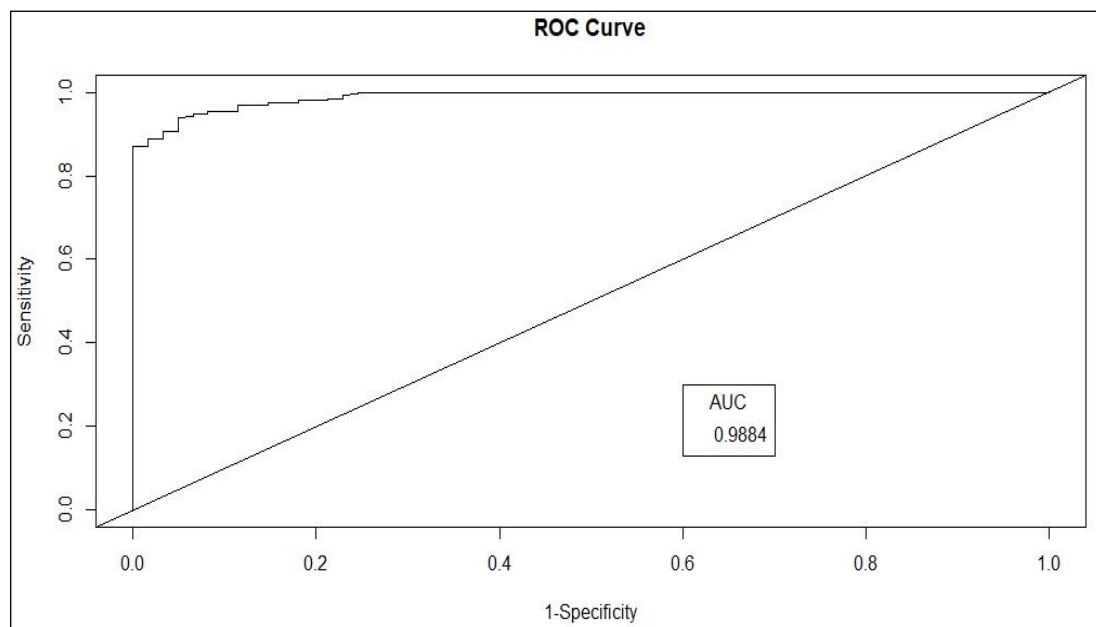


Figure 4.9: Receiver Operation Characteristics /Area Under Curve.

Good model performance is indicated by a high value of the area under the curve. In addition to ROC and AUC, model validation uses kernel density and hotspot analysis shown in Figure 4.10: Hotspot and density analysis which determines the density distribution of malaria

cases, as well as hotspot analysis to locate clusters and assess their statistical significance for the confirmed malaria cases.

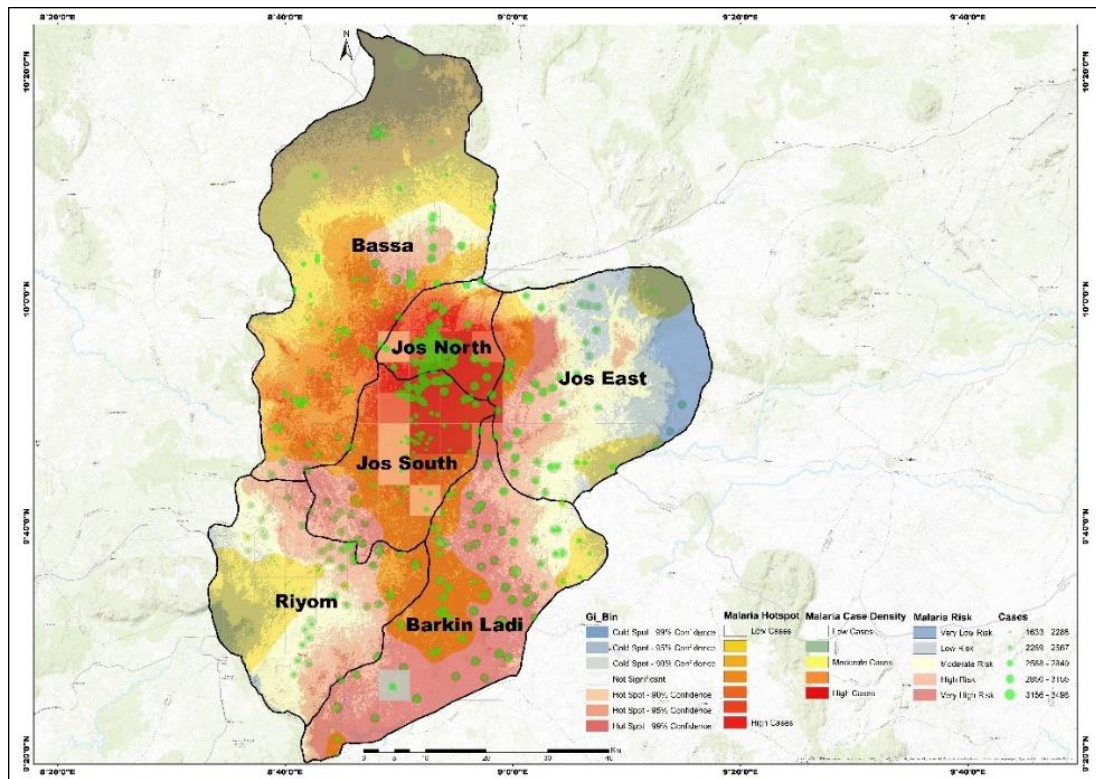


Figure 4.10: Hotspot and density analysis

Chapter 5: Results, interpretations, and discussions

Chapter five evaluates the impact of the various risk factor parameters associated with malaria transmission risk in the northern zone of Plateau State, Nigeria. The chapter also discussed the implications of using the expertise of experts in different malaria-related fields to determine relative importance. The assessment evaluates the susceptibility of each parameter as this correlates with the suitable breeding habitats of the vector and the risk of malaria transmission in the study area. The chapter also discusses the results of the various parametric analyses that relate the breeding habitats suitable for the vector and the risk of malaria transmission to estimate the overall risk of the disease in the study area. Finally, the implications and analysis of the risk factors and synthesis into a malaria risk model was done to analyse the risk of malaria as they correspond to the ground conditions is also discussed in this chapter.

5.1 Results

The “Results” section discusses the findings of the analysis of the different risk factors and the implementation of the different expert’s composition used to determine the relative importance of the different risk factor parameters analysed in the study area. This section also discusses the findings and implications of the paired comparison matrix conducted in the study area with regard to the risk of malaria transmission and suitable vector breeding habitats. The implications of the spatial distribution of malaria risk and the various risk factors that determine a region's vulnerability to the risk of the disease are also discussed. Finally, the impact and significance of the validation techniques used in the study area were also discussed.

5.1.1 Spatial-MCDA

The spatial MCDA section of the chapter discusses the implications of using experts from different malaria-related fields to determine the relative importance of the various risk

factor parameters. This section further discusses the expert intuition results used in the pairwise comparison matrix of risk factor parameters in the study area related to vector suitable breeding habitats and malaria transmission risk. Finally, the study examines the implications of assessing the degree of consistency with which these experts determined the relative importance of the risk factors.

Risk factor identification and expert composition: This research uses two techniques of expert consensus and interviews from different malaria-related fields to identify risk factors and determine the relative importance of these factors (see Figure 5.1: expert composition: years of service, qualifications, and areas of expertise) to ensure efficacy in assessing the parameters of the various risk factor in the study area. In order to guarantee equitable representation in the analysis and assessment of the relative importance of the risk factors, the research considered years of service, qualifications, and areas of expertise in the various fields related to malaria when selecting experts.

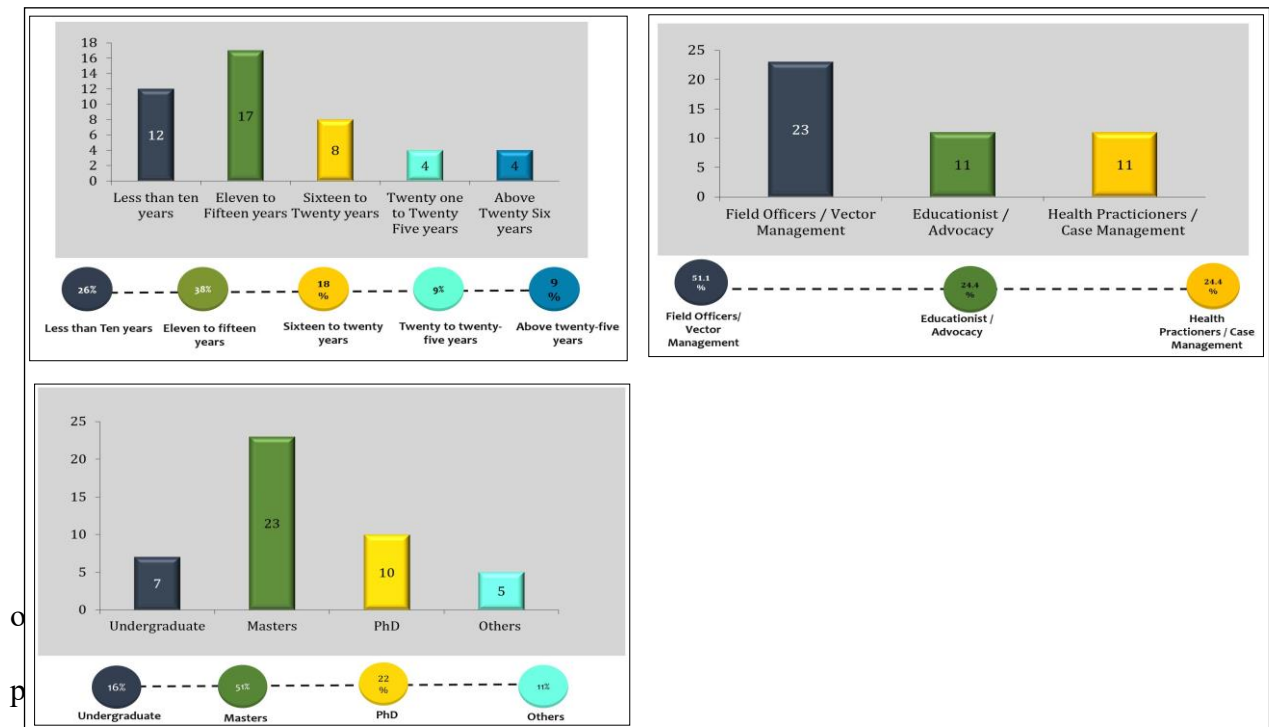


Figure 5.1: expert composition: years of service, qualifications, and areas of expertise

this study. This combination helps to ensure maximum accuracy and unwavering consistency in assessing the complex interrelationship between the various ecological, meteorological, and socio-economic variables as these correlates with host, vectors and associated factors that influence malaria transmission risk in the study area.

Identification of relative importance: Based on their relative importance of the different malaria risk factors parameters in relation to malaria transmission in the study area, a pairwise comparison matrix ranking of the 17 parameters that constituted the three major risk factors for malaria was performed using a 9-degree matrix. The result of the consolidated pairwise comparison matrix is presented Table 5.1: consolidated pairwise comparison matrix for ecological risk factors. below.

Table 5.1: consolidated pairwise comparison matrix for ecological risk factors.

Ecological Factors	Dams/Ponds Buffers	Stream Network Buffers	Elevation	Landuse/Landcover	Soil Moisture Index	Vegetation Health Index	Topographic Wetness Index	Aspect	Soil Types	Land Surface Temperature	Criteria Weight (%)
Dams/Ponds Buffers	1	2	2	3	5	5	6	6	7	9	24
Stream Network Buffers	0.5	1	3	5	5	6	4	4	7	9	22
Elevation	0.5	0.3 3	1	2	5	5	7	7	7	9	17
Landuse/Landcover	0.3 3	0.2	0.3 3	1	2	3	5	5	7	9	11
Soil Moisture Index	0.2	0.2	0.2	0.5	1	2	4	5	7	9	9
Vegetation Health Index	0.2	0.1 7	0.2	0.33	0.33	1	2	5	7	9	7
Topographic Wetness Index	0.1 7	0.2 5	0.1 4	0.2	0.25	0.33	1	2	5	7	5
Aspect	0.1 7	0.2 5	0.1 4	0.2	0.2	0.2	0.33	1	2	5	3
Soil Types	0.1 4	0.1 4	0.1 4	0.14	0.14	0.14	0.2	0.33	1	2	2
Land Surface Temperature	0.1 1	0.1 1	0.1 1	0.11	0.11	0.11	0.14	0.2	0.33	1	1
Total	3.3 2	4.6 5	7.2 7	12.4 9	19.0 4	22.7 9	29.6 8	35.5 3	50.3 3	69	10 0

Based on the analysis of environmental risk factors for malaria transmission risk, the matrix revealed that proximity to ponds/dams and stream networks accounted for about 45% of malaria transmission risk in the study area. Other parameters such as elevation, LULC, SMI, TWI, aspect, soil types, and LST accounts for the remaining 55% of malaria transmission risk in the study area as shown in Table 5.1 above.

Table 5.2: consolidated pairwise comparison matrix for meteorological risk factors.

Meteorological Factors	Temperature	Rainfall	Relative Humidity	Criteria Weight
Temperature	1	0.2	0.333	0.106
Rainfall	5	1	3	0.633
Relative Humidity	3	0.333	1	0.26
Total	9	1.533	4.333	1

Table 5.2 above illustrates how meteorological risk factors affect the risk of malaria transmission based on a pairwise comparison matrix ranking of meteorological risk factor parameters in the study area. Analysis of meteorological parameters shows that relative humidity and ambient temperature account for 40% of malaria transmission in the study area, while rainfall influences 60% of it.

Table 5.3: consolidated pairwise comparison matrix for socioeconomic risk factors.

Socio-economic Factors	Population Density	Distance to Roads	Distance to Hospitals	Population Children under 5years	Criteria Weight
Population Density	1	5	5	0.5	0.33
Distance to Roads	0.2	1	0.5	0.2	0.07
Distance to Hospitals	0.2	2	1	0.143	0.091
Population Children under 5years	2	5	7	1	0.509

Total	3.4	13	13.5	1.843	1
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The relationship between demographics, infrastructure development and malaria transmission risk are assessed through a socioeconomic risk factor analysis based on a pairwise comparison matrix conducted in the study area. Analysis of these factors shows that vulnerable groups (children under 5 years of age) and the general population account for more than 80% of the risk of malaria transmission in the study areas.

A comprehensive assessment of various risk factors in the study area using a correlation matrix conducted by experts in malaria-related fields highlighted the relative importance of these factors. The analysis revealed the following vulnerability hierarchy: ecological > climatic > socioeconomic, as shown in Table 5.4 below.

Table 5.4: correlation matrix

Malaria Risk	Meteorological Risk Factors	Ecological Risk Factors	Socio-economic Risk Factors	Criteria Weight
Meteorological Risk Factors	1	0.25	0.333	0.115
Ecological Risk Factors	5	1	3	0.626
Socio-economic Risk Factors	3	0.333	1	0.258
Total	9	1.583	4.333	1

The evaluation of the consistency of the pairwise matrix based on the consistency ratio and consistency degree and the results are shown in the following table.

Table 5.5: Risk factors degree of consistency

Risk Factor	Eigen value (λ_{max})	Consistency Index (CI)	Random Index (RI)	Degree of Consistency (DC)
Ecological	11.24	0.138	1.49	0.093
Climatic	3.04	0.019	0.58	0.033
Socio-economic	4.14	0.047	0.9	0.052

Compared to the random index, the degree of consistency of this study was estimated at 0.093, 0.033 and 0.052, respectively, to account for environmental, meteorological, and socioeconomic risk factors. When compared with random index values of 1.49, 0.58, and 0.90, the degree of consistency showed that the pairwise matrices were performed accurately and with high levels of consistency.

5.1.2 Malaria risk

The analysis and integration of ecological, meteorological, and socio-economic variable layers by calculating relative weights with their respective risk factors to prepare the malaria hazard/risk map for the northern zone of Plateau State is shown in Figure 5. 2: Malaria Risk Model..

To establish a close resemblance with the corresponding ground conditions, the study area was further stratified into very high, high, medium, low, and very low risk zones based on malaria risk vulnerability. An assessment of the malaria risk model shown in the Figure 5.2 shows that the very low risk zone has an area coverage of about 427.016km², the low-risk area is 753.740km², the moderate risk is 1106.309km², the high risk is 1264.734km², and the very high-risk region is around 1754.398km² respectively.

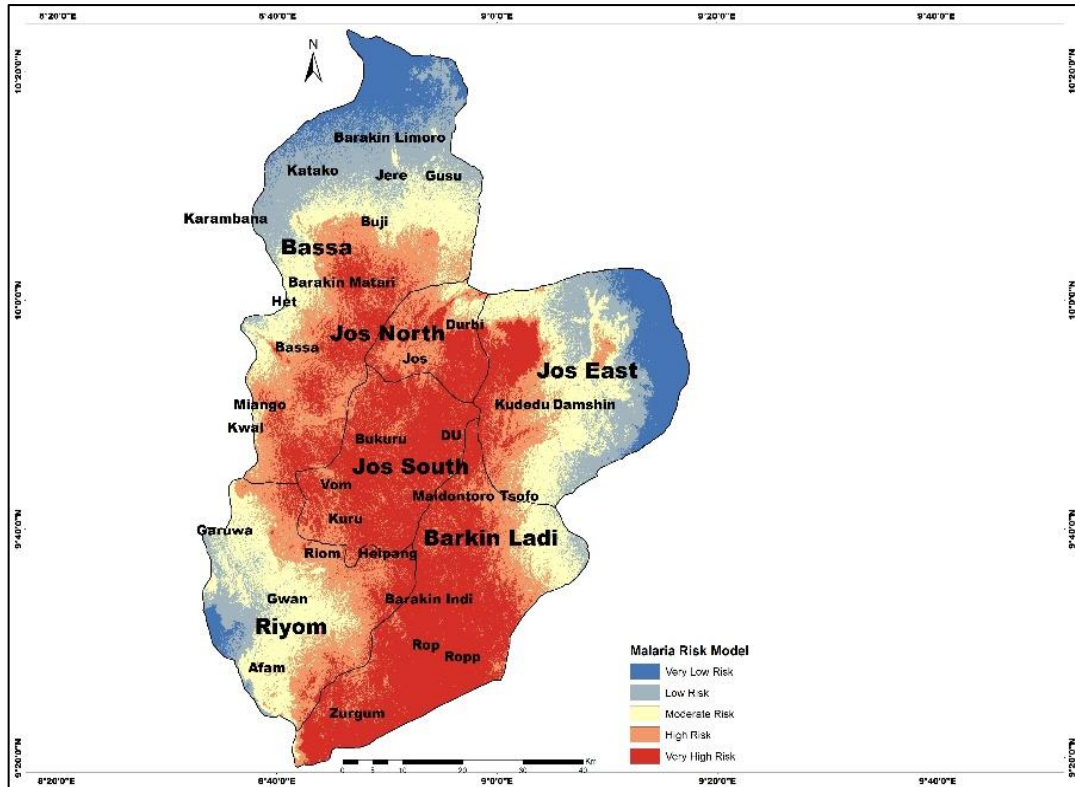


Figure 5. 2: Malaria Risk Model.

An analysis of the risk model shows that the extreme southwest parts of Riyom L.G. A, upper northern parts of Bassa L.G. A, and extreme north-eastern parts of Jos East L.G. A are observed to have very low risk of malaria transmission, whereas the majority of Jos North, Jos South L.G. A, and Barkin Ladi L.G. A as shown in Figure 5. 2: Malaria Risk Model. are observed to have very high risk of malaria transmission. Further assessment of the malaria risk model revealed that the malaria transmission risk covers an estimated area of 1815.49 km² in the southwestern parts of Bassa Local Government Area, mainly around Buji, Miango and Kwai villages. The central parts of Jos North Local Government Area were found to be extremely high risk, including Yelwa, Jos Metropolis and Arim villages. Gero, Shen, Du and Zawan villages are among the highest risk areas in Jos South Local Government Area. High-risk areas were also identified in the northern parts of Barkin Ladi local government area, particularly in Bisichi and surrounding villages. An evaluation of the correlation matrix shows that of the three risk factors listed in Table 5.4: correlation matrix, the ecological risk factor has

the greatest influence on malaria transmission in the study area with an estimated weight of 62.6%. This means that ecological risk factors have the greatest influence on the risk of malaria transmission in the study area. The weights assigned to climatic and socioeconomic risk factors are 11.5% and 25.8%, respectively, to reflect their influence on malaria transmission risk in the study area.

Table 5.6: Ecological risk factor’s vulnerability

S/No.	Risk factors	Parameters	Classes	Rank	Degree of vulnerability
1		Aspect (°)	0-68.37	5	Very low
			68.38-141.98	4	Low
			141.99-215.60	3	Moderate
			215.61-287.80	2	High
			287.81-360	1	Very high
2		Elevation (m)	539-917.58	1	Very High
			917.59-1056.55	2	High
			1056.56-1190.73	3	Moderate
			1190.74-1320.12	4	low
			1320.13-1761	5	Very low
3		LST(°C)	7.32-27.84	1	Very high
			27.85-30.91	2	High
			30.92-33.05	3	Moderate
			33.06-35.19	4	Low
			35.20-46.37	5	Very low
4	Ecological	LULC	Bare Surfaces	1	Very low
			Rock outcrops	2	Low
			Settlements	3	Moderate
			Vegetations	4	High
			Waterbodies	5	Very high
5		SMI	0-0.28	1	Very low
			0.29-0.34	2	Low
			0.35-0.39	3	Moderate
			0.40-0.47	4	High
			0.48-1.00	5	Very high
6		VHI	22.52-45.31	1	Very low
			45.32-49.54	2	Low
			49.55-54	3	Moderate
			54.01-59.64	4	High
			59.65-82.43	5	Very high
7		TWI	2.61-6.57	1	Very low
			6.58-8.21	2	low
			8.22-10.61	3	Moderate
			10.62-14.15	4	High
			14.16-23.63	5	Very high

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8	Soil type	Sandy clay loam	5	Very low
		Loamy soil	4	Low
		Sandy loam	3	Moderate
		Sandy loam	2	High
		Sandy loam	1	Very high
9	Ponds/dams (Km)	0-4.45	1	Very high
		4.46-10.28	2	High
		10.29-17.03	3	Moderate
		17.04-24.85	4	Low
		24.86-39.11	5	Very low
10	Streams (Km)	0-2.025	1	Very high
		2.026-4.41	2	High
		4.42-7.16	3	Moderate
		7.17-10.63	4	Low
		10.64-18.44	5	Very low

Additional analysis of the environmental risk factor susceptibility to malaria transmission reported in Table 5.6 above shows the following risk levels: Dams/Ponds > Stream Networks > Altitude > Land Use/Land Cover > Soil Moisture Index > Vegetation Health Index > Aspect > Soil Types > Land Surface Temperature, indicating the level of their vulnerability.

Table 5.7: Meteorological risk factor's vulnerability

S/No.	Risk factors	Parameters	Classes	Rank	Degree of vulnerability
1		Temperature(°C)	21.78-22.22	1	Very low
			22.23-22.50	2	Low
			22.51-22.77	3	Moderate
			22.78-23.05	4	High
			23.06-23.45	5	Very high
2	Climatic	Rainfall(mm)	273.66-285.53	1	Very low
			285.54-293.35	2	Low
			293.36-298.98	3	Moderate
			298.99-304.91	4	High
			304.92-313.51	5	Very high
3		Humidity (%)	57.91-60.27	1	Very low
			60.28-61.73	2	Low
			61.74-63.12	3	Moderate
			63.13-64.54	4	High
			64.55-66.77	5	Very high

Based on the susceptibility of the climate factor to malaria transmission, the degree of vulnerability to malaria transmission is as follows: precipitation > relative humidity > ambient temperature as shown in Table 5.7: Meteorological risk factor's vulnerability above. Finally,

an assessment of the vulnerability of the socio-economic risk factors for malaria transmission in the Table 5.8: Socioeconomic risk factor’s vulnerability below shows that the risk for malaria transmission is as follows: vulnerable group > population density > proximity to health facilities > road network.

Table 5.8: Socioeconomic risk factor’s vulnerability

S/No.	Risk factors	Parameters	Classes	Rank	Degree of vulnerability
1		Population	142487-224214	1	Very low
			224214-300492	2	Low
			300492-360425	3	Moderate
			360425-416272	4	High
			416272-489826	5	Very high
2	Socioeconomic	Vulnerable population	25145-38213	1	Very low
			38213-50669	2	Low
			50669-59449	3	Moderate
			59449-661888	4	Low
			66188-77214	5	Very low
3		Road network (Km)	2.52-3.82	5	Very high
			3.83-5.07	4	High
			5.08-5.95	3	Moderate
			5.96-6.62	2	Low
			6.62-7.72	1	Very low
4		Health facilities (Km)	0-1.45	5	Very high
			1.46-2.67	4	High
			2.68-4.25	3	Moderate
			4.26-6.44	2	High
			6.45-11.17	1	Very high

5.1.3 Epidemiological data

Epidemiological data collected from various health facilities in the study area were used to analyse and visualise the spatial spread and trend of malaria transmission risk as a tool to validate the malaria risk model in the study area. The malaria risk model developed in this study, which examined the spatial risk of the disease over a five-year period, from 2017 to 2021, was used to determine the spatial trend and transmission rate of the disease. Validation of the malaria risk model was achieved by plotting the ROC to determine the sensitivity and specificity of the malaria risk model. The average sensitivity of the malaria risk model for the

period under study (see **Error! Reference source not found.** above) shows that the risk model accurately predicted identified areas with malaria cases with an accuracy of 98% and a specificity of 54%. On the other hand, the average optimal threshold for classifying the malaria-positive or malaria-negative cases in the study area was reported to be 0.808, as shown in **Error! Reference source not found.** above. The risk model for the period under study was validated and found to be a good fit for the highest values of the AUC.

The AUC was used to estimate the model performance rate based on its discriminative ability indicated that the risk model for the period under study was shown to be a good fit by its high values. This further indicates that the malaria risk model had a 98% performance rate in discriminating between the positive and negative cases of the disease.

AUC, on the other hand, was used to estimate the model performance rate based on its discriminative ability. The high AUC values indicates that the risk model performed well for the period under study. The average AUC analysis further indicates that the malaria risk model had a 98% performance rate in discriminating between positive and negative cases of the disease in the study area as shown in **Error! Reference source not found.**

Table 5.9: Model benchmark and performance rate

Period	Area Under Curve	Benchmark	Confirmed Cases
2017	0.8014	0.7149	1308601
2018	0.9101	0.814	1107171
2019	0.9023	0.814	1309146
2020	0.9023	0.8118	1481705
2021	0.9578	0.888	895057

Additionally, a spatial kernel density statistical technique was used to determine the density distribution of malaria incidence cases. This analysis showed that the concentration of incidence cases of the disease was mainly concentrated in Jos North L.G.A, Jos South, and

Barkin Ladi L.G.A as shown in the Figure 4.10. On the other hand, in most parts of the Bassa L.G.A., Riyom L.G.A. and Jos East L.G.A. showed a low concentration and distribution of malaria cases. Furthermore, an overlay of the reported incidence cases of the disease in the study area using kernel density and hotspot analysis (see **Error! Reference source not found.** above) shows that the distribution of cases confirms the prediction of the malaria risk model that states that Jos North, Jos South and Barkin Ladi L.G.As exhibit a densely clustered and concentrated pattern of malaria cases compared to other regions in the study area. Using a classification analysis of the reported cases based on the confidence level of the identified cold spots and hotspots in **Error! Reference source not found.**, it is clear that the distribution and density of cases is spread across the different levels in the study area.

The density and hotspot analysis shows that the North, South and Barkin Ladi L.G.As have the largest distribution and density of cases and have a confidence level of 90-99%, indicating a higher level of certainty in predicting hotspots of malaria transmission risk in the regions indicates the study area as shown in Figure 5.3: **Overlay of incident cases in the risk model.**

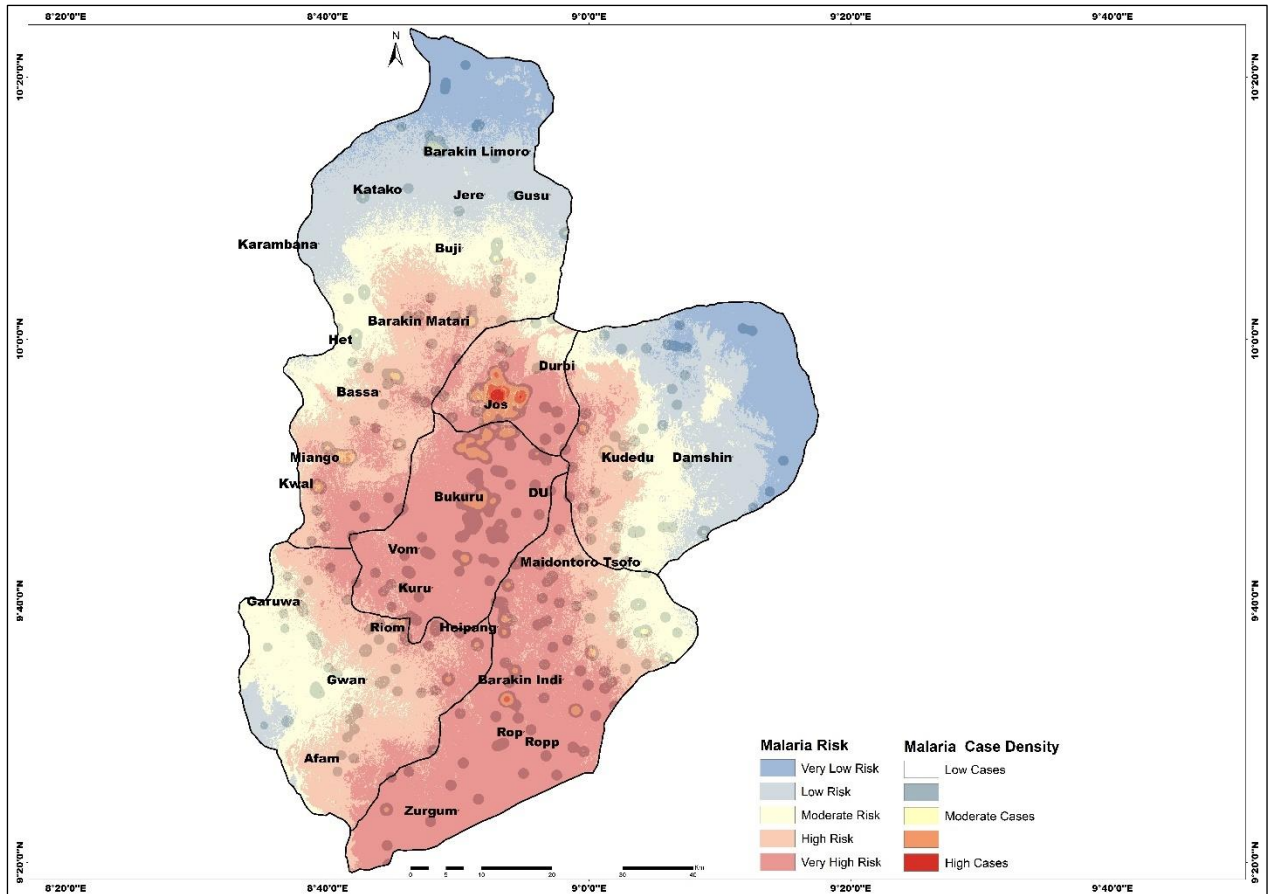


Figure 5.3: Overlay of incident cases in the risk model.

Finally, the analysis of the malaria distribution rate of reported malaria cases relative to the local population, which is an essential factor in determining the regions most affected by malaria, shows that the L.G.A.s Jos East, Bassa and Barkin Ladi bear the highest burden of disease during the study period, as shown in Figure 5.4: **Incident cases distribution rate**. This means that Jos East L.G.A. despite having the lowest distribution of health facilities and the lowest number of confirmed malaria cases during the study period, has the highest burden of disease relative to the risk of population distribution.

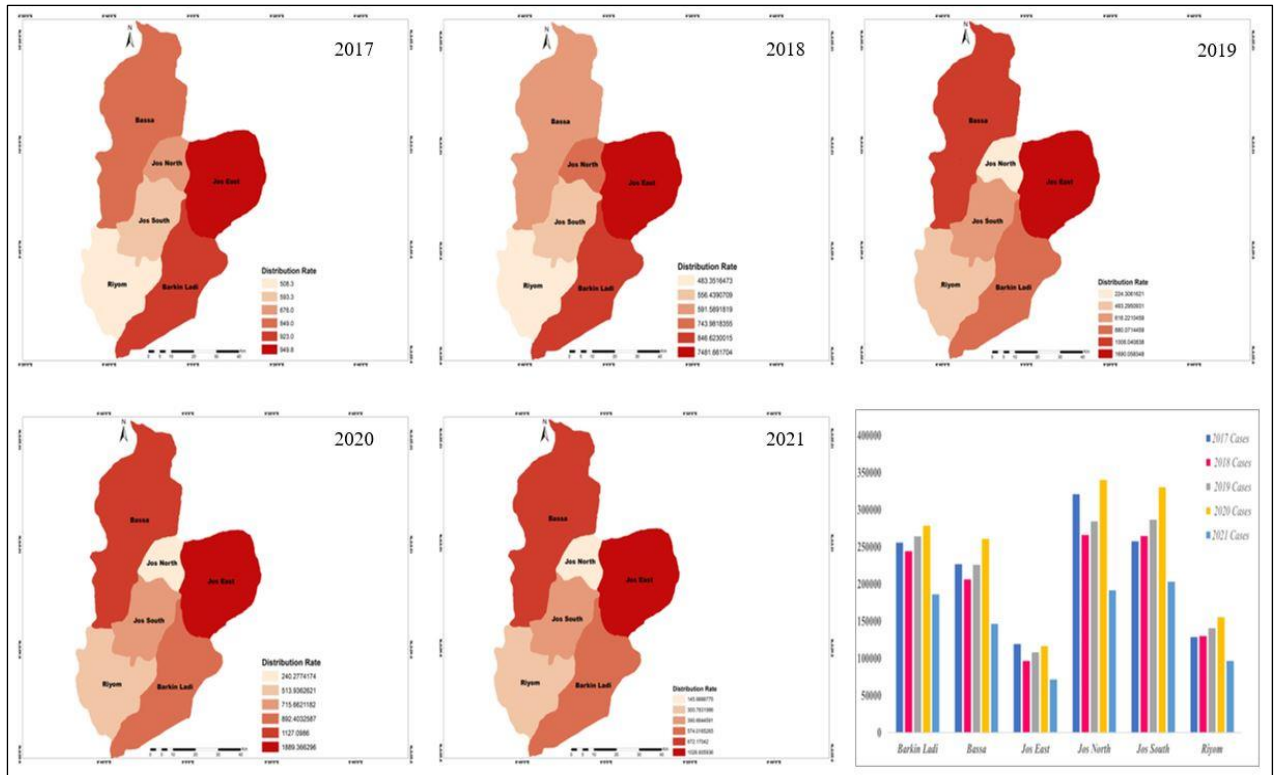


Figure 5.4: Incident cases distribution rate

5.2 Discussion

To determine the risk of malaria transmission, a thorough assessment of the ecological, climatic, and socioeconomic characteristics of the study area was conducted. This assessment includes an in-depth analysis of malaria risk in Northern Zone of Plateau State, Nigeria this includes assessing its topography, hydrological features, anthropogenic activities, demographic trends, infrastructure, and climate influences. This rigorous analysis ensures thorough identification, classification, and analysis of malaria risk factors in the study area and provides insights into the proper management of the disease.

Furthermore, the high level of accuracy and consistency in the pairwise comparison matrix analysis and the consistency of the overall disease risk assessment in the study area was ensured through the inclusion of a diverse group of experts with different qualifications, expertise, and experience in malaria-related fields in the study area. The pairwise comparison matrix analysis of the various malaria risk factor parameters conducted in the study area not

only indicates the level of vulnerability of the risk factors but also provides necessary guidance to decision makers regarding the types of vector management practices that should be implemented to address the malaria risk factor disease burden in the study area. In addition to understanding the spatial distribution of malaria transmission risk, the risk model is also critical for understanding the suitability of vector breeding habitats, vector-host interactions, and the dynamics of malaria transmission. Based on the correlation matrix analysis in Table 5.4: correlation matrix above, ecological risk factors have the greatest influence on malaria transmission, accounting for 62% of the weights in the study area. Therefore, a comprehensive assessment of the various ecological risk factor parameters is crucial for understanding the interrelationships between the disease vector and host as well as the dynamics of malaria transmission risk in the study area. Analysis of risk factor parameters in the study area shows that elevation with vulnerabilities of 500-1200m (see Table 5.6: Ecological risk factor's vulnerability) plays an important role as it has been observed to influence the life cycle of most vector species in the study area.

The assessment of this parameter in the study area further indicates that as elevation decreases, temperatures increase and so does the risk of mosquitoes breeding, and ultimately leads to likelihood of mosquito breeding and malaria transmission. Based on the analysis of the study area, aspects with vulnerability to malaria risk of 140-360° (see Table 5.6: Ecological risk factor's vulnerability) and orientation ranging from NW340 to NE70 were observed to have an impact on malaria transmission as this orientation has limited concentration of sunlight and high moisture content, thus favoring high vegetation growth, which serves as a suitable vector-breeding habitat and therefore increase the risk of malaria transmission. Analysis of the TWI with vulnerability ranging from 8-23 to malaria risk of in the study area (refer to Table 5.6: Ecological risk factor's vulnerability) revealed that areas with flat terrain tend to accumulate water compared to high altitude areas, which promotes vegetation growth and

ultimately provides good breeding space for mosquitoes, thus favouring the transmission of malaria. Ambient and LST analysis in the study areas with vulnerability to malaria risk of 22-46°C (see Table 5.6: Ecological risk factor's vulnerability and Table 5.7: Meteorological risk factor's vulnerability) shows that temperatures were observed to have a significant impact on the developmental stages of the vector, ranging from incubation rate, feeding behaviours, growth rate, biting rates and overall survival to its population density. It was observed that there is a high risk of malaria transmission in areas with favourable temperatures, especially at temperatures between 15 and 32 °C within the study area. Land use types such as agricultural activities such as crop cultivation, animal husbandry, construction, and mining actively carried out in the study area were observed to promote mosquito breeding habitats to varying degrees and have a direct and indirect relationship with malaria transmission. It has also been observed that other anthropogenic activities such as water storage, use and disposal are poorly managed, contributing to mosquito breeding habitats and hence malaria transmission.

Furthermore, improper waste disposal and poor drainage system management, which appear to be the norm in the study area, result in a favourable environment for mosquito breeding habitats in the study area. On the other hand, the water bodies distributed in the study area such as stream networks, dams, ponds, and lakes, which were mainly used for irrigated agriculture during the dry season, are surrounded by lush natural vegetation and thus provide suitable breeding habitats for mosquitoes as it was observed that most of the activities around prevail around most settlements. Construction materials, building types, building clusters, and building layouts were also observed as another land use factor contributing to the risk of malaria in the study area.

The accuracy assessment of the study area revealed that malaria prevalence was mainly observed in areas where buildings were densely packed as these mostly provide shaded areas and further influence the distribution of sunlight, thereby creating suitable breeding habitats

and consequently increasing the risk of malaria in such areas. The vulnerability of land use activities and land cover types to malaria transmission risk conducted in the study area as shown in Table 5.6: Ecological risk factor's vulnerability is as follow: bare surface > rock outcrops > settlements > vegetation > waterbodies. Analysis of vegetation indices with vulnerability ranging from 45-82 in the study areas shows that areas with denser and healthier vegetation have a higher risk of malaria than areas with less healthy and sparser vegetation most especially in regions such as Jos North, Jost South and Barkin Ladi L.G.As. The analysis also shows that places with denser and healthier vegetation have higher levels of organic and moisture decomposition content serves as a suitable and conducive temperature and environment for mosquito breeding as shown in Table 5.6: Ecological risk factor's vulnerability. Based on the analysis of the different soil types and their moisture content in relation to malaria risk, the study found that soil properties such as physical composition, texture and water retention capacity have both a direct and indirect relationship with malaria transmission in the study area (see Table 5.6: Ecological risk factor's vulnerability). The vulnerability of the various soil types to malaria transmission risk based on the degree of permeability conducted in the study area as shown in Table 5.6: Ecological risk factor's vulnerability as follow: sandy clay loam > loamy soil > sandy loam > sandy loam > sandy loam. Additionally, based on water retention capacity in the study area, malaria transmission was observed to be high in areas with soil types such as loamy soils with a moderate permeability of 2.0-6.3 cm/h compared to sandy loam soils with high permeability of 6.3-12.7cm/h. In general, the analysis in the study area also indicates that soil types with high water retention capacity promote vegetation growth during rain, providing suitable breeding habitats and thus increasing the risk of malaria transmission. In comparison, there are areas with low water retention capacity where vegetation is less dense, creating a less favourable environment for vector breeding and malaria transmission.

Results, interpretations, and discussions

The spatial analysis of climatic risk factors with a criteria weight of 11.5% in the study area shows that vector development, density and transmission are associated with these risk factor parameters. Malaria risk analysis in the study area shows that climatic factors play an important role in malaria transmission, particularly parameters such as ambient temperature, rainfall, and relative humidity, as they have been shown to influence vector breeding habitats and malaria transmission in the area. The spatial analysis of climatic risk factors shows that relative humidity with a criterion weight of 26% of malaria transmission propensity in the study area promotes the maintenance of lush green vegetation and provides a favorable environment for vector breeding as shown in Table 5.7: Meteorological risk factor's vulnerability. It was observed that the large presence of abandoned mining ponds, dams and stream networks in the study area increases the relative humidity and influences the high risk of malaria transmission. Further analysis of the climatic risk factor in relation to malaria transmission shows that rainfall with a criteria weight of 63.3% (see Table 5.7: Meteorological risk factor's vulnerability) was an important factor in determining vector density and malaria transmission in the study area. However, heavy rainfall often leads to flooding and destruction of mosquito breeding habitats in the study area.

Cultural norms, socio-economic activities and behavioural patterns of societies are observed to have a significant impact on malaria transmission risk in the study area. This is because socioeconomic factors significantly influence the approach to modelling malaria risk and the necessary control strategies that need to be implemented in the study area. Socioeconomic risk factor parameters such as population density, vulnerable age group population, distribution of health facilities and road networks were assessed to understand the influence of this risk factor on the overall malaria risk in the study area. Based on ground truthing and malaria risk model analysis, it has been determined that malaria is common in most densely populated areas, making population density a good predictor of risk.

Results, interpretations, and discussions

Anthropogenic activities and human interactions were observed to increase malaria incidence in most populated regions of the study area. Rural (malaria-prone) urban migration in search of a better life was observed to increase the incidence of the disease in the study area. Malaria prevalence was found to be more common in most slums where the standard of living is low due to low income in the study area as most residents cannot afford the necessary resources for personal expenses to prevent the disease as shown in Table 5.8: Socioeconomic risk factor's vulnerability. Furthermore, most slums in the study area cannot afford adequate housing with screened doors and windows, which helps limit mosquito contact with humans. The research also found that vulnerable populations, particularly children under 5, have disproportionately high malaria morbidity and mortality compared to adults who develop partial immunity to malaria.

The malaria risk analysis in the study area shows that the distribution of the road network with vulnerability of 0-6km proximity from settlements also influences the accessibility and effectiveness of the necessary intervention measures to reduce the impact of malaria transmission as shown in Table 5.8: Socioeconomic risk factor's vulnerability. In addition, the analysis of the risk model also indicates that a high dispersion of the road network leads to high commuting traffic and increases the incidence of the disease. The risk model assessment conducted in this research also included a comprehensive assessment of access to healthcare services, which includes the availability, accessibility, acceptability, and affordability of such healthcare facilities in the study area. Risk model analysis in the study area also shows that the distance between 2-11km to a patient's home and the nearest health facility is an important risk factor, reflecting not only the timely and efficient delivery of malaria control but also malaria treatment.

Assessment of the distribution of health facilities in the study area shows that urban settlements in Jos North, Jos South and Barkin Ladi L.G.As have a higher concentration of

health facilities and services than rural communities. This means that patients living in rural areas within the study area will have to travel long distances to the nearest healthcare facility. Based on the analysis of the field studies conducted during the study period, the presence of healthcare facilities in the study area does not always mean a better healthcare system, as most of these facilities lack the state-of-the-art equipment required for improvement and more efficient healthcare delivery.

Based on the overall susceptibility and analysis of the various risk factor parameters listed in the Table 5.6: Ecological risk factor's vulnerability, Table 5.7: Meteorological risk factor's vulnerability and Table 5.8: Socioeconomic risk factor's vulnerability as well as the risk assessment of the study area, it was observed that malaria risk transmission is more prevalent in areas such as Jos North, Jos South, Barkin Ladi and parts of Bassa L.G.As. It is observed that these areas have a high prevalence of abandoned mining ponds, dams and stream networks compared to other areas in the study area, which increases the high risk of malaria transmission in such areas. Due to the location of these water bodies such as stream networks, abandoned mining ponds, dams, etc. in these areas, land use activities such as agriculture and animal husbandry are also observed to be associated with increased risk of malaria transmission in these regions. Furthermore, the presence of these water bodies has been observed to increase the vegetation density and thus provide suitable breeding habitat for the vectors and thus increase malaria transmission in such areas.

The topographical analysis of the study area indicating the effects of parameters such as aspect, elevation and topographic wetness index also shows that malaria risk is also prevalent in areas such as Jos North, Jos South, and part of Barkin Ladi L.G.As. These areas are subject to less topographical controls as they are proven to be at lower elevations and therefore tend to collect and accumulate more water during rainfall than the low-risk areas such as Riyom, Jos East, and Bassa L.G.As which are proven to be at higher elevations. Since high-risk areas such

as Jos North, Jos South and Barkin Ladi L.G.As lie within the Plateau State capital, the population appears to be concentrated in this region due to its robust economic activities and rural-urban migration. In addition to the lack of mechanisms to distinguish between indigenous and imported cases of the disease, these areas are also responsible for the high rate of malaria transmission, as they are largely transit zones from other regions of the country and the West African region in general. Denser populations in these areas will also lead to an increase in anthropogenic activities and ultimately increase both ambient, land surface temperatures, and the urban heat island, creating suitable breeding habitats for the malaria vectors. The increase in vectors also leads to increased malaria transmission, thus explaining the high risk of the disease in areas such as Jos North, Jos South, and Barkin Ladi L.G.As compared to areas such as Bassa, Jos East and Riyom L.G.As.

The model validation technique used in this research demonstrated that the malaria risk model demonstrated exceptional performance in identifying both positive and negative malaria cases in the northern zone of Plateau State, Nigeria, as evidenced by its average sensitivity of 98% during the study period. The model performance is a very good indication that the model is a valuable tool to guide decision makers in implementing the required vector management practices as well as the required intervention measures in the study area.

In addition to plotting ROC and calculating AUC, kernel density statistical techniques were used to determine malaria hotspots and analyse the spatial distribution of the disease in the study area. The analysis showed that malaria incidence was also densely clustered in regions such as Jos North, Jos South, and Barkin Ladi L.G.As with a confidence level of 90-99% in predicting the disease hotspots compared to other parts of the study area. This lends further credibility to the meticulous work of the various malaria experts in identifying and determining the relative importance of the risk factor parameters and the overall disease risk modelling process. Furthermore, because the parametric data of the various malaria risk factors were

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easily accessible and easy to analyse, the risk model provides a time-efficient and cost-effective technique for assessing malaria risk in other regions.

Chapter 6: Conclusion, recommendation, and future perspectives.

Developing effective strategies that delineate malaria foci is a vital step in combatting the daunting challenges posed by the malaria burden in Nigeria. By identifying endemic malaria-prone regions and using different risk factor parameters covering the different areas of societal composition, such as: Such as environmental, climate and socio-economic activities, this research provides policymakers with the necessary tools to plan and implement targeted malaria intervention measures, in addition to appropriate vector surveillance and optimal use of scarce resources. The fact that this research carefully identified various risk factors and, moreover, used various experts from different malaria-related fields with different expertise, qualifications, and years of experience to determine their relative importance ranking, ensured a high accuracy and unwavering consistency in evaluating complexes interrelationships between the various risk factors as they correlate to host, vectors and associated factors that influence malaria transmission risk in the study area.

In contrast to traditional malaria risk analysis, mapping, and modelling methods, which are often characterized by high cost, labour intensity and time constraints, the risk model developed to assess, map and model malaria risk in the study area utilizes easily accessible data sets with minimal effort and increased time efficiency. This approach provides a cost-effective

Conclusion, recommendation, and future perspectives.

and convenient way to identify malaria risk hotspots, thereby serving as a key tool to effectively manage the disease burden in the northern zone of Plateau State, Nigeria, and other regions. Furthermore, the reproducibility of research can be easily carried out in any malaria-prone region with the necessary skills as the datasets used to model malaria risk in this study are readily available, inexpensive and require less labour.

Based on a comprehensive assessment of the topography, hydrological composition, geomorphology and other anthropogenic activities of the study area, this study also carefully identified and classified various risk factors and parameters that influence the suitability of vector breeding habitats and transmission risks. Furthermore, integrating these parameters into a comprehensive malaria risk model not only facilitates the assessment and identification of disease hotspots, but also represents a key advantage in addressing several deficiencies identified in the National Malaria Elimination Programme, as outlined in Chapter Two. These include deficiencies in informed decision-making, judicious allocation of scarce resources, effective monitoring and control of malaria initiatives, entomological surveillance to identify additional vector species, and improvement of vector management practices in the study area and Nigeria.

In addition, by examining the distribution rate of confirmed malaria cases, this study provides useful guidelines for the National Malaria Elimination Program and local health authorities in allocating intervention programs to appropriate locations based on assessment of the urgent population needs. This approach ensures that resources are equitably distributed and optimally used to achieve the desired impact of the programme.

Furthermore, because this research holistically assesses, analyses, models, and maps malaria risk hotspots, it can be used by policymakers and the various levels of government to determine the distribution of needed health programs and facilities based on the analysis of vulnerable local populations.

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Given the lack of entomological data on vector distribution, the risk model can also help authorities identify the geographical regions where vector control programs and surveillance should be focused. Additionally, because the model is region-specific, it can help authorities accurately assess local transmission risk, which is critical for developing and managing malaria control programs. Thus, this model can contribute to better resource allocation and targeted interventions to combat malaria transmission in the region.

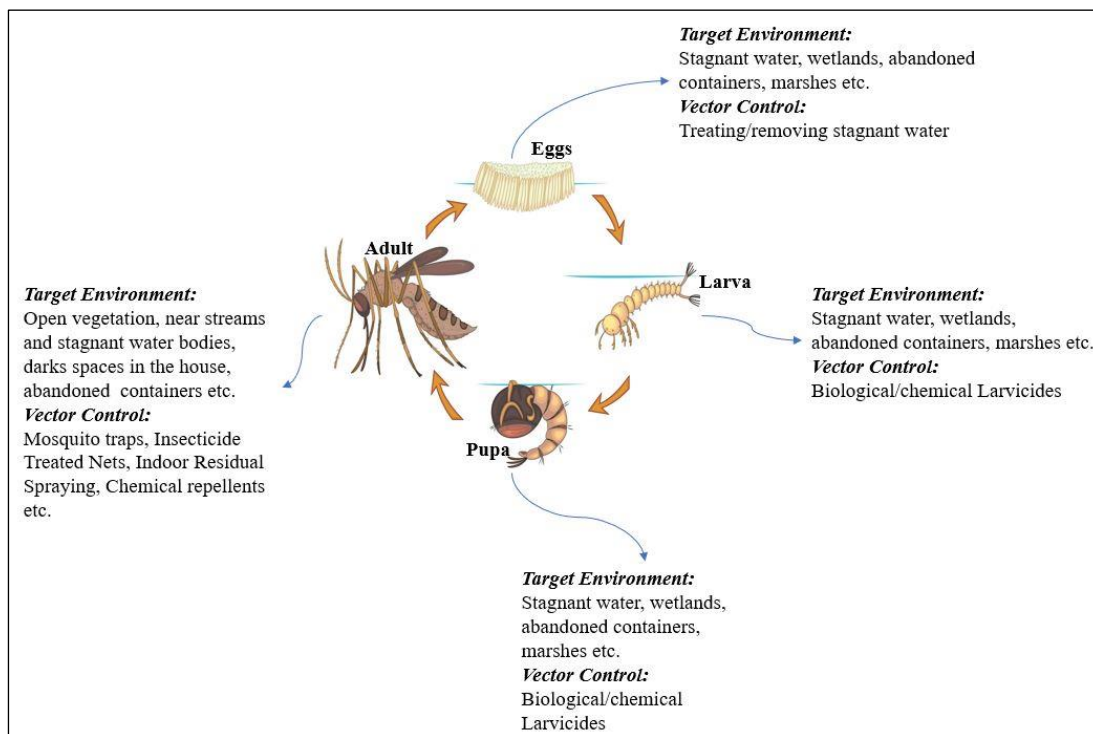


Figure 6.1: Mosquito life cycle and vector control measures (Bay, 2023)

Since the model developed in this research can identify regions at high risk of malaria transmission, combined with different experts' consensus on the weighting of the various parameters and risk factors, this research provides guidance on appropriate vector control measures for the areas with the highest risk of transmission and burden of the disease in the northern zone of Plateau State, Nigeria. By comprehensively assessing the various risk factors that have parameters on the risk of malaria transmission. As shown in Figure 6.1: Mosquito life cycle and vector control measures (Bay, 2023) above, the model developed in this study can help authorities determine which vector control strategies are most effective in reducing the

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burden of malaria in these high-risk regions. By targeting interventions tailored to the specific factors or parameters that influence malaria transmission risk identified in the model, this research represents an important tool to maximize the efficiency of vector management and ultimately help reduce the overall burden of malaria in the study area.

Since the correlation matrix analysis of the main risk factors identified in this study shows that the environmental risk factor has the largest weight compared to other risk factors, accounting for more than 60%. Therefore, the intervention strategies in the study area should prioritize ecological risk factors based on the risk model analysis. Further analysis of the parameters representing the ecological risk factors, using the pairwise comparison matrix, shows that dams/ponds, stream networks, elevation and land use/land cover activities account for over 50% of the weight of influence on malaria transmission risk in the study area. This finding highlights the importance of considering these parameters when developing targeted interventions to reduce malaria transmission risk in the region. The weights assigned to parameters and risk factors suggest that malaria control measures and interventions should prioritize control or elimination of the immature stages of the mosquito life cycle, including eggs, larvae, and pupae, before they develop into adult mosquitoes. Vector control strategies that target these immature stages, such as: Such as source reduction, larviciding (using biological and chemical methods), biological control, environmental management, and integrated vector management, should be the focus of vector control and elimination programs in the study area. These interventions should be complemented by other strategies aimed at reducing the adult mosquito population. Although no single method of malaria control or elimination can be completely effective in controlling the vector, the use of multiple interventions is critical for optimal and effective vector control and elimination. In other words, a combination of interventions is often required to achieve the desired results in controlling and eliminating malaria. This approach allows for a more comprehensive and integrated strategy

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that can target different aspects of the mosquito life cycle and transmission cycle. By combining different strategies and interventions, there is a high probability of eliminating or reducing the burden of malaria in the region.

Although our study has made undeniably commendable progress in using ecological, meteorological and socioeconomic risk factors to assess and understand the complex vector-host-environment relationship in modelling malaria risk in the study area. It is also important to recognize that in addition to these factors, more comprehensive and holistic approaches that include a broader range of environmental, climate and socioeconomic risk factors, in addition to the risk factor parameters used in this work, need to be used in order to better understand the dynamics of malaria transmission risk to enable.

Furthermore, this study recognizes the inherent sensitivity of certain ecological and meteorological parameters to variations in local climatic conditions. Because these factors undergo seasonal variation in response to local climate variations, the study also recognizes the likelihood that malaria infections vary seasonally. Due to this inherent variability, the study proposes as a future perspective to examine the seasonal dynamics of disease transmission risk in the northern zone of Plateau State to better understand the risk of malaria transmission.

The use of spatiotemporal modelling techniques to analyze weekly or monthly malaria incidence data to comprehensively assess temporal and spatial variations in disease prevalence within the region is another future perspective to consider. Finally, the use of machine learning algorithms to predict the disease prevalence patterns in the study area is another important future perspective that should be considered in the study area.

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Appendix

This survey aims to model the relationship between ecological, climatic, and socioeconomic malaria risk factors in the Northern Senatorial District of Plateau State to predict and monitor malaria vulnerabilities and risks. The survey consists of three sections and takes less than 10 minutes to complete. Your participation is anonymous as the researcher has no knowledge of participants' biases. The results of this research will also be kept confidential. By checking the “Yes” box below, you agree to participate in this study.

Yes

No

SECTION 1: Demographic Question

- a. What is your level of Education?
- Undergraduate
 - Masters
 - PhD
 - Others (Specify).
- b. How many years have you been working the health sector or in the field of Epidemiology.
- 5-10
 - 11-15
 - 16-20
 - 21-25
 - Above 26years.
- c. Which of these fields does your expertise fall in?
- Field officer / Integrated Vector Management
 - Educationist / Advocacy Communication and Social Mobilization
 - Health Practitioner / Case Management
 - Others (Kindly Specify)

SECTION 2: Expertise Work Experience

Kindly state your the current position:

SECTION 3: Pair-Wise Comparison Matrix of Malaria Risk Factors

Based on your expertise knowledge in the field of malaria, kindly evaluate the following malaria risk factors using Saaty's Pair-Wise Comparison Matrix of relative importance shown in table 1 below.

Appendix A.1: Saaty's 9 Degree Pair-wise Comparison matrix

Intensity of Importance	Definition	Explanation
1	Equal Importance	Two criteria contribute equally to the objective
3	Moderate Importance of one over another	Experience and judgment slightly favour one criterion over another
5	Essential or Strong Importance	Experience and judgment strongly favour one criterion over another
7	Very Strong or demonstrated Importance	A criterion is favoured very strongly over another; its dominance demonstrated in practice
9	Extremely Importance	The evidence favouring one criterion over another is of the highest possible order of affirmation
2, 4, 6, 8	Intermediate values between the adjacent scale values (when compromise is needed)	
Reciprocals	If criteria i has one of the above numbers assigned to it when compared with criteria j, then j has the reciprocal value when compared with i	

b. Climatic risk factors

Appendix C.1: Climatic risk factors

	Temperature	Rainfall	Relative Humidity
Temperature	1		
Rainfall		1	
Relative humidity			1

c. Socioeconomic risk factors

Appendix D.1: Socioeconomic risk factors

	Population density	Distance to road	Distance to hospitals	Vulnerable age group population
Population density	1			
Distance to road		1		
Distance to hospitals			1	
Vulnerable age group population (>5years)				1

d. Correlation matrix

Appendix E.1: Correlation matrix

Malaria risk	Ecological	Climatic	socioeconomic
Ecological	1		
Climatic		1	
socioeconomic			1