ED730-LH

Order N°:

DOCTORAL THESIS OF THE UNIVERSITY OF LOMÉ

Presented for the award of the grade of

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Doctoral School of Letters and Humanities ED730-LH

West African Science Service Centre on Climate Change and Adapted Land Use

Domain: Human and Social Sciences

Mention: Geography

Speciality: Climate Change and Disaster Risks management

By

Gouvidé Jean GBAGUIDI

Malaria Risk Modelling and Prediction, Vulnerability of Communities to Malaria in the Context of Climate Change in the Northern part of Benin, West Africa

Publicly defended on 29th January 2025 before a jury composed of :

Edinam KOLA	Full Professor	University of Lomé, Togo	**President of jury**
Hoinsoudé SEGNIAGBETO	Full Professor	University of Lomé, Togo	**Examinator**
Anges.T. YADOULETON	Full Professor	University of Abomey, Benin	**Examinator**
Guillaume Koffivi. KETOH	Full Professor	University of Lomé, Togo	**Director**
Nikita Kwési A. TOPANOU	Associate Professor	University of Abomey, Benin	**Co-Director**
Walter LEAL	Full Professor	Hamburg University of Applied sciences, Germany	**Co-Director**

Université de Lomé | **ED730-LH**

WASCAL West African Science Service Centre on Climate Change and Adapted Land Use

Federal Ministry of Education and Research

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The University of Lomé do not intend to give any approval or disapproval to the opinion expressed in this thesis. They should be considered as the authors 'own.

Summary

Dedication

I dedicate this doctoral research thesis to my spouse, *Emilienne Tchomakou*, my son, *Jesudji Ebenezer* and my daughter *Jesumè Priscille* may you receive the fruits of your sacrifices and efforts.

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List of abbreviations and acronyms

ACP: Analyse en Composantes Principales

AVHRR:Advanced Very High Resolution Radiometer

CFA: Confirmatory Factor Analysis

CFI: Comparative Fit Index

Cor: Correlation

CORDEX: Coordinated Regional Climate Downscaling Experiment

CSS: Cascading Style Sheets

DHS: Demographic and Health Survey

DOAJ: Directory of Open Access Journals

DRR: Disaster Risk Reduction

EIR: Entomological Infection Rate

ENS: Ecole Normale Supérieure

EVI: Enhanced Vegetation Index

EWS: Early Warning Systems

FGSAM: Functional Generalised Spectral Additive Model

GHGs: Greenhouse Gases

GIS: Geographic Information Systems

GPM: Retrievals for Global Precipitation Measurement

GPS: Global Positioning System

GTS: Global Technical Strategy

HDI: Human Development Index

HTML: HyperText Markup Language

ICT: Indice de Condition Thermique

IPCC: Intergovernmental Panel on Climate Change

IRS: Indoor Residual Spraying

ITCZ: Inter-Tropical Convergence Zone

ITNs: Insecticide-treated nets

LiR: linear regression

LLINs: Long-Lasting Insecticidal Nets

LOR: Lack of resilience

LST: Land Surface Temperature

MAE: Mean Absolute Error

Max: Maximal

Min: Minimal

MK: Mann Kendall

MOVE: Methods for the Improvement of Vulnerability Assessment in Europe

MSE: Mean Square Error

NASA: National Aeronautics and Space Administration

NBiR: Negative Binomial Regression

NDVI: Normalized Difference Vegetation Index

NDWI: Normalized Difference Water Indice

NOAA: National Oceanic and Atmospheric Administration

OLS: Ordinary Least Square

PCA: Principal Component Analysis

PCI: :Iprecipitation Concentration index

PCR: Principal Component regression

PhD: Doctorat of Philosophy

RCP: Representative Concentration Pathway

RGPH: General Census of Population and Housing

RMSE: Root Mean Square Error

RS: Remote sensing

SDGs: Sustainable Development Goals

SEM: Structural Equation Model

SPOT: Satellite

SR: Sporozoite Rate

SSA: Sub-Saharan Africa

Std.Dev: Standart Deviation

SUS: susceptibility

SVM: Support Vector Machine

TCI: Thermal Condition Index

TLI: Tucker–Lewis Index

UN: United Nations

UNFCCC: United Nations Framework Convention on Climate Change

VBD: Vector-Borne Disease

VCI: Vegetation Condition Index

VHI: Vegetation Health Index

VI: Vulnerability Index

WASCAL: West African Science Service Centre on Climate Change and Adapted Land Use

WHO: World Health Organisation

WMO: World Meteorological Organization

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Abstract

Africa stands as the most susceptible continent to the ramifications of changes in climate. The repercussions of climate change on human well-being have garnered increased scrutiny in recent times. Malaria, a prevalent vector-borne ailment, emerges as one of the principal diseases profoundly influenced by climatic variations in West Africa. Malaria is the leading cause of mortality in Benin. Malaria Prevention and Reduction Poses Significant Challenges in Benin due to Prevalent Poverty, environmental challenges, and the economic status of the country.

This study aims to model the effect of climate change and vegetation health on the transmission of malaria and develop an intelligent outbreak warning system for the prediction of the incidence of malaria in Northern Benin. In addition, the study assesses the vulnerability of the community to malaria.

Monthly data on climatic variables and the number of malaria cases were collected over the period 1991 to 2021 and 2009 to 2021 respectively. As well as the weekly Vegetation Health Index data. The study used Mann-Kendall, Sen's slope, and PETITT tests to characterise the climate of the study area. Pearson correlation and structural equation model were used to assess climate change's impact on the malaria transmission. Different regression algorithms were applied to model the impact of malaria transmission due to climate change. We predict the incidence of malaria in northern Benin over 2021-2050 period using Cordex Africa data. An online malaria early warning web application was developed using the Streamlit framework. The impact of vegetation on the infection of malaria was determined, and a malaria forecast model was developed using vegetation health indices. The vulnerability of the community is assessed using socio-economic and environmental data. PCA was used to determine the weight of each indicator.

The findings revealed that temperature and relative humidity are the major climatic factors influencing malaria transmission in northern Benin. An advanced model for malaria epidemics predicts 82% malaria incidence, with an increase in 2021–2050 under RCP4.5 and RCP8.5 and a decrease under RCP8.5 over 2021-2030. The web-based application developed predicts accurately the malaria outbreak risk. Moisture (TCI) predicts 75% of the monthly malaria cases during intense mosquito activities, while 78% of the monthly occurrence of malaria is predicted by the Vegetation Health Index (VHI) and soil temperature index (TCI). Materi, Cobli, Boukoumbe, and Perere districts exhibit the highest vulnerability to malaria in northern Benin.

The findings of this research provide tools for stakeholders and policymakers at different levels. They can use these tools to take target actions to lessen the transmission of malaria in Benin and mitigate the impact of climate change on the community's health by developing adaptation strategies.

Keywords: Climate change, Malaria, Prediction, Mitigation, Northern Benin

Résumé

L'Afrique est le continent le plus vulnérable aux impactes du changement climatique. Les effets du changement climatique sur la santé humaine ont attiré plus d'attention ces dernières années. Le paludisme est l'une des principales maladies vectorielles les plus sensibles au changement climatique en Afrique de l'Ouest. Le paludisme est la principale cause de mortalité au Bénin. La prévention et la réduction du paludisme sont très difficiles au Bénin à cause de la pauvreté, des défis environnementaux et de la situation économique du pays.

Cette étude vise à modéliser l'impact du changement climatique et de la végétation sur la transmission du paludisme et à développer un système d'alerte précoce intelligent pour prédire l'incidence du paludisme dans le Nord du Bénin. En outre, l'étude évalue la vulnérabilité de la communauté au paludisme. Des données mensuelles sur les variables climatiques et le nombre de cas de paludisme ont été collectées de 1991 à 2021 et 2009 à 2021 respectivement. Les données hebdomadaires sur l'indice de santé de la végétation ont également été collectées. L'étude a utilisé les tests de Mann-Kendall, de Pente de Sen et de PETITT pour caractériser le climat de la zone d'étude. La corrélation de Pearson et le model d'équation structurelle ont été utilisées pour évaluer l'impact du changement climatique sur la transmission du paludisme. Différents algorithmes de régression ont été appliqués pour modéliser l'impact du changement climatique sur la transmission du paludisme. Nous avons prédit l'incidence mensuelle du paludisme dans le nord du Bénin sur la période 2021-2050 en utilisant les données de Cordex Africa. Une application Web d'alerte précoce au paludisme a été développée en utilisant le cadre Streamlit. L'impact de la végétation a été déterminé et un modèle de prévision du paludisme a été construit en utilisant les indices de végétation. La vulnérabilité de la communauté au paludisme est évaluée à l'aide de données socio-économiques et environnementales. L'ACP a été utilisée pour déterminer le poids de chaque indicateur.

Les résultats ont révélé que l'humidité relative et la température sont des facteurs climatiques qui affectent la transmission du paludisme au nord du Bénin. Un modèle intelligent d'alerte précoce du paludisme prédit 82 % de l'incidence mensuelle du paludisme et révèle une augmentation sur la période 2021-2050 sous les scénarios RCP4.5 et RCP8.5 et une diminution sous RCP8.5 de 2021 à 2030. L'application Web développée prédit très bien le risque d'épidémie de paludisme dans les différentes communes du nord du Bénin. L'indice de condition thermique (ICT) prédit 75 % des cas de paludisme pendant les périodes de forte activité des moustiques, tandis que TCI couplée avec l'indice de santé de la végétation (VHI) prédire 78 % de l'incidence mensuelle du paludisme. Les communes de Matéri, Cobli, Boukoumbé et Pèrèrè sont les plus vulnérables au paludisme dans le nord du Bénin.

Les résultats de cette recherche fournissent de outils aux parties prenantes et aux décideurs à différents niveaux. Ils peuvent utiliser ces outils pour prendre des mesures de résilience appropriées afin de réduire la transmission du paludisme au Bénin et d'atténuer l'impact du changement climatique sur la santé humaine.

Mots clés : Changement climatique, Paludisme, Prévision, Résilience, Nord du Bénin

General introduction

Climate Change's Effects due to global warming are expected to be very harmful in recent decades. Global warming caused by the release of Greenhouse Gases (GHGs) is becoming a major concern for all governments. The planet is warming by 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways and will likely harm the communities at all levels of development (IPCC, 2022a, p.3). Emerging scientific evidence suggests a high probability that global temperatures will reach or surpass the 1.5°C threshold above pre-industrial levels in the foreseeable future, even under the most optimistic greenhouse gas emissions scenario. This affects temperature and rainfall in different parts of the world unevenly (Salman, 2019, p.429).

Climate change poses a dual threat by exacerbating existing risks and introducing new risks to ecosystems encompassing animal, plant life, and human systems. These risks are not evenly distributed and tend to disproportionately affect disadvantaged persons and groups in nations at varied stages of development. As the magnitude of warming intensifies, the probability of severe, widespread, and irreversible consequences for humans, wildlife, and habitats rises significantly. If high emissions persist, the predominantly negative impacts on biodiversity, ecosystem services, and economic progress would exacerbate risks to livelihoods, food security, and human well-being (IPCC, 2014, p.69). Climate change encompasses a comprehensive threat to human development and survival, encompassing social, political, and economic aspects, as it has the potential to affect all-natural systems. Despite Africa contributing only 4% of global greenhouse gas (GHG) emissions, the continent remains the most vulnerable to the impacts of climate change (IPCC, 2022b, p.5). African countries bear the brunt of climate change impacts, experiencing its consequences to the greatest extent.

Over the past decade, there has been a notable rise in the level of academic and public interest and attention paid to the effects of climate change on human well-being. There's mounting proof that climate change is having a negative effect on health around the world, both directly and indirectly through disruptions in ecological and socioeconomic systems. The global warming caused by greenhouse gas emissions (GHGs) is becoming a big challenge for countries all over the world. Due to its low adaptive capacity and high sensitivity of socioeconomic systems, Africa is the most vulnerable continent to the impacts of climate change (IPCC, 2014, p.7; IPCC, 2022b, p.5).

The IPCC special reports on regional impacts of climate change have provided authoritative evidence of the influence of climate on vector-borne diseases, with malaria dynamics and distribution being particularly influenced by climatic factors (Paaijmans *et al.*, 2009, p.13844, M'Bra *et al.*, 2018, p.11, Ayanlade et al., 2013, p.16, p.12; Diouf *et al.*, 2021, p.1, IPCC, 2022b, p.35) all found a strong relationship between malaria prevalence and meteorological variables. Temperature, humidity, rainfall, and wind speed all have an impact on malaria incidence by influencing the duration of mosquito and parasite life cycles and the behaviour of humans, vectors, and parasites (F. Kogan, 2020a, p.237; Parham *et al*, 2010, p.620). Climate factors such as temperature, humidity, and rainfall, together with the degree of immunity among human populations, are all closely related to the spread of malaria (Olson JAP and SH, 2006, p.5635; Opoku *et al*., 2021, p.4). The intensity and duration of the rainfall season, as well as changes in air temperature, are critical factors, alongside the spatiotemporal distribution of diseases.

Climate is really important in the abundance and distribution of mosquitoes, both directly and indirectly through its impact on habitats and ecosystems. The effects of climate change can significantly influence the geographical range of mosquitoes. In particular, rainfall plays a crucial role in the epidemiology of malaria. Mosquitoes thrive in stagnant water, typically freshwater pools or marshes, and their abundance is strongly influenced by rainfall patterns and the availability of surface water (Tchigossou *et al.*, 2017, p.1). Rainfall also affects relative humidity, which in turn impacts the lifespan of adult mosquitoes (Endo & Eltahir, 2016, p.6; Lieshout *et al.*, 2004, p.87).

The burden of malaria-related mortality and morbidity is particularly severe in impoverished countries and among the most disadvantaged populations within these countries (Adefemi *et al.*, 2015, p.347; Leal Filho *et al.*, 2019, p.2). Socioeconomic factors also contribute to the occurrence of malaria, both in rural and urban areas (Lowe *et al.*, 2013, p.1).Malaria has emerged as the most significant vector-borne disease in regions such as Africa (especially West Africa), parts of Asia, and Latin America (Kogan, 2020a, p.237).

Benin, being classified as a least developed country with a rapidly growing population, faces severe malaria challenges (Yankson *et al.*, 2019, p.2). The country is significantly impacted by the prevalence of malaria due to environmental challenges, climate change and its low socioeconomic status.

CHAPTER ONE: BACKGROUND AND STATEMENT OF PROBLEM

Chapter one: Background and statement of problem and justification

1.1. Background

Malaria continues to pose a significant public health challenge in many regions, particularly in sub-Saharan Africa (Opoku *et al.*, 2021 ,p.4). The northern part of Benin, located in West Africa, is no exception, experiencing a high burden of malaria cases. The relationship between malaria transmission patterns, environmental factors, and the consequences of climate change needs a complete study of this region's vulnerability (Moiroux *et al.*, 2012, p.1; Padonou *et al.*, 2018, p.40).

Temperature, humidity, rainfall, and wind speed all contribute to malaria incidence by affecting the duration of mosquito and parasite life cycles or by influencing the behavior of humans, vectors, or parasites (Boussari *et al.*, 2014, p.237; Leal Filho, *et al.*, 2019, p.2; Leal Filho *et al.*, 2023, p.9; Vincent, 2015, p.17 ; F. Kogan, 2020 , p.237). In Northern Côte d'Ivoire the duration of the rainfall season is also crucial in malaria transmission (M'Bra *et al.*, 2018, p.11). Rainfall ensures the persistence of larval sites with continuous vector biting rates in Benin (Subtil *et al.*, 2014, p.237). In a suburban area in Niger and other African countries, high temperatures limited malaria incidence (Dieng *et al.*, 2014, p.10; Sissoko *et al.*, 2017a, p.2). In Burkina Faso, rainfall and temperature are positively associated with malaria incidence (Donovan *et al.*, 2012a, p.87; Kasasa *et al.*, 2013a, p.4; Rouamba *et al*., 2019, p.1). Intense precipitation can destroy mosquito breeding, developmental, and resting sites, as demonstrated by Hunter in a study conducted in Malawi (Hunter.PR, 2003, p.37).

Human infection occurs when parasites enter the body via the bite of a Plasmodium-infected mosquito. Malaria parasites include *Plasmodium falciparum, Plasmodium vivax, Plasmodium malariae, and Plasmodium oval*. *Falciparum Plasmodium*, which is carried by Anopheles mosquitos, is the leading cause of malaria in Africa (Ayanlade *et al.*, 2013, p.16, p.12). It is to blame for the vast majority of severe instances and deaths related with the condition, and it has shown resistance to therapy *(Djègbè et al.*, 2011, p.2; Sominahouin *et al.*, 2018, p.9). The transmission of malaria varies over time in Mali (J. Gaudart *et al.*, 2009a, p.1). In most African countries such as Ghana, Nigeria, Benin, Togo, Mali, Senegal rainy season is the favorable period for the infection of malaria (Dery *et al.*, 2010a, p.3, Gadiaga *et al.*, 2011a, p.8; Coulibaly *et al.*, 2013a, p.1; Kasasa *et al.*, 2013a, p.4; Okunlola & Oyeyemi, 2019, p.1; Thomas *et al.*, 2021a, p.1).

Thus climate change will have an impact on human health and well-being through diverse direct and indirect pathways, which are contingent upon exposure to hazards and vulnerabilities(Leal Filho *et al.,* 2022, p.3). These hazards and vulnerabilities exhibit heterogeneity and variation within societies and are influenced by social, economic, and geographical factors(Lieshout *et al.,* 2004, p.87; Lowe *et al.,* 2013, p.1; Leal Filho *et al.,* 2019 , p.2). Poverty, inadequate access to healthcare and preventive measures, population density, and human behaviour patterns all play important roles in defining a community's susceptibility and resilience to malaria in West Africa(Anyanwu *et al.,* 2017, ; p.7, Olukosi *et al.,* 2020a, p.6; Sonko *et al.*, 2014a, p.7).

Understanding the intricate links between climate change, environmental factors, and community malaria risk in northern Benin is critical for effective malaria control and prevention methods. It is now possible to analyse the future risks and patterns of malaria transmission in the context of changing climatic circumstances using advanced modelling and prediction tools (Leal Filho, *et al.,* 2023, p.4980).

1.2. Problem statement and justification

Malaria remains one of the most significant and persistent public health concerns facing sub-Saharan Africa, a region that continues to bear a disproportionate burden of the global malaria caseload and mortality. Within this broader context, the West African nation of Benin is not immune to the devastating impacts of this vector-borne disease. Plasmodium parasite infection of red blood cells causes this vector-borne illness. The tiny parasites of the genus Plasmodium, which cause malaria, enter the human host through the bite of an Anopheles mosquito carrying the infection. There are four primary species of Plasmodium that can infect humans: *Plasmodium falciparum, Plasmodium vivax, Plasmodium malariae, and Plasmodium ovale*. The driver of malaria in Africa is the mosquitos of the Anopheles Plasmodium falciparum and causes most of the severity and deaths attributable to the disease and resists the treatment (Ayanlade *et al*., 2013, p.16).

Malaria is a serious public health problem in many countries, despite national and international efforts, and sanitary systems are hampered by a lack of information on the true burden of malaria, the risk of plasmodium transmission, and their geographical distribution (Donnees *et al.,* 2010, p.6). According to the latest data from the World Health Organization (WHO), in 2020, the number of cases of malaria worldwide was disproportionately high in the African area. The estimated prevalence of malaria in the WHO African Region during this period was 228 million cases, accounting for approximately 95% of all reported malaria cases and 96% of all malaria-related mortalities occurring worldwide. In 2021, the number of malaria cases continued to rise, reaching 234 million (WHO, 2022, p.xx). The number of deaths rose from 534,000 in 2019 to 602,000 in 2020 (WHO, 2021, pxix). Children under the age of 5 continue to be the most vulnerable group, with the risk of death being particularly concentrated among those under the age of 3 (WHO, 2021, p.xix).

In Benin, despite the government's consistent efforts over the years, malaria remains a serious burden in terms of both morbidity and mortality, accounting for a staggering 95% of deaths. In 2021, the reported annual figures are 3,163,648 malaria cases with a slight increase of 1.4% between 2020 and 2021 and 2,956 deaths (Bénin-Rapport Trimestriel d'ALMA , 2022, p1). The provinces of Couffo, Atacora, Donga, and Borgou belonging to the northern region exhibit the highest levels of malaria prevalence, with cases of 51%, 50%, 47%, and 45% respectively(EBSBV, 2019a, p.2). With these proportions, the rural areas have the highest prevalence of 43% and the urban areas come at the last position with 32% (Diouf *et al.*, 2021, p.1).

The future projections indicate an anticipated rise in malaria prevalence within the southern region of West Africa. Given the already high prevalence of malaria in Benin, failure to take specific action to mitigate the risk of infection could have severe consequences. Thus, it is imperative to initiate targeted measures now to reduce the risk. In this context, modelling the associations between environmental and climatic factors with malaria prevalence can provide valuable insights into the relationship between malaria and climatic variables. Understanding such dynamics holds significant strategic value for policymakers in formulating interventions pertinent to health planning. Early warning systems, when based on skillful forecasts and accompanied by timely responses, can serve as valuable tools for adapting to climate-related risks associated with infectious diseases (IPCC, 2022, p.51).

Advanced seasonal weather forecasting, which takes advantage of documented correlations between weather/climate conditions and infection/transmission patterns, allows for the early detection of situations which can lead to disease epidemics months in advance. This gives adequate time to implement effective population health interventions. Various statistical models, including linear, logistic, Poisson, and negative binomial regressions, have been employed by numerous authors to model the relationships between environmental factors, climatic variables, and malaria prevalence (Ayanlade *et al.*, 2020,p.1; Diouf *et al.*, 2021, p.1; Mackey, 2016, p.3; Salman, 2019, p.429; Zhou *et al.*, 2004, p.2375).

By employing proactive, timely, and effective adaptation measures, it is possible to mitigate numerous risks to human health and well-being, thereby reducing or even avoiding their potential negative impacts (IPCC, 2022, p.51). Evaluating the burden of malaria at both spatial and temporal levels holds paramount importance in informing decision-makers and facilitating the planning, organization, and prioritization of interventions where the burden is most severe. Risk maps, generated at appropriate scales, can provide valuable information for targeted malaria control efforts. Risk mapping serves as an efficient and effective tool for monitoring transmission patterns and evaluating the effectiveness of control measures (Yankson *et al.*, 2019, p.2).

Furthermore, anticipating future risks is a crucial aspect in the ongoing fight against malaria. Since Landsat-1 satellite launch in 1972, which introduced a spatial resolution of 30 meters, various research endeavors have focused on spatially mapping malaria risk. These endeavors rely on identifying breeding sites and quantifying mosquito abundance. Utilizing environmental information derived from space platforms, such as image processing techniques, Geographic Information Systems (GIS), and Global Positioning System (GPS), numerous studies have leveraged these tools for investigating infectious diseases, including malaria (Kogan *et al.*, 2008, p.10).

There is a large variety of vegetation indices available; the Normalised Difference Vegetation indicator (NDVI) is the indicator that is most frequently used in research pertaining to human health. Nevertheless, depending exclusively on the NDVI could not encompass all the important environmental factors linked to malaria. The Vegetation Health Index (VHI) is more appropriate for identifying malaria risk, according to research by Kogan and colleagues (Kogan *et al.*, 2008, p.10).

The state of the vegetation is crucial in promoting mosquito activity, which in turn affects the transmission of malaria indirectly. An important step in the process of controlling malaria is the inclusion of the Vegetation Health Index (VHI) in this study, which will provide insightful information about the risk of malaria. In addition, vulnerability is an important indicator to consider in the context of malaria control efforts.

The Intergovernmental Panel on Climate Change (IPCC) asserts that changes in climate will engender a myriad of impacts upon human health and welfare, manifesting through both direct and indirect pathways. The extent of these effects depends on individuals' exposure to hazards and their vulnerabilities, which are influenced by various social, economic, and geographical factors. Vulnerability to climate change exhibits temporal and spatial variations, not only across different communities and regions but also within communities on an individual level. These variations are shaped by broader non-climatic macro-scale factors, such as changes in population dynamics, economic development, educational levels, infrastructure, behavior patterns, technological advancements, and ecosystem conditions. Additionally, vulnerability is also influenced by individual or household-specific characteristics, including age, socioeconomic status, access to livelihood assets, pre-existing health conditions, and abilities, among other factors (IPCC, 2022, p.51).

The assessment of malaria vulnerability is crucial for informed decision-making, particularly in high-risk areas, to develop targeted and effective control measures. By combining vulnerability indicators with transmission risks and early detection indicators from health facilities, a valuable tool can be created to confirm the onset of a malaria outbreak. This integrated approach enables proactive interventions and timely responses to mitigate the impact of malaria and improve control strategies.

In Benin, there is a lack of comprehensive studies evaluating the link between malaria incidence and climatic variables. Understanding these dynamics is of paramount importance as it enables the forecasting of seasonal malaria prevalence, thereby providing valuable insights for policymakers to develop targeted interventions for malaria control planning. This study, titled "*Malaria Risk Modelling and Prediction, Vulnerability of Communities to Malaria in the Context of Climate Change in the Northern Part of Benin, West Africa,*" has been undertaken with the primary objective of addressing this knowledge gap.

The selection of the northern part of Benin as the study area is based on its notably high prevalence rates, particularly in the provinces of Borgou, Atacora, and Donga. These provinces rank among the top four departments in Benin with the highest malaria prevalence rates. The study intends to shed light on the specific issues by focusing on this region and the vulnerabilities faced by these communities in relation to malaria incidence in term of climate change.

1.3. Research questions

The warming of our planet is a big concern. Climate change influences the infection of malaria. Understanding how temperature, precipitation patterns, and extreme weather events, have been changing over the recent decades in the Northern region of Benin and identifying the relevant contextual indicators necessary for developing an integrated early warning system for malaria morbidity could help to improve the ability to predict and respond to malaria outbreaks, ultimately enhancing public health interventions and reducing the burden of the disease.

It is critical to answer the following important questions in order to obtain a full understanding of the topic and effectively execute the study's objectives.

❖ How do climatic variables in Northern Benin influence the incidence of malaria?

❖ How can an intelligent malaria early warning system be set up to predict malaria incidence using climatic variables?

❖ How can seasonal weather forecasts using NOAA/AVHRR satellite environmental data enhance malaria prediction in northern Benin?

❖ What is the degree of vulnerability of local communities to the transmission of malaria?

To address these questions, the following objectives have been formulated:

1.4.Objectives

1.4.1- Global objective

The general objective of this study is to model the impact of climate change on the risk of malaria in Northern Benin, employing an intelligent predictive model and real-time vegetation health indicators to inform proactive prevention strategies.

1.4.2- Specific objectives

The purpose of this study is

- ❖ To analyze the climate in Northern Benin in relation to malaria incidence.
- ❖ To develop an intelligent malaria early warning system for predicting malaria incidence in Northern Benin using climatic variables.
- ❖ To investigate the relationship between vegetation health and malaria incidence, while generating seasonal weather forecasts for malaria prediction using NOAA/AVHRR satellite data.

- Assess the vulnerability of communities to malaria and propose adaptative responses to reduce the infection of malaria in the Northern part of Benin.

1.5. Hypothesis

Malaria morbidity in Northern Benin is most likely influenced by socioeconomic factors. It is hypothesised, however, that variations in rainfall and temperature patterns play a significant role in determining malaria sensitivity in this region. Significant information may be acquired to identify the areas most vulnerable to malaria outbreaks by evaluating rainfall and temperature trends and understanding the factors that affect malaria transmission. To achieve the study's objectives, the following hypotheses will be tested:

H1 : Climatic variables significantly influence the incidence of malaria in Northern Benin.

H2: An intelligent malaria early warning system based on climatic variables improves the prediction of malaria incidence in Northern Benin.

H3: There is a significant relationship between vegetation health and the prevalence of malaria in Northern Benin.

H4: Socio-economic and environmental factors significantly affect the vulnerability of communities to malaria in Northern Benin.

The study intends to investigate the significance of meteorological and socioeconomic parameters in connection to malaria transmission in the study area by testing these null hypotheses. The findings will provide important insights into the factors influencing malaria vulnerability and will help to influence the development of targeted interventions and strategies to reduce malaria morbidity in Benin's northern region.

1.6. Significance of the study

The aims of this work conform with the Global Technical Strategy (GTS) for malaria. which aims to reduce malaria case incidence and mortality by 90% by 2030 compared to a 2015 baseline. This work contributed to the well-being of the population, the reduction of the mortality related to malaria and the reduction of poverty. All of these promote the first goal (End of poverty), third goal (Good health) and the thirteenth goal (Climate actions) of the UN’s Sustainable Development Goals (SDGs) and in addition to the aims of the Sendai Framework for Disaster Risk Reduction 2015-2030. The results of this study are a baseline for the decision-makers to enhance the control of malaria in Benin.

Furthermore, the assessment of the vulnerability of the communities to malaria risk is a good tool for the policymakers and the community to have adapted preparedness responses to lessen the impacts of climate change. The findings of this research strengthen the adaptation capacity of the communities to reduce their vulnerability to malaria and climate change in general.

1.7. Thesis structure

This thesis is divided into five chapters. The conceptualization and methodological framework are covered in the first section, which is separated into three chapters. The initial chapter provides the background and problem statement, while the second chapter clarifies concepts, establishes the theoretical framework, and conducts a comprehensive literature review. The third chapter discusses the physical and human characteristics of the studied location, as well as the methods used in this study. The fourth chapter of this thesis is dedicated to the presentation and discussion of results. Finally, the fifth chapter concludes the work and highlights the limits of the research by providing some recommendations.

1.8. Output of the study

Through this research, we develop valuable malaria tools for policymakers and the wider community of Benin. These tools serve to enhance efforts to combat malaria and mitigate the broader effects of climate change. The study successfully establishes a connection between climate change and malaria morbidity by creating a Malaria Early Warning Model and system specific to Northern Benin. Furthermore, we conduct an assessment of community vulnerability to malaria infection to highlight where urgent actions need to be undertaken.

An important aspect of this study is the promotion of the first goal (End of poverty), third goal (Good health) and the thirteenth goal (Climate actions) of the UN’s Sustainable Development. Lastly, the research provides adaptive responses designed to empower both vulnerable communities and policymakers, enabling them to strengthen their actions against malaria infection and minimise the adverse effects of climate change on Africa's development, particularly in West Africa.

CHAPTER TWO: CLARIFICATION OF CONCEPTS, THEORETICAL FRAMEWORK AND LITERATURE REVIEW

Chapter two: Clarification of Concepts, Theoretical Framework and Literature Review

Introduction

Malaria is prevalent in Sub-Saharan Africa and a serious public health issue (Gbalégba *et al.*, 2018a, p.1). High death rates remain a serious public health issue in Sub-Saharan Africa (Otte Im Kampe *et al.,* 2015, p.1; Segun et al., *2020a*, p.1). It is a climate-sensitive vector-borne disease that is influenced by a variety of hydroclimatological, biological, socioeconomic, and environmental factors (Ebhuoma & Gebreslasie, 2016, p.8, p.2).

The enormous complexity of malaria determinants makes malaria prediction and control problematic (Endo & Eltahir, 2016b, p.6).

The environment has a tremendous impact on any civilization's health results. Unfortunately, the environment has a particularly harmful impact on health in many underdeveloped nations (Ndiaye *et al.*, 2020a, p.1). The environment, climate, and socioeconomic factors are major determinants of malaria transmission (Gaudart *et al.,* 2009b, p.9).

Despite increased malaria control and elimination efforts, meteorological patterns and socioeconomic factors continue to play key roles in the dynamics of malaria transmission (Magombedze *et al.,* 2018, p.2; Segun *et al.,* 2020b, p.5). Malaria transmission is complex, requiring many factors to be considered (Endo & Eltahir, 2016c, p.3; Ouedraogo *et al.,* 2018, p.5). It is linked with changes in temperature, rainfall, humidity as well as the level of immunity in humans (Jane Ugwu & Zewotir, 2020, p.309; Machault *et al.,* 2012, p.1; Okunlola & Oyeyemi, 2019, p.9; Taconet *et al.*, 2021, p.9).

Socio-economic factors such as education, poverty, income, health facilities, land use/land cover, quality of information, and urbanization. Also, social and environmental factors play an important role in malaria incidence (Labbo *et al.*, 2016, p.1; Rouamba *et al.,* 2019 p.1).

The increasing resistance of mosquitoes to insecticides, changes in mosquitos' behavior due to control efforts, and the changes in ecology due to human activities undermine the control of malaria.

To reduce the burden of malaria on health care systems, there is a need to detect and comprehend the socio-economic and environmental determinants which influence the transmission and the incidence to reduce the risk and the challenges in the treatment. For this the clarification of some important concepts and literature review of the environment and socio-economic factors of malaria could help to identify the most influenceable determinants of malaria transmission and to have vital information for the control of malaria programs in West Africa.

This chapter is divided in three parts. First and foremost, we clarified numerous key concepts relevant to the study, expanded on the theoretical framework, and, equally important, did a thorough literature analysis to get a thorough understanding of prior research in the subject.

II1. Clarification of concepts

Climate change

According to the Intergovernmental Panel on Climate Change (IPCC), Climate change is defined as a phenomenon due to natural internal processes or external forcing such as modulations of the solar cycles, volcanic eruptions and persistent anthropogenic changes in the composition of the atmosphere or in land use (IPCC *et al.*, 2014, p.69). The United Nations Framework Convention on Climate Change (UNFCCC) elaborates in Article 1 that climate change refers to alterations in climate attributed directly or indirectly to human activity, which affects the composition of the atmosphere beyond natural variability observed over comparable periods (UNFCCC, 1992, p.3).
Consequently, climate change encompasses long-term changes in temperature, precipitation, and other atmospheric conditions driven by both human actions and natural factors. As illustrated in Figure 1, global warming is characterized by a rise in global surface temperatures over a defined baseline reference period (1850-1900), which helps eliminate short-term fluctuations (Hansen *et al.*, 2010, p.8).

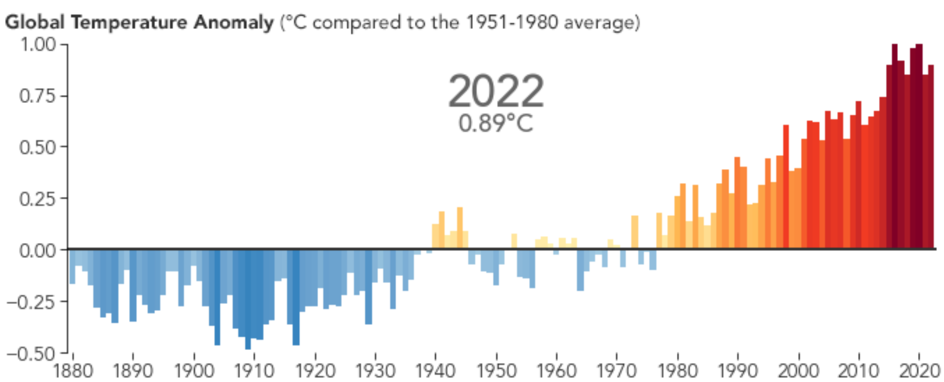


Figure 1: Global temperature anomaly over 1880 to 2020 *(*Hansen *et al.*, 2010, p.8*).*

The impacts of climate change are profound and multifaceted, leading to an increased frequency and intensity of extreme weather events such as hurricanes, floods, droughts, and heatwaves.

Rising sea levels, driven by melting ice sheets and glaciers, pose significant threats to coastal communities. Additionally, climate change disrupts ecosystems, affecting wildlife habitats and leading to species migration and extinction. Human health is increasingly at risk, with heightened occurrences of heat-related illnesses, respiratory issues from poor air quality, and greater vulnerability to infectious diseases (WMO, 2022, p.17). For instance, climate change can create conditions conducive to malaria transmission by influencing the life cycle of its vector, mosquitoes, and altering their geographical distribution.

Climate variability

The IPCC defined climate variability as deviation from a stated mean condition of various climate variables, including the occurrence of extreme occurrences, manifests across spatial and temporal scales surpassing individual weather events. The variability can be categorized as intrinsic, resulting from fluctuations within the climate system's internal processes (internal variability), or extrinsic, arising from variations in natural or human-induced external factors (forced variability)(IPCC, 2007, piii). The UNFCCC does not provide a formal, standalone definition of climate variability but discusses it in the context of climate change impacts and adaptation: Climate variability refers to variations in climate parameters (such as temperature, precipitation, and wind) that can occur on different time scales, from months to decades (IPCC, 2019, p.429). Variability affects rainfall and temperature patterns, which can impact mosquito breeding sites and malaria transmission rates (Ayanlade *et al.*, 2020, p.1; Houedegnon *et al.*, 2019, p.625) .

Communicable diseases

The World Health Organization (WHO) defines a communicable disease as a condition produced by an infectious agent or one of its hazardous components that spreads from a contaminated human, animal, or reservoir to a vulnerable host, either indirectly or directly via a plant or animal host, vector, or inert environment. Pathogens responsible for communicable diseases encompass bacteria, viruses, fungi, parasites, and prions (WHO, 2020, p.10). The transmission can occur through various means, including direct contact with infected individuals, contact with bodily fluids, inhalation of airborne pathogens, or consumption of contaminated food and water.

According to the Centres for Disease Control and Prevention (CDC, 2022, p.1), communicable diseases are a significant public health concern because they can lead to widespread outbreaks and impact communities globally. The CDC categorises these diseases based on their causative agents, which include viruses, bacteria, fungi, and parasites.

The National Institutes of Health (NIH, 2021, p.2) provides a more detailed classification of communicable diseases. Viral diseases include well-known conditions such as influenza, HIV/AIDS, and hepatitis, which can spread through respiratory droplets, sexual contact, or contaminated surfaces. Bacterial diseases, such as tuberculosis and strep throat, are transmitted through direct contact, contaminated food or water, and respiratory droplets.

The specific focus of this study is malaria, a vector-borne disease caused by the female Anopheles mosquito transmitting the *Plasmodium falciparum* parasite in the West African region.

Vector-borne disease

Diseases resulting from infections caused by parasites, viruses, and bacteria can be transmitted through various vectors. These vectors include a range of organisms such as mosquitoes, sandflies, triatomine bugs, blackflies, ticks, tsetse flies, mites, snails, and lice (WHO, 2016, p.xii, WHO,2021, p.xix). Through the bites or contact with these vectors, individuals can contract illnesses caused by these infectious agents. The World Health Organization (WHO) highlights that vector-borne diseases account for more than 17% of all infectious diseases, leading to over 700,000 deaths annually. Malaria alone causes an estimated 219 million cases globally, resulting in more than 400,000 deaths each year, primarily among children under five years old (WHO, 2021, p.xix)). This underscores the importance of studying vectors like Anopheles mosquitoes to develop effective control strategies and reduce the burden of malaria (WHO, 2021, p.xix). Malaria is the concern of this study.

This high burden of disease underscores the importance of studying vectors, particularly Anopheles mosquitoes, to develop effective control strategies aimed at reducing the incidence and impact of malaria (WHO, 2021, p.xix). As such, malaria is the primary focus of this study, highlighting the need for ongoing research and intervention efforts to combat this critical public health challenge.

Malaria

Malaria, an infectious disease transmitted by mosquitoes, afflicts human populations and is transmitted by protozoan parasites which are the *Plasmodium genus*. Although four species accounts for nearly all human infections, Plasmodium falciparum is particularly prevalent in Africa and is responsible for the most severe manifestations of the disease, leading to the highest mortality rates. When a human host is bitten by an infectious mosquito, this last can inject the parasite inside the individual's bloodstream through its saliva. Numerous mosquito species serve as vectors for malaria transmission through this mechanism. Each of these malaria-transmitting mosquito species exhibits distinct life cycle durations, aquatic habitat preferences, and feeding patterns (WHO, 2021, p.xix).

Malaria remains a significant public health challenge in Sub-Saharan Africa, characterized by notable trends in prevalence, transmission, and control efforts. The region accounts for a large majority of global malaria cases and deaths. According to the World Health Organization (WHO, 2022, p.xx), in 2021, there were approximately 241 million cases of malaria worldwide, with Sub-Saharan Africa contributing significantly to this burden.

Transmission dynamics are influenced by various factors, including climate, geography, and socio-economic conditions. Regions with high rainfall and warmer temperatures typically see increased transmission, as these conditions favor the breeding of Anopheles mosquitoes, the vectors responsible for spreading malaria (Ayanlade *et al.*, 2013, p.16, p.12; 2019.; M'Bra *et al.*, 2018, p.11; Samdi *et al.*, 2012, p.105).

The introduction and scaling up of control measures, such as insecticide-treated bed nets (ITNs), indoor residual spraying (IRS), and antimalarial medications, have led to a decline in malaria incidence and mortality in some areas. However, the effectiveness of these measures can be hindered by insecticide resistance among mosquito populations and challenges in healthcare access.

Malaria transmission often exhibits seasonal patterns, with peaks occurring during and shortly after the rainy seasons (PAS-PNA BENIN, p.27, 2019.; Filho *et al.*, 2019, p.2; Leal Filho *et al.*, 2023, p.4980). This seasonality affects both infection rates and control efforts, necessitating targeted interventions during high transmission periods (Filho *et al.*, 2019, p.2).

There is growing concern about the emergence of drug and insecticide resistance in malaria vectors and parasites. This resistance threatens the effectiveness of existing treatment regimens and vector control strategies, complicating malaria control efforts (WHO, 2022, p.xx).

Malaria disproportionately affects vulnerable populations, including children and pregnant women. Socioeconomic factors contribute to the high burden. Research and development focus on vaccines is increasing. The RTS,S malaria vaccine has shown promise in clinical trials and is being deployed in pilot programs in several Sub-Saharan African countries.

Risk

Risk refers to the likelihood of an adverse event occurring, often quantified as a function of hazard, exposure, and vulnerability. The Centers for Disease Control and Prevention (CDC) describes risk as the probability of an event occurring that could lead to harm, emphasizing the importance of understanding both exposure to malaria and the vulnerability of populations (CDC, 2022, p.1). Similarly, the Intergovernmental Panel on Climate Change (IPCC) discusses risk in terms of the potential for adverse consequences resulting from climate-related hazards, which can exacerbate malaria transmission in affected regions (IPCC, 2014, p.69). Additionally, the National Institutes of Health (NIH) defines risk as the likelihood of exposure to a hazard and the potential severity of the consequences, which is crucial for understanding the dynamics of malaria transmission (NIH, 2022, p.1).

In the field of epidemiology, risk refers to the probability of experiencing adverse effects due to exposure to a specific agent. A more comprehensive approach to risk assessment is necessary, taking into account stressors such as climate change, genetically modified organisms, disturbances, natural disasters, and socio-economic trends. As showing in figure2, *Risk is represented as a function of hazard (H), vulnerability (V), and exposure (E), emphasizing the interconnected nature of these factors*.(IPCC, 2022a, p.3).

Risk=F(V,E,H).

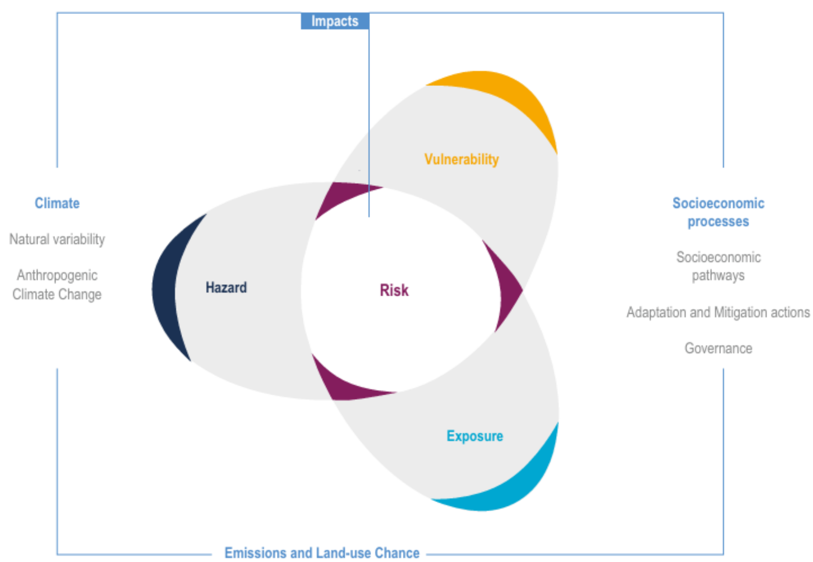


Figure 2: Interactions between hazard, exposure and vulnerability that generate impacts on health systems and outcomes, with selected examples (IPCC, 2022b, p.146)

There are many types of risks including:

Biological risk involves exposure to pathogens or vectors, such as the *Plasmodium* parasites transmitted by Anopheles mosquitoes, which can lead to diseases like malaria (WHO,2021, pxix).

Environmental risk encompasses risks arising from environmental factors, including climate change, which can affect mosquito breeding patterns and malaria transmission dynamics (IPCC,2014, p.69).

Social risk refers to the vulnerabilities associated with social determinants of health, such as poverty, education, and access to healthcare, which can increase susceptibility to malaria (IPCC,2014, p.69).

Economic risk includes the financial implications and costs associated with malaria outbreaks, such as healthcare expenditures and loss of productivity due to illness (WHO,2021, p.xix).

Health risk relates to the probability of adverse health outcomes, including the likelihood of contracting malaria based on exposure and vulnerability factors (CDC,2022, p.1).

Technological risk refers to risks associated with the use of technology in disease prevention and control, including the efficacy and safety of insecticides and vaccines (NIH,2022, p.2).

Political risk encompasses the impact of political instability, governance, and policy decisions on malaria control efforts and resource allocation (UNDP,2015, p.47).

Psychosocial risk involves the mental and emotional impacts of experiencing or fearing malaria, which can affect community behavior and health-seeking practices (Goffman, 1963, p.3).

Risk management

Risk management is the systematic process of identifying, assessing, and mitigating risks that could negatively impact an organization or project. It involves a structured approach to understanding potential threats and uncertainties, allowing for informed decision-making and strategic planning (Hillson, 2017, p.281).

According to (IPCC, 2019, p.11), Risk management refers to Plans, actions, strategies, or policies intended to reduce the probability and/or severity of anticipated negative outcomes based on measured or perceived risks. To achieve effective risk management, it is imperative to comprehensively address the hazard, exposure, and vulnerability components, with the objective of minimizing the susceptibility of communities. (figure3)

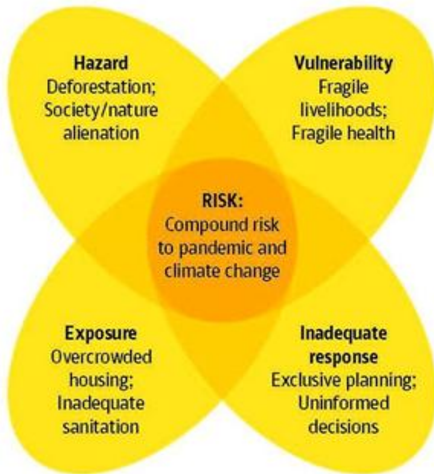


Figure 3 : Compound risk to pandemic and climate change (IPCC, 2022, p.18)

Key components include risk identification, risk assessment, risk mitigation, and monitoring and review. This structured approach allows for informed decision-making and strategic planning, ensuring the organization's success.

Disaster risk

It refers to the probability, within a specified timeframe, of significant disruptions to the normal functioning of a community or society (IPCC *et al.*, 2022, p.51). These disruptions are caused by dangerous physical events interacting with sensitive societal situations, resulting in widespread negative human, material, economic, or environmental consequences. The United Nations Office for Disaster Risk Reduction emphasizes that disaster risk is determined probabilistically as a function of hazard, exposure, vulnerability, and capacity. This definition highlights that disaster risks can vary significantly based on social, economic, and environmental contexts. Acceptable risk, or tolerable risk, is a critical aspect, reflecting the extent to which a community deems a certain level of risk acceptable based on its specific conditions. Disaster risk is a multifaceted issue influenced by social and environmental factors, necessitating a comprehensive understanding for effective risk management and resilience-building.

Vulnerability

The propensity or predisposition to be adversely affected. Vulnerability encompasses a variety of concepts and elements including sensitivity or susceptibility to harm and lack of capacity to cope and adapt (IPCC *et al.*, 2022, p.51). The concept of vulnerability assessment in the risk framework focuses on understanding the intrinsic predisposition of people, systems or communities to be affected in case of a hazard, and can include the assessment of the factors which lead to, augment, reduce, or maintain such vulnerabilities at a given scale i.e., national, state or province, district or municipal level, local community, single household.

The World Health Organisation (WHO) defines vulnerability as the inability of a population, individual, or organisation to predict, withstand, and resist calamities while healing from their aftermath. Malaria disease vulnerability may also be described as a function of exposure, susceptibility, and a lack of resilience (lack of resilience includes the ability to predict, cope with, resist, respond to, and recover from disease occurrences).

The concepts of hazard and vulnerability are intrinsically linked within the context of risk. The notion of hazard only makes sense when considered in reference to something vulnerable and that vulnerability only makes sense when it is linked to a hazard (Birkmann *et al.*, 2013, p.200) Figure(2).

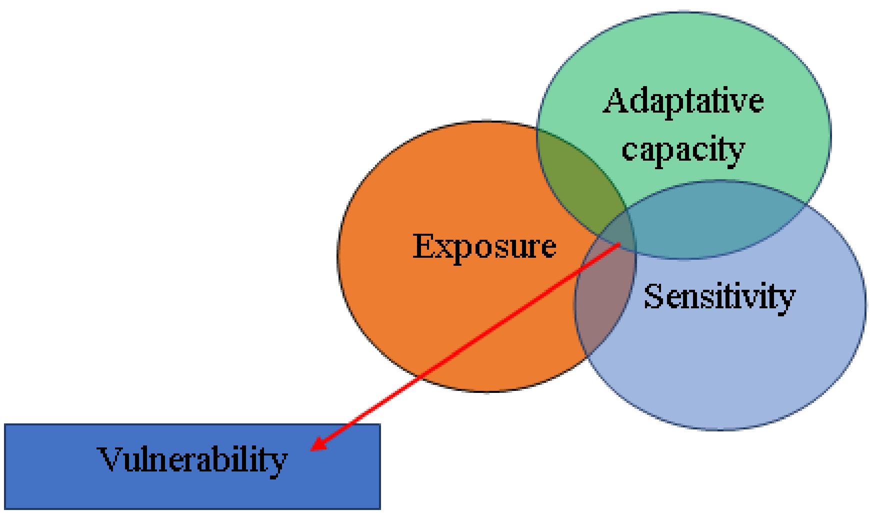


Figure 4: Research Approach for Vulnerability Assessment (IPCC, 2014, p.2)

Health outcomes may be strongly impacted by several types of vulnerability, particularly when it comes to diseases like malaria. From **(**WHO,2022, p.xx), these vulnerabilities fall into the following categories:

Biological vulnerability encompasses inherent physical and genetic factors that heighten susceptibility to diseases, such as age, sex, and pre-existing health conditions. This form of vulnerability is often tied to the biological characteristics of individuals that may predispose them to specific health risks.

Environmental vulnerability involves risks stemming from environmental factors, including climate change, which can influence the breeding patterns of disease vectors like mosquitoes. Shifts in environmental conditions can lead to increased transmission of diseases such as malaria.

Social vulnerability is shaped by social determinants of health, including poverty, education, and access to healthcare. Individuals in disadvantaged social positions may lack the resources needed to protect themselves from health risks.

Economic vulnerability pertains to the financial implications of health issues, including healthcare costs and the economic burden of disease outbreaks. This vulnerability can restrict access to essential health services and treatments.

Geographical vulnerability affects individuals living in remote or underserved areas, presenting barriers to accessing healthcare services and increasing their risk of adverse health outcomes.

Psychosocial vulnerability relates to the mental and emotional effects of experiencing or fearing disease, which can influence health-seeking behaviors and community responses to health interventions.

Cultural vulnerability arises from cultural factors, such as language barriers and differing health beliefs, which can hinder individuals' willingness to seek care and adhere to treatment protocols.

Political vulnerability reflects how political instability and governance issues can impact the delivery of health services and resource allocation, making populations more susceptible to health disparities.

Technological vulnerability pertains to the risks linked to the use of technology in health interventions, including concerns about access, efficacy, and the potential for technological failures.

Understanding vulnerability in malaria risk assessment is crucial for designing targeted interventions, prioritizing resources, enhancing surveillance systems, and fostering community involvement. It helps identify at-risk populations, enhances surveillance, and provides critical data for policymakers. Vulnerability assessments also provide insights into behavioral factors contributing to malaria transmission, guiding educational campaigns and behavior change initiatives. They can identify how climate change impacts malaria risk and help develop adaptive strategies. Addressing interconnected vulnerabilities can lead to comprehensive health strategies and sustainable interventions, improving overall health and well-being in communities.

Vulnerability Index (VI)

The IPCC defined VI as a measure that describes a system's vulnerability. A climate vulnerability index is typically derived by combining, with or without weighting, several indicators assumed to represent vulnerability (IPCC *et al.*, 2022, p.47).

The Vulnerability Index is a framework used to assess community vulnerability to adverse impacts, especially in the context of climate change and social factors. Key sources include the U.S. Climate Vulnerability Index (CVI), the Social Vulnerability Index (SVI), and the National Risk Index (Us, nd,p.1; CDC,2021, p.2, FEMA,2021, p.2). These indices use indicators from various sources, including health, social and economic factors, infrastructure, and environmental conditions, to evaluate vulnerability and identify areas needing support (CDC, 2021, p.2). Understanding social factors is crucial for disaster risk and resilience assessment (FEMA, 2021, p.2).

Exposure

It refers to the presence of individuals, livelihoods, species, or ecosystems, as well as environmental functions, services, resources, infrastructure, and economic, social, or cultural assets in locations and settings that could potentially experience adverse effects (Carter, 1996, p.36 IPCC, 2022, p.18). In the specific context of vector-borne diseases, such as malaria, exposure is characterized by the presence of individuals in areas at risk of high populations of female mosquito vectors especially falciparum . Geographical location, socioeconomic position, urban design, and infrastructure resilience are some of the elements that affect exposure to disasters including the spread of infectious diseases, floods and earthquakes (WHO,2018, p.2).

Understanding the different types of exposure is essential for identifying vulnerabilities and implementing effective risk mitigation strategies. (Nguyen *et al.*, 2016, p.1).

Physical exposure refers to tangible elements affected by hazards, such as buildings and infrastructure. *Social exposure* considers the characteristics of the population at risk, such as demographics and socioeconomic status. *Economic exposure* evaluates economic assets impacted by hazards, while *environmental exposure* refers to ecosystems and natural resources. *Cultural exposure* considers the impact on cultural heritage and community identity. *Temporal exposure* considers the timing of hazards and how they align with community activities. Understanding these forms of exposure helps develop targeted strategies to enhance resilience and reduce vulnerability.

Resilience

Resilience refers to the inherent ability of interconnected social, economic, and ecological systems to effectively cope with hazardous events, trends, or disturbances (Council, 2016, p.89). It involves the capacity of these systems to respond and reorganize in a manner that preserves their essential functions, identity, and transformative potential. In simpler terms, resilience entails the reduction of vulnerability, exposure, and hazard, as depicted in the accompanying figure (IPCC, 2022, p.37). Climate change and disaster risk refer to the abilities and resources that individuals, communities, and institutions possess to cope with, adapt to, and recover from climate-related hazards. There are different types of capacity relevant to this context, including capacity to anticipate, capacity to prepare, capacity to respond, capacity to recover, capacity to adapt, and capacity to cope. Understanding these capacities is essential for building resilience, as enhancing these capacities can help communities better prepare for, respond to, and recover from climate-related hazards, ultimately reducing vulnerability and improving overall adaptive capacity.

Key components of resilience include anticipation, preparation, response, recovery, and adaptation. Community resilience is the collective capacity of a community to respond to and recover from disasters, while economic resilience involves the ability of an economy to withstand and recover from shocks. Environmental resilience refers to the capacity of ecosystems to recover from disturbances while maintaining their functions and services. Infrastructure resilience refers to the robustness and adaptability of physical infrastructure to withstand and recover from disasters.

Enhancing resilience is critical in the face of climate change, as it helps communities reduce vulnerabilities and risks associated with disasters, ensure the continuity of essential services and functions during crises, and foster sustainable development by integrating risk management into planning and decision-making.

Adaptation

adaptation is defined by the Intergovernmental Panel on Climate Change (IPCC), as the process of adjustment to actual or expected climate and its effects, which can occur in both human and natural systems. The goal is to moderate harm or exploit beneficial opportunities (IPCC, 2014, p.69). The United Nations Framework Convention on Climate Change (UNFCCC) describes adaptation as the adjustments made in response to climate change, encompassing both anticipatory actions taken before climate impacts occur and reactive measures implemented after impacts have been experienced (UNFCCC, 1992, p.92.).In the health sector, the World Health Organization (WHO) defines adaptation as the adjustments made to health systems and practices to minimize the negative health impacts of climate change, thereby improving resilience and health outcomes (WHO, 2018, p.2).

The notion of adaptation in human systems refers to the process of responding to and adapting to existing or predicted climate conditions and its related impacts, with the goal of minimising negative consequences and capitalising on potential advantages. Adaptation in natural systems refers to the natural processes of adjusting to and responding to existing climate conditions and their impacts. However, human intervention can play a significant role in facilitating adjustments to the expected climate conditions and their associated impacts.

Adaptation strategies for malaria include structural, behavioural, health system, ecosystem, community engagement, and research. Behavioural adaptation entails implementing measures like bed nets and insect repellent, structural adaptation entails enhancing the physical infrastructure to lessen mosquito transmission. Ecological adaptation entails managing ecosystems to lower mosquito populations, health system adaptation entails bolstering healthcare services for disease detection and treatment. While research can provide new technologies for malaria prevention and control, community participation and education can increase knowledge about malaria and preventative measures.

Capacity: Based on the Intergovernmental Panel on Climate Change, capacity" refers to the abilities and resources that individuals, communities, and institutions possess to cope with, adapt to, and recover from climate-related hazards (IPCC, 2022, p.7). Capacity includes anticipating hazards, preparing for disasters, responding effectively, recovering after disasters, adapting to changing climate conditions, and coping with the effects of disasters. ***Capacity to anticipate*** involves using climate forecasting tools and vulnerability assessments to predict weather patterns and assess at-risk areas. Additionally, the ability to reduce risk is contingent upon ex post actions, which entail making informed choices subsequent to an event with the aim of minimizing the impact of future occurrences (Birkmann *et al.*, 2013a, p.196). In the context of vector born disease management, the World Health Organization (WHO) emphasises the need for surveillance and early warning systems to mitigate health impacts related to climate change (WHO,2021, p.xix). ***Capacity to respond*** involves developing disaster response plans and training communities.

Capacity to recover involves financial resilience and rehabilitation programs. ***Capacity to adapt*** involves adjusting practices and strategies to climate conditions. ***Capacity to cope*** involves providing social safety nets and community support networks. Understanding these capacities is crucial for building resilience and reducing vulnerability in climate change-affected communities.

Hazard

An act, occurrence, or human activity that has the potential to inflict death, damage, or other adverse effects on health, as well as property destruction, disturbance of the social and economic systems, or degradation of the environment. It is important to note that this potential for harm may exist either inherently within an agent or substance or in its latent property, making it capable of causing adverse effects on people or the environment when exposed under certain conditions (WHO, 2021, p.xix.). It is characterized by its specific location, magnitude, frequency, or probability. Climate-related hazards are increasingly contributing to the proliferation of malaria risks.

A biological hazard is a process or occurrence that arises from organic sources or is spread by biological vectors in Disaster Risk Reduction (DRR). It encompasses exposure to pathogenic microorganisms, toxins, and bioactive substances, which have the potential to cause loss of life, injury, illness, health impacts, property damage, loss of livelihoods and services, social and economic disruption, as well as environmental damage (Robert *et al.*, 2003, p.277; UNISDR, 2009, p.30).

Within the scope of this research, the potential for malaria transmission in a specific area during a given period is described by the level of transmission of malaria parasites, also known like the Entomological Infection Rate (EIR). Hence, the concept of malaria epidemics aligns with the notion of biological hazards. Human infection with malaria occurs through exposure to female Anopheles mosquitoes that feed on blood and carry infective sporozoite-stage parasites. Even a single infectious mosquito can cause human malaria infection, which poses a life-threatening disease.

To assess the intensity of malaria parasite infection in real-world conditions, the EIR needs to be determined (WHO, 2021, p. xix). This is calculated by multiplying the human biting rate (average number of mosquito bites per person per night) by the sporozoite rate (percentage of female Anopheles mosquitoes carrying sporozoites in their salivary glands) (Robert et al., 2003, p.268).

Disaster risk management (DRM)

Disaster Risk Management (DRM) is a systematic approach to managing risks associated with natural hazards and disasters, focusing on reducing risk, enhancing resilience, and promoting sustainable development. The UN Office for Disaster Risk Reduction (UNDRR) defines DRM as a comprehensive strategy that includes understanding risk, risk reduction, and preparedness and response (UNDRR, 2015, p. xvii). The Intergovernmental Panel on Climate Change (IPCC) emphasizes the intersection of climate change and DRM, advocating for a multi-sectoral approach that incorporates climate science into risk assessments and disaster planning(IPCC,2014, p.69). The World Health Organization (WHO) emphasizes the health implications of DRM, including preparedness for health emergencies and strengthening health systems (WHO, 2019, p.63). The Sendai Framework for Disaster Risk Reduction 2015-2030, developed by the UNDRR, outlines key priorities for action, including understanding disaster risk, strengthening disaster risk governance, investing in disaster risk reduction for resilience, and enhancing disaster preparedness for effective response. The Sendai Framework's primary objective is to significantly reduce disaster risk and associated losses. This reduction encompasses various aspects, including the preservation of lives, livelihoods, and health, as well as the protection of economic, physical, social, cultural, and environmental assets at the individual, business, community, and national levels(IPCC *et al.,* 2022, p.14)

Disaster risk reduction (DRR)

According to United Nations Office for Disaster Risk Reduction, Disaster Risk Reduction is a systematic approach to identifying, assessing, and reducing disaster risks, aiming to protect communities and enhance resilience (UNDRR, 2015, p.xvii). It entails anticipating future disaster risks, reducing existing exposure to hazards, mitigating vulnerabilities, and enhancing resilience (WHO Glossary, 2020, p.15.).

Disaster Risk Management (DRM) is a comprehensive approach to reducing disaster risks through various strategies and actions. It can be categorized into prospective, corrective, and compensatory types, with community involvement and local knowledge integration being essential components. DRM includes activities like prevention, mitigation, preparedness, response, and recovery, and is crucial for building resilience against future disasters (IPCC,2014, p.69). It is often used interchangeably with Disaster Risk Reduction (DRR), but is more focused on operational aspects of implementing risk reduction initiatives. Effective DRM requires adequate funding and prioritization within governmental frameworks.

Early warning systems (EWS)

It is designed as a complete framework that incorporates hazard monitoring, forecasting, prediction, disaster risk assessment, communication, and operations. This system is made up of integrated systems and processes that allow individuals, societies, and institutions, corporations, and other stakeholders to take prompt action to mitigate catastrophe risks before hazardous occurrences occur. By proactively addressing potential risks, this integrated system aims to prevent or minimize the adverse impacts of hazardous events (WHO Glossary, 2020, p.15.).

When employed using highly accurate forecasts and accompanied by effective responses within the forecasted timeframe, it is expected to be a valuable tool in the adaptation to climate-related risks linked with infectious illnesses. By leveraging recognised links between weather/climate patterns and infection/transmission circumstances, advanced seasonal weather forecasting techniques are used, it becomes possible to identify conditions that are conducive to disease outbreaks several months in advance. This early identification allows for the implementation of timely and effective population health responses. The significance of this approach has been highlighted by Morin et al. (2018) and cited by the Intergovernmental Panel on Climate Change (IPCC, 2022, p.15).

II2. Theoretical framework

Concerns about greenhouse-gas-induced climate change and its likely consequences have risen in recent years. In response to these concerns, researchers have made considerable progress in formulating a general set of methods for assessing the impacts of climate change *(*J. B. Smith *et al,* 1996, p.1). The Technical Guidelines lay forth a seven-step methodology for assessing climate impact and response (Figure5). The steps are summarised below in brief.:

- ❖ Define the problem. Step 1 outlines the assessment's accurate goals, the environment, the economic sector, and/or the geographic region that matters (exposure unit), the study's time horizon, data requirements, and the larger context of the activity.
- ❖ Choose the method. The availability of resources, models, and data determines step 2. Methods can be qualitative, descriptive, quantitative, or prognostic.

- ❖ Test the approach and its sensitivity. Step 3 is required before doing a comprehensive assessment. This step frequently employs viability studies, data collecting and quality control, as well as predictive model validation and sensitivity analysis. *Select the scenarios.*
- ❖ Step 4 estimates potential environmental and socioeconomic circumstances that could produce if there is no change in climate (the future baseline), as well as the equivalent conditions consistent with specific climate change projections. These "scenarios" set the stage for the impact evaluation.
- ❖ Evaluate the biophysical and economical consequences. Step 5 compares the effects of the scenario conditions with climate change on an exposure unit to the effects of future baseline conditions without climate change.
- ❖ Evaluate autonomous adjustment. Step 6 distinguishes between spontaneous or "autonomous" adjustments in reaction to changing climate, routine adjustments, and tactical adjustments.

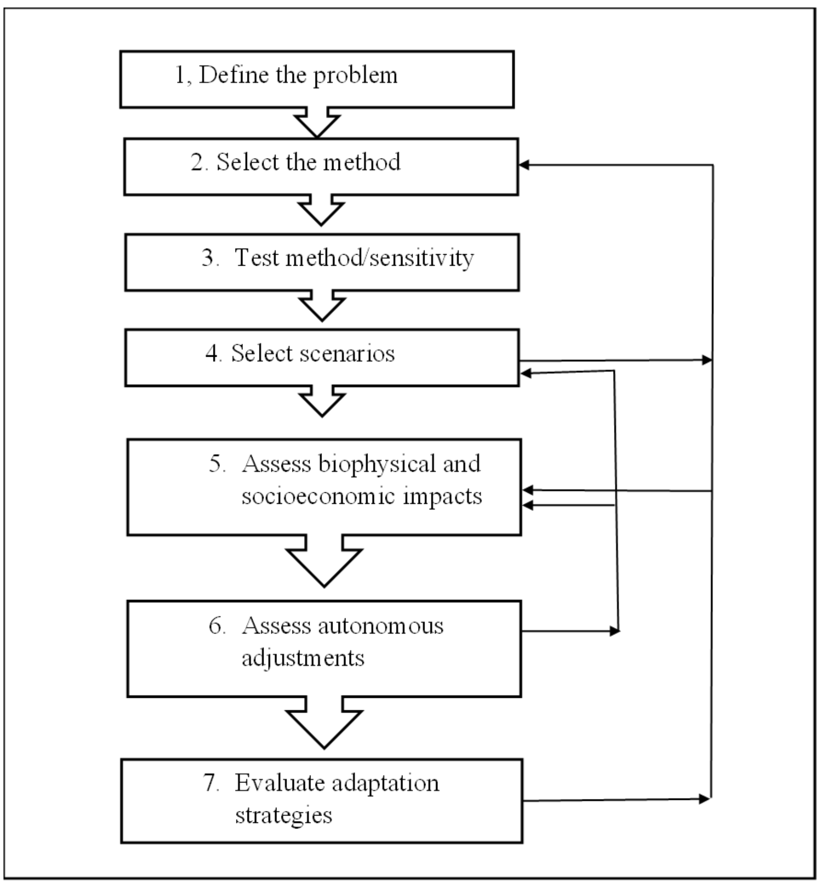


Figure 5: Framework of climate impact and adaptation assessment (IPCC, 2014, p.13)

A number of frameworks exist for the assessment of vulnerability. Various authors around the world have assessed malaria vulnerability using several framework, methodologies and approaches. Each framework has its limits and gaps in the vulnerability assessment in different domain of intervention.

To assess the vulnerability of the community in the context of natural hazards and climate change, we employed the MOVE ((Methods for the Improvement of Vulnerability Assessment in Europe) framework (Birkmann *et al.*, 2013, p.199). The MOVE conceptual framework (Figure 6) emphasises that hazards are of natural or socio-natural origin, whereas vulnerability is primarily associated with social conditions and activities. The MOVE framework, to assess vulnerability, uses three key factors: (a) exposure to a hazard or stressor; (b) susceptibility (or fragility); and (c) societal response capacities or lack of resilience. The framework's capacity to integrate different methodologies and epistemologies in the natural and social sciences, as well as disaster risk reduction, is a significant advantage. The MOVE framework is relevant to assess socio-economic and environmental vulnerability to malaria. In contrast to other school frameworks, the MOVE framework considers exposure separately from vulnerability (IPCC, 2022, p.51) or as a combination of vulnerability and a natural hazard or physical event. In this study, susceptibility (SUS), lack of resilience (LOR), and exposure make up the concept of vulnerability (Birkmann *et al.*, 2013, p.199).

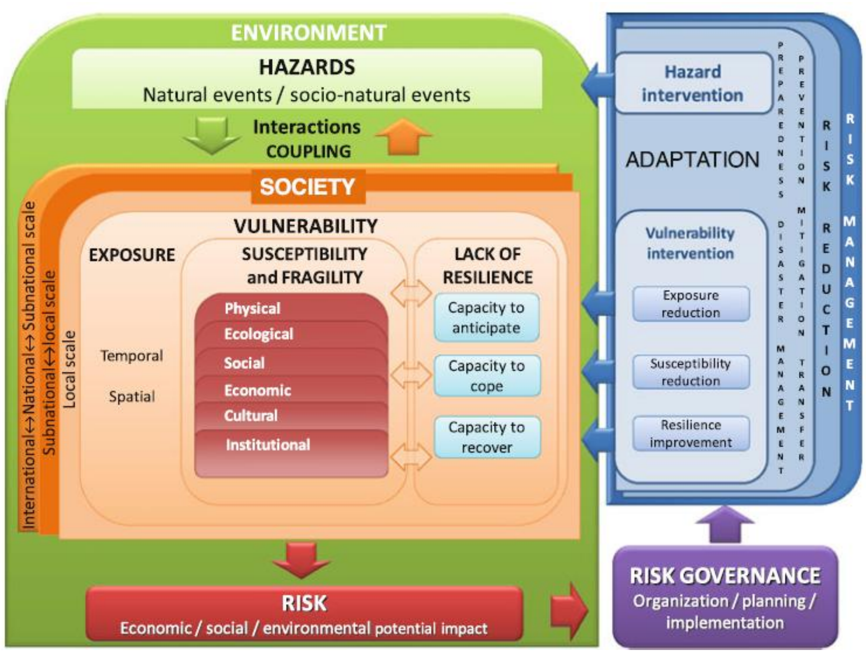


Figure 6: The MOVE framework adapted from (Birkmann *et al.*, 2013a, p.199)

II3. Literature review

II3.1. environmental and socio-economic determinants of malaria transmission in West Africa

2.3.1.1. Environmental determinants

Precipitation

Climatic factors control the transmission of malaria in West Africa *(*Diouf *et al., 2020*, p.1038*;* Thomas *et al.,* 2021, p.1). The spread of malaria is influenced by rainfall patterns and the distribution of particular environmental triggers, potholes, shallow excavations, bottles, and receptacles are also good nesting sites (M'Bra *et al.,* 2018, p.11). These parameters modify the multiplication and abundance of the population of mosquitoes, the duration of the parasite cycle in the mosquito development, the malaria dynamics, and the emergence of epidemics in the areas of low endemicity (Krefis *et al.,* 2011, p.285). Mosquito abundance was greatly influenced by rainfall (Taconet *et al.,* 2021, p.9) and is abundant in the rainy season associated with malaria peak (Dery *et al.,* 2010, p.3; Gbalégba *et al.,* 2018, p.1; Epopa *et al.,* 2019, p.1;Sondo *et al.,* 2020, p.4). There is a significant link between the incidence of malaria and rainfall variation and temperature (Klutse *et al.,* 2014, p769; M'Bra *et al.,* 2018, p11; Diouf *et al.,* 2020, p.1037; Akinbobola & Hamisu, 2022, p.59), rainfall and temperature were positively and significantly associated with malaria incidence (Donovan *et al.,* 2012, p.87; Rouamba et *al.,* 2019, p.1). Precipitation with high-resolution predicts accurately malaria incidence (Krefis *et al.,* 2011, p.285). Malaria transmission is influenced both by rainfall and its intensity. Land use especially the type of vegetation modifies also the distribution of mosquitoes (Ndiaye *et al.,* 2020b, p.1). As a result, the conclusion of the rainy season is marked by extensive malaria transmission (Coulibaly *et al.,* 2013, p.1). Malaria transmission is high at the end of the rainy season (Ndiaye *et al.,* 2020, p.5; Thomas *et al.,* 2021, p.1). Several authors found that malaria incidence is higher in the rainy than in the dry season and this is due to the presence of water in ponds and ditches, canals and gutters, and the presence of vegetation around homes, work places, and construction sites (Diouf *et al.,* 2020, p.1037; Akinbobola & Hamisu, 2022, p.59) . Such conditions increase the mosquito reproduction and, in turn disease transmission (Machault *et al.,* 2012, p.1; Segun *et al.,* 2022, p.5).

The duration of the wet season is also an important factor of malaria transmission because it takes time for mosquitoes to increase their population (Endo & Eltahir, 2016, p.3). In West Africa, malaria incidence increases progressively immediately after the first rains with a peak in the middle of the rainy season toward October, while the peak of the rain was recorded earlier between August and September (Ndiaye *et al.*, 2020, p.1; Traore *et al.*, 2017, p.8).

In contrast, heavy rainfall washes off many of the developmental sites of mosquito vectors of malaria parasites (Okunlola & Oyeyemi, 2019, p.1), and may also flush away the developing larvae, thereby decreasing the number of vectors (Jane Ugwu & Zewotir, 2020, p.309). Development habitats become constantly flooded, and the runoff of water causes the death of larvae (Ndiaye et al., 2020, p.1; Krefis *et al.*, 201, p.285). However, heavy rainfall may also later results in the formation of temporary or permanent pools and puddles that are developmental grounds for mosquito larvae and abundant vector populations (Ankrah *et al.*, 2016, p.103; Gouzile *et al.*, 2022, p.248). Malaria transmission requires at least 80 mm of rainfall over a four-month period with average temperatures (Gouzile *et al.*, 2022, p.248). A better understanding of the association between rainfall variation and malaria incidence is thus required for successful climate change adaptation techniques that include disease control intervention planning and implementation (Klutse *et al.*, 2014, p769).

Air temperature

Climate change is projected to increase the impact on human health, particularly the incidence of water-related and vector-borne diseases, such as malaria (Klutse *et al.*, 2014, p769). Temperature, relative humidity, and rainfall are predictors of malaria because they influence malaria transmission either directly or indirectly (Canelas *et al.*, 2016, p.12,; Akinbobola & Hamisu, 2022, p.59).

Temperature influences malaria transmission, and it has a significant and positive impact on malaria incidence (Canelas *et al.*, 2016, p.12; Okunlola & Oyeyemi, 2019, p.1, Rouamba *et al.*, 2019, p.1 Thomas *et al.*, 2021, p.1). The link between temperature and the distribution of malaria vectors is complex(Moiroux *et al.*, 2013, p.1). A positive impact of minimum temperature on malaria transmission, suggests that mosquito development is usually interrupted at a higher temperature, as higher temperatures could reduce the growth of anopheline mosquitoes, the incubation period as well as the viral rate of development (Jane Ugwu & Zewotir, 2020, p.309).

Where temperature is limiting during the rainy season, mosquito populations increase slowly at the onset of rain, with gradually rising temperatures, owing to long developmental cycles (M'Bra *et al.*, 2018, p11.). Temperatures above 30°C or close to 40°C reduce mosquito survival, hence their density and loss of some mosquito habitats (*Mattah et al.*, 2017, p.13; Magombedze *et al.*, 2018, p.2). The reduction temperatures favors the transmission of malaria incidence, while rising temperatures have a negative impact(Ouedraogo *et al.*, 2018, p.5). Mean and minimum temperatures are the best factors for the prediction of malaria (Krefis *et al.,* 2011, p.285). A part from larval growth, temperature influences many aspects of the mosquito lifecycle such as adult survival, and biting activity (Moiroux *et al.,* 2013, p.1; Taconet *et al.,* 2021, p.9).

Air temperature can also influence water temperature; higher water temperature is not associated to the presence of anopheline larvae but is linked to the density of larvae in a collection (Gadiaga *et al.,* 2011, p.8). Temperature controls the duration of the development of mosque its larvae in the environment and the development of the parasite within the vector (Moiroux *et al.,* 2013, p.1; Okunlola & Oyeyemi, 2019, p.1).

Relative humidity

Climate and environmental factors influence malaria transmission (Kasasa *et al.,* 2013, p.4). Relative humidity is one of the important determinants of malaria transmission and malaria incidence. Relative humidity also plays a dominant role in the prevalence of malaria (Canelas *et al.*, 2016, p.12; Akinbobola & Hamisu, 2022, p.59). Malaria transmission is positively associated with humidity(Rouamba et al., 2019, p.1). The increase in the malaria incidence is linked to humidity (Ouedraogo *et al.*, 2018, p.5). A range 60% and 86% of relative humidity is most suitable for the Anopheles mosquitoes to thrive and for the Plasmodium parasite to widespread the transmission of malaria (Ateba *et al*., 2020, p.1; Segun *et al.*, 2020a, p.8).

Wind speed and direction

Wind speed is one of the environmental factors to be considered in the prediction of malaria, there are no significant relationships between wind speed and malaria incidence (Ouedraogo *et al.,* 2018, p.5; Thomas *et al.,* 2021, p.1). Although anopheline mosquitoes can fly 10 km, and be carried by wind much further, dispersal studies have shown that 95% do not move than 2km (Thomas *et al.*, 2021, p.1). Otherwise, because high wind speeds are associated with drought and high temperatures, studying the impact of wind independent of temperature and dryness is difficult (Ouedraogo *et al.,* 2018, p.5). Mean wind speed <1.8 m/s is associated with a higher malaria incidence (Ateba *et al*., 2020, p.1)

Vegetation

Malaria occurrence is influenced by social and environmental variables. Integrating data on these parameters into existing malaria control technologies would aid in the creation of sustainable malaria control policies tailored to the local context (Rouamba *et al.,* 2019, p.1). Vegetation is a predictor of malaria transmission (Kasasa *et al.,* 2013, p.4). Low-floating vegetation is a favourable factor for anopheline larval occurrence (Gadiaga *et al.,* 2011, p.8).

Normalized Difference Vegetation Index (NDVI), and the Enhance Vegetation Index (EVI) are environmental factors used for malaria prediction in West Africa (Gaudart *et al.*, 2006; Gadiaga *et al.*, 2011; Kasasa *et al.,* 2013, p.4; Ebhuoma & Gebreslasie, 2016, p.8; Louisa *et al*., 2020, p.311). Normalized Difference Vegetation Index presents significant and positive correlations with climate variables, such as precipitations, particularly in Sudanese savannah environments (Gouzile *et al.,* 2022, p.248). Increasing surfaces of grassland areas and the % of landscape occupied by forest increase the presence or abundance of mosquitoes and are considered aggravating biting risk factors (Taconet *et al.,* 2021, p.9). In areas beside vegetation or to forests (≤ 500 m), the risk of becoming a hotspot only increases when rainfall exceeds 10- 15mm/week. (Dieng *et al.,* 2020, p.8.) Agriculture in urban areas contributes to a rise in the number of malaria breeding sites. Living close to crop marsh areas increases the risk of malaria infection (M'Bra *et al.,* 2018, p.11). Normalized Difference Vegetation Index, vegetation cover is highly associated with an increase in biting rates and directly with malaria incidence (Machault *et al*, 2012, p.1; Kasasa *et al.,* 2013, p.4; Ebhuoma & Gebreslasie, 2016, p.8). A monthly NDVI unit is associated with the monthly increase of malaria count (M'Bra *et al.*, 2018, p.11). The EVI is considered a proxy of the development of the habitat of mosquitoes and the physical environment is strongly correlated with disease environments in determining the intensity of a childhood exposure to infectious diseases such as malaria (Ugwu & Zewotir, 2020, p.309).

Maize farm increases the risk of malaria infection. In addition, maize pollen constitutes a good nutritional source for *An. Gambiae larvae* and has been linked to elevated incidence of malaria (Dieng *et al.*, 2020, p.8).

Surface water and soil moisture

Water bodies can be favorable developmental grounds for mosquito abundance in neighboring compounds (Kasasa *et al.,* 2013, p.4; Mattah *et al.,* 2017, p.13; Akinbobola & Hamisu, 2022, p.59). Perpetual sources of water are adequate to increase the likelihood and abundance of Anopheles mosquitoes (Taconet *et al.,* 2021, p.9). Anopheles mosquitoes could develop in sites where water is present for at least 10–15 days (Jane Ugwu & Zewotir, 2020, p.309), and larval is high in density where there are rivers, and water pools (Epopa *et al.*, 2019, p.1). Furthermore, the presence of small pools of stagnant water in the wet seasons or at the beginning of the dry season favours mosquito survival and larvae I development. Variation in river levels is related to malaria incidence (Sissoko *et al.*, 2017a, p.2). Saline or moderately saline hydro-morphic and holomorphic soils is good indicator for the retention of water. These types of soils constitute potential larval developmental sites (Ndiaye *et al.*, 2020, p.1). Soil moisture (NDWI) increases the risk of malaria transmission (Gouzile *et al.*, 2022, p.248). Paved drains, puddles, and ditches/dugouts are permanent developmental sites (Mattah *et al.*, 2017, p.13).

The proximity to water with vegetation has a positive effect on malaria incidence (Okunlola & Oyeyemi, 2019, p.1; Rouamba et al., 2019, p.1). Malaria risk is significantly higher among children near hydrographic networks (Baragatti *et al.*, 2009, p.7).

Variation of the density of Anopheles mosquito larvae is related to the physical, chemical, and biological compositions of water in the various habitats (Mattah *et al.*, 2017, p.13). The quality of water controls the development of mosquito larvae. The incidence of malaria can be low when the Physico-chemical parameters are not suitable for the development of mosquitoes (Gbalégba *et al.*, 2018, p.1).

Elevation

Environmental factors influence vector mortality and aggressiveness, as well as the incidence of malaria (Gaudart *et al.*, 2009a, p.1). Improving information and understanding of the environmental factors that influence malaria vector abundance and its distribution can help to design locally tailored vector control interventions (Ankrah *et al.*, 2016, p.103; Endo & Eltahir, 2016, p.6; Taconet *et al.*, 2021, p.9). The topography also influences malaria transmission and landscape variables are correlated with the vectors' biting rates (Taconet *et al.*, 2021, p.9; Thomas *et al.*, 2021, p.1). Elevation is used as a primary predictor of the presence and abundance of Anopheles mosquitoes and indirectly helps to determine the intensity of malaria risk.

Malaria infection is lower at higher altitude. Areas below 500 m are associated with elevated risk of malaria incidence, whereas areas greater than 500 m were discovered to have the lowest risk of malaria exposure. Altitude could indirectly impact the spread and distribution of malaria through its effect on temperature; that is, malaria transmission does not occur at specific altitudes due to high temperatures, which are unfavourable to the parasite's life cycle (Louisa *et al.*, 2020, p.311). In addition, the presence of water bodies decreases with the increase of altitude and water is an important factor in mosquito developmental sites.

Land use land cover (LULC)

In West Africa, good management of land can help to improve malaria control. Land cover/land use are potential factors in malaria prevention (Sissoko *et al.,* 2017a, p.2). Many activities contribute to changes in land use, the expansion of cities into new residential areas, increased urban agriculture, as well as a growth in the number of construction sites, which has an impact on malaria transmission (M'Bra *et al.,* 2018, p.11).

Urbanisation has a significant impact on the risk of malaria in African cities. Increasing housing density, and reducing non-polluted water resources (Labbo *et al.*, 2016, p.1; Millar et al., 2018, p.7). The occurrence of malaria is high in rural dwellers and this may be due to increased crops in those areas which provide a suitable platform for the development of mosquitoes (Nwaneli *et al.*, 2020, p.179). Proper environmental management through good land use can reduce mosquito developmental sites in urban and rural areas (Mattah *et al.,* 2017, p.13; Nwaneli *et al.*, 2020, p.179)

2.3.1.2. Socio-economic determinants

Level of education/ Knowledge about malaria

Socioeconomic factors play an important role in the control of malaria infection. Education is a significant predictor of malaria transmission, and the level of education in a population benefits public health. (Olukosi *et al.*, 2020, p.6). The level of education affects people's ability to read and comprehend written instructions describing how to use anti-malarial medications; otherwise, malaria information determines preventive and treatment-seeking attitudes. An educated community may be capable of recognising the crucial role of ITNs (insecticide-treated nets) in malaria prevention and comprehending the information contained in outreach efforts (Eteng et al., 2014, p.7; Anyanwu *et al.,* 2017, p.7). Lower-educated communities perceive a greater threat of malaria than the most-educated (Donovan *et al.,* 2012, p.87; Saleh *et al.,* 2018, p.9). Educated mothers have a positive effect on their children's health (Diabaté et al., 2014, p.4; Eteng *et al.*, 2014, p.7; Nwaneli *et al.,* 2020, p.179). This is because they may possess a deeper comprehension of health-related issues, which will affect their approaches to disease prevention and care-seeking conduct (Olukosi *et al.,* 2020, p.6).

Gender/ Age

Gender is linked with the incidence of malaria infection, and in general female predominance is noted. Children are more vulnerable to malaria than adults (Salako *et al.,* 1990, p.435; Mooney *et al.,* 2022, p.3). In rural areas, males bear the malaria brunt more than females(Sonko *et al.*, 2014, p.7). The use of ITN is also elevated in households when mothers maintain the house and eradicate stagnant water and larval breeding grounds from the surrounding environment. This shows that activities done by women to reduce mosquito density are often combined with actions taken to safeguard their children and may represent a broader concern among mothers regarding avoiding malaria at home (Diabaté *et al.,* 2014, p.4).

A child's age is an independent predictor of his or her malaria status; little children have less skin surface subjected to mosquito bites and so are less susceptible to transmission of malaria. Otherwise, children under the age of five are more vulnerable to malaria infection. The age spectrum of malaria is linked to different types of health-care participation by age group based on socioeconomic status and access to care facilities.

Place of residence/ Housing structure

Socioeconomic factors like place of residence and settlement style constitute structural factors that can enhance the health of the community. These facets are considered to influence how malaria therapy is thought of and how anti-malarial medications are used (Anyanwu *et al.*, 2017, p.7). Housing quality improvements can significantly reduce malaria transmission and incidence. Housing building supplies (type of wall, floor, roof, and window) have a strong connection with the likelihood of infection in a number of ages, though this is only confirmed in the overall population for poor wall housing materials (Sonko *et al.,* 2014, p.7). Metal roof houses have fewer hotspots of malaria compared to thatch roof houses, this may be the result of the indoor climate of the different typologies of houses (Yaro *et al.,* 2021, p.1). In addition, metal roof houses tend to be warmer and less humid than thatch roof houses, which can reduce the survival of malaria vectors resting indoors; additionally, metal roofs may simply be a marker for a higher-quality home that is less porous to mosquitoes because metal roof houses are often better built, with fewer mosquito entry points, than thatch-roofed houses (Yaro *et al.,* 2021, p.1).

Malaria parasite prevalence in rural areas is higher than in urban areas. This could be attributed to differences in socioeconomic characteristics such as educational level, occupation, and health coverage (Owusu *et al.,* 2018, p.18). The variety and number of house entries may increase the danger of getting bit by mosquitoes and becoming infected with malaria *(Okebe et al., 2014, p.1; Anyanwu et al., 2017, p.7*; Nwaneri *et al.*, 2017, p.5). Doors and windows are screened to prevent mosquito-human contact, and combined environmental control is used (Okebe *et al.,* 2014, p.1). Independent of land ownership, malaria risk is higher in sparsely built-up areas than in densely built-up areas (Meili *et al.*, 2009, p.1).

Poverty

Malaria is frequently linked to poverty. Macro-level figures demonstrate strong linkages between malaria and poverty, and new data suggests that the causal association between malaria and poverty is bidirectional (Sonko *et al.,* 2014, p.7). The income level affects the choice of where to seek medical attention for malaria and whether or not to utilise a malaria diagnostic test prior to treatment (Anyanwu *et al.*, 2017, p.7). The risk of malaria can be lessened when the household's economic situation is good which means, they have a high income (Okebe *et al.,* 2014, p.1).

Socioeconomic factors serve a substantial part in identifying anti-malarial drug use habits that foster drug resistance; impoverished communities use cheaper malaria prevention methods than more prosperous socioeconomic groups, and they are more exposed to mosquito bites, making them more likely to contract malaria (Onwujekwe *et al.,* 2014, p.1; Anyanwu *et al.*, 2017, p.7; Donovan *et al.,* 2012, p.87). Furthermore, when compared to lower socioeconomic categories, the wealthy spend more on window and door nets because housing structure plays a crucial role in the prevention or control of malaria (Awuah *et al.*, 2018, p.1).

The economic status of the community contributes to the use of bed nets where the distribution of bet nets is not free. The most ownership of bed nets are the household with good economic status. Households with a good wealth index have the lower odds of malaria. This can be justify by their ability to buy easily INTs and to use it for the prevention of malaria (Okebe *et al.*, 2014, p.1). On the other hand, Children from poor households have a high incidence of malaria because the households don’t have enough INTs (Eteng *et al.*, 2014, p.7).

Urbanization

The influence of urbanisation on malaria risk in African cities is significant (Labbo *et al.,* 2016, p.1). While Anopheles mosquitoes have been discovered to adapt to urban development sites over time, they are known to breed more in rural settings (Nwaneli *et al.*, 2020, p.179).

Increased urbanisation will not necessarily contribute to less malaria. Malaria epidemics may continue to be a severe public health issue in densely populated places, impacting an increasing number of individuals (Klinkenberg *et al.*, 2006, p.583). Malaria transmission is higher in the communities located more towards the periphery of urban areas than in the highly inhabited and polluted centre metropolitan area (Klinkenberg *et al.*, 2006, p.583).

Buildings can be a proxy for a high human population density, resulting in an attenuation of Anopheles bites and indirectly improving the control of malaria infection (Machault *et al.*, 2012, p.1). In addition, variances in malaria incidence may be explained by variances in population growth, emigration, and migration. Urban children have lower odds of malaria transmission due to the presence of pharmacy, the exposure to TV in order to be informed about all the news concerning malaria transmission (Klutse *et al.*, 2014, p769).

Quality of information

Malaria early warning information is a key factor in the control of malaria infection. Good and early information can help to take preparedness action to prevent the risk of being infected by malaria. Enhancing the standard of malaria-related health knowledge may result in communities becoming empowered by engaging and aiding them in improving their social communication and assistance. Individuals ought to be offered knowledge that will enable them to handle their health, and the internet serves as a helpful instrument in doing so (Kate *et al.*, 2014, p.46). Internet constitutes a major resource for malaria education and information in West Africa (Kate et al., 2014, p.46). The use of the internet to share daily information with the community and prevention from exposure to TV prevention campaigns may potentially save millions of lives (Rouamba *et al.*, 2019, p.1).

In addition, the use of Geographic Information Systems, with the improvements in technology over the last three decades, has enabled researchers to run preliminary research readily and swiftly (Canelas *et al.*, 2016, p.12).

Health facilities

Other factors, such as hospital accessibility, may influence malaria transmission or mosquito density (Krefis *et al.*, 2011, p.285) .The positive association between malaria risk and distance to the nearest health facility becomes high after 2–4 km (Millar *et al.*, 2018, p.7).

Indigenous knowledge can help improve malaria prevention when the prescription is fair. Self-medication and herbal/traditional treatment depend on health insurance status and place of residence(Awuah *et al.*, 2018, p.1). Disparities in malaria age distribution are related to health facility attendance in different parts of the city based on socioeconomic status and health-care access.

II3.2. An overview of studies in West Africa that used Remote sensing-derived meteorological factors and malaria epidemiology data.

In west Africa, several studies have been done to predict the risk of malaria transmission using remote sensing (RS)-derived data and climatic variables. Beyond the West African countries, Benin, Mali, Ghana, Coted'Ivoire, Senegal, Nigeria, and Burkina-Faso have used remoted sensing -derived data , climatic variable to predict the risk of malaria infection(table1). In Benin base on the databases (Web of Science and Science Direct, google scholar, PubMed) we used, just two studies have been done by the same authors. The first study used only the NDVI to predict the risk of malaria transmission. This study found that NDVI was negatively correlated with the density of malaria vectors (Moiroux *et al.*, 2012, p.1).

The second in 2013 using Land Surface Temperature (LST), Normalized Difference Vegetation Index (NDVI), rainfall mean elevation and mean slope (Moiroux *et al.*, 2013, p.1). This study shown that landscape data were effective in distinguishing between species distributions (Table 1).

Mali is the West African country that has done many studies that used NDVI, rainfall, temperature, wind and humidity to predict the risk of malaria. The findings of these studies showed that NDVI presents significant correlations with climate variables, such as precipitations (Gaudart *et al.*, 2009, p.1), Humidity, wind speed and precipitation contributed the most to the transmission of malaria (Taconet *et al.*, 2021, p.9). On the other hand, (Kleinschmidt et al., 2000, p.355) finds that Mean NDVI from June–November (wet season), mean maximum temperature from March–May, months with more than 60 mm of rainfall and distance to water bodies were the significant independent variables for predicting malaria prevalence using logistic regression analysis and kriging. The non-stationary model used by (Gosoniu *et al.*, 2006, p.127) ,showed that NDVI and minimum temperature had a positive statistical relationship with malaria risk, while rainfall had a negative statistical relationship. (Gaudart, 2009, P.1) study in Bancoumana, Mali using the seasonal analytical approach revealed that the seasonality of P. falciparum incidence was significantly explained by NDVI with 15-day lag ($p = 0.001$). The NDVI threshold was 0.361 ($p = 0.007$). Most of the studies conducted in Mali finds a positive correlation with the incidence of malaria and the climatic variables (Table1).

Coted'Ivoire is the second country which used several remote sensing- derived data such as NDVI, elevation, Normalized Difference Water Indices (NDWI), Derived Elevation Model (DEM), and REF to predict the risk of malaria infection. Through these studies, (M'Bra *et al.,* 2018, p.11) finds that the seasonal variation in the number of malaria cases parallels the seasonality of rainfall and NDVI and is opposite to the seasonality of temperature using negative binomial regression models. The work conducted by (Gouzile *et al.*, 2022, p.248) conclude that NDVI, NDWI, altitude and water points predict malaria risk. The normalized difference vegetation index (NDVI), rainfall estimation (RFE), and proximity to rivers were found to be significantly linked with Plasmodium falciparum infection in bivariate non-spatial models. However, after employing the spatial correlation, NDVI showed only a 'borderline. In 2009 , (Raso *et al*., 2009, p.9) study finds that the bivariate non-spatial analysis identified NDVI, RFE, LST and close proximity to standing water (rivers, swamps and irrigated fields) as significant risk malaria factors. Only mean RFE remained significant after using geographic analysis throughout the malaria transmission season (June-August). At last, but not least, in the non-stationary spatial model, the covariates rainfall (OR = 0.76; Bayesian credible interval (BCI) = 0.70, 0.83) and maximum LST (OR = 0.72; BCI = 0.64, 0.79) were significantly negatively associated with Plasmodium prevalence (Raso et al., 2012, p.6) (Table1).

In Nigeria, the only study done finds that malaria infection decreased monotonically with increasing altitude (areas below 500 m were found as being at the highest risk of malaria prevalence, whereas areas over 500 m were found as having the lowest risk of malaria exposure); vegetation indices such as EVI are considered proxies of vector habitat using Generalized Additive Model (GAM) with malaria incidence data (Jane Ugwu & Zewotir, 2020, p.309).

There is no study in West Africa using Vegetation Health Indices (VHI) extracted from Advanced Very High Radiometer Resolution to predict the risk of malaria infection apart from the global study done by Kogan and his collaborators (Table1).

In his study in Burkina Faso, Taconet found that the spatiotemporal variations in the biting rates of Anopheles coluzzii and Anopheles gambiae sensu stricto were found to be strongly associated with climatic conditions, such as temperature and precipitation. Conversely, the biting patterns of

Anopheles funestus appeared to be more closely linked to landscape-level factors (Table 1) (Taconet *et al.*, 2021, p.9)

Table I: An overview of studies in West Africa that used remote sensing-derived meteorological factors and malaria epidemiology data

Authors	**Study area(s)**	**Epidemiological data on malaria**	**Meteorological/environmental data obtained via Remote sensing Technic**		**Statistic Method(s)**	**Main Findings**
			Climatic/environmental data used	Satellite website(S)		
(Gaudart *et al.*, 2006, p.1)	Mali	Incidence of *P. falciparum*	NDVI (Normalized Difference Vegetation Index	Advanced Very High Resolution Radiometer (NOAA AVHRR)satellite	ARIMA analysis, SIRS-type model	Significant relationships exist between NDVI and climate factors such as precipitation.
(Kasasa, *et al.*, 2013b, p.4)	Navrongo (Ghana)	Mosquitoes were collected randomly	LST (Land Surface Temperature), NDVI (Normalised Difference Vegetation Index), and EVI (Enhanced Vegetation Index)	Imaging with a Moderate Resolution MODIS is a spectro-radiometer.	Independent Bayesian geostatistical models	Spatial variance was greater than temporal variance, particularly in the sporozoite rate (SR).
(Moiroux *et al.*, 2013, p.1)	southern Benin	Mosquitoes were collected	LST, NDVI, Rainfall mean elevation, mean slope	MODIS 3B42 Version 6 Satellite for the earth observation (SPOT)	binomial mixed-effects models	Landscape data were significant in identifying the distributions of the species.
(Moiroux, *et al.*, 2012, p.1)	Benin	Mosquitoes were collected	NDVI	Satellite for the earth observation (SPOT-5)	A non-parametric mixture of Poisson model (NPMP)	The density of malaria vectors was adversely associated to NDVI.

Authors	Study area(s)	Epidemiological data on malaria	Meteorological/environmental data obtained via Remote sensing Technic		Statistic Method(s)	Main Findings
(Taconet *et al.*, 2021, p.9)	Burkina Faso	Mosquitoes were collected	Rainfall, Temperatures and LST	Integrated Multi-satellitE Retrievals for Global Precipitation Measurement (GPM), MODIS Terra and Aqua items	multivariate machine-learning models , Correlation coefficients analysis	Meteorological parameters (temperature, precipitation) had a considerable influence on the spatiotemporal patterns of An. coluzzii bite rates and An. gambiae s.s, whereas An. funestus was more directly related to landscape characteristics.
(Ateba et al., 2020, p.1)	Dangassa, Mali	Incidence of malaria through observation	Rainfall, temperature, humidity, and wind speed	Earth Observing System Data and Information System (EOSDIS) of the National Aeronautics and Space Administration (NASA).	FGSAM (Functional Generalised Spectral Additive Model), FGLM (Functional Generalised Linear Model), and FGKAM (Functional Generalised Kernel Additive Model)	Humidity, windspeed. and rain contributed the most to the transmission of malaria

Authors	Study area(s)	Epidemiological data on malaria	Meteorological/environmental data obtained via Remote sensing Technic		Statistic Method(s)	Main Findings
(Jane Ugwu & Zewotir, 2020, p.309)	Nigeria	Malaria incidence	Enhanced Vegetation Index (EVI), Temperature, Precipitation, Population, Travel time to nearest settlement, population density, Travel time to the nearest settlement, Potential Evapotranspiration, altitude, wet day, urban-rural settlement	Demographic and Health Survey (NDHS Spatial)	Generalized Additive Model (GAM)	Malaria infection decreased monotonically with increasing altitude (areas below 500 m had the highest malaria prevalence risk, while areas over 500 m had the lowest risk of malaria exposure); vegetation indices such as EVI are viewed as proxies of vector habitat.
(Jane Ugwu & Zewotir, 2020, p.309)	Nigeria	Malaria incidence	Enhanced Vegetation Index (EVI), Temperature, Precipitation, Population, Travel time to nearest settlement, population density, Travel time to the nearest settlement, Potential Evapotranspiration, altitude, wet day, urban-rural settlement	Demographic and Health Survey (NDHS Spatial)	Generalized Additive Model (GAM)	Malaria infection decreased monotonically with increasing altitude (areas below 500 m had the highest malaria prevalence risk, while areas over 500 m had the lowest risk of malaria exposure); vegetation indices such as EVI are viewed as proxies of vector habitat.

Authors	Study area(s)	Epidemiological data on malaria	Meteorological/environmental data obtained via Remote sensing Technic		Statistic Method(s)	Main Findings
(M'Bra *et al.*, 2018,p.11)	Côte d'Ivoire	Clinical malaria cases	NDVI	MODIS	negative binomial regression models	Fluctuation in of malaria incidence by season matches the seasonal variation of rainfall and NDVI and is diametrically opposed to the seasonal fluctuation of temperature.
(Gouzile *et al.*, 2022, p.248)	Côte d'Ivoire	-	NDVI, NDWI, Elevation	USGS	Multicriteria Analysis	NDVI, NDWI, altitude and water points predict malaria risk.
(Kleinschmidt et al., 2000, p.355)	Mali	Data on the prevalence of malaria collected from the MARA/ARMA database	NDVI	NOAA-AVHRR	logistic regression analysis and Kriging	Mean Normalised Difference Vegetation Index (NDVI) during June to November, During March to May, the average maximum temperature, months with over 60mm of precipitation, and proximity to water bodies.
(Gemperli *et al.*, 2006, p. 289)	Mali	Malaria incidence Data were retrieved from the MARA/ARMA database	NDVI	NOAA/NASA-AVHRR	Garki mode, Bayesian models and kriging	temperature and Normalised Difference Vegetation Index (NDVI) had no association with the EIR (entomological inoculation rate) during the rainy season. The distance to water was highly associated to transmission intensity, demonstrating that high infection occurred within 4 kilometers of the water bodies.
(Gosoniu et al., 2006, p.127)	Mali	Malaria incidence statistics (children aged 1 to 10) were collected from the MARA/ARMA database.	Normalised Difference Vegetation Index (NDVI)	NASA-AVHRR	Bayesian non-stationary model, Bayesian logistic regression	The non-stationary model found that minimum temperature and NDVI had a significant and positive relationship with malaria risk, but rainfall had a significant and negative relationship.

Authors	Study area(s)	Epidemiological data on malaria	Meteorological/environmental data obtained via Remote sensing Technic		Statistic Method(s)	Main Findings
(Silue, 2008, p.1)	Man , Ivory Coast	P. falciparum confirmed census in children around 6 to 16 years	REF, Land Surface Temperature (LST) and Normalised Difeference Vegatation Index (NDVI)	MODIS-USGS Meteosat 7	Bivariate logistic regression models	Normalised Difference Vegetation Index (NDVI)and distance to water bodies, RFE were substantially linked with P. falciparum infection in bivariate non-spatial models. However, when the geographical correlation was applied, NDVI indicated only a 'borderline' association with P. falciparum prevalence.
(Gaudart, 2009, p.9)	Bancouman a ,Mali	P. falciparum confirmed survey in children aged 0 to 12 years	Normallised Difference Vegetation Index (NDVI)	NASA-AVHRR	ARIMA model	The seasonal analysis method demonstrated that the seasonality of P. falciparum incidence was highly predicted by NDVI with a 15-day lag ($p = 0.001$). The cutoff for NDVI was 0.361 ($p = 0.007$).
(Gosoniu *et al.*, 2013, p.13)	West Africa	MARA/ARMA Malaria prevalence in children aged one to ten years	NDVI, land use	USGS , NOAA-AVHRR	Non-parametric regression models, logistic regression models	The Equatorial forest, Guinea savannah, and tropical forest are the four designated agro-ecological zones, Sahel region, and Sudanese savannah, NDVI was not linked with malaria.
(Raso *et al.*, 2009, p.9)	Man , Côte d'Ivoire	Confirmed malaria cases from Grades 3-5 students	Land Surface Temperature (LST), Normalised Difference Vegetation Index (NDVI) and RFE DEM	SRTM, MODIS-USGS And Meteostat 7	Bayesian kriging, Bayesian negative binomial regression models	NDVI, RFE, LST, as well as exposure to a body of water were revealed as potential malaria risk factors in a bivariate non-spatial analysis. Only mean RFE remained significant after using geographic analysis throughout the transmission of malaria season (June-August).

Authors	**Study area(s)**	**Epidemiological data on malaria**	**Meteorological/environmental data obtained via Remote sensing Technic**		**Statistic Method(s)**	**Main Findings**
(Giardina, 2012, p.1)	Senegal	Census of confirmed number of cases of malaria in children under 5 years	Day Land Surface Temperature (LST) Altitude, and Normalised Difference Vegetation Index (NDVI)	USGS-DEM MODIS	Zero-inflated binomial (ZIB) Bayesian geostatistics, Bayesian kriging	The factor precipitation (OR = 0.76; BCI = 0.70, 0.83) and maximal LST (OR = 0.72; BCI = 0.64, 0.79) were substantially higher. adversely linked with the occurrence of Plasmodium pin the non-stationary geographic model.
(Raso *et al.*, 2012, p.6)	Côte d'Ivoire	children under the age of 16 malaria incidence data	Elevation, LST and NDVI	MODIS USGS-DEM	Bayesian non-spatial and geostatistical logistic regression models, as well as Bayesian kriging	Rainfall (OR = 0.76; BCI = 0.70, 0.83) and maximum LST (OR = 0.72; BCI = 0.64, 0.79) were strongly related. adversely linked with Plasmodium occurence in the non-stationary spatial model.

II3.3. Contribution of remote sensing data in malaria modelling and prediction

This panoramic view on the studies that used remote sensing-derived data in Sub-Sahara Africa proved that remote sensing data is a good tool in malaria modelling and prediction. The transmission of malaria is complex and come from the climatic factors, environmental factors, socio-economic parameters. Remote sensing served as mean to obtain potential environmental and climatic data from satellite favorising the diseases. The combination of these data help to determine or understand the link between climate variables, environmental factors and the transmission of malaria. Remote sensing (RS) data give the opportunities to create a model and predict the incidence or the transmission of malaria in the malaria endemic regions. It can contribute the development of the tools to control the infection of malaria and plan actions to reduce the burden of malaria.

Factors such as National health policy, trustworthy meteorological data, research capacity, availability, and cost all influence the use of Remote Sensing (RS) in malaria modelling. The use of remote sensing data helps to reduce the challenges relative to the availability of quality data. The use of RS is accepted in the application of public health and environment. Several studies have been done in Sub-Sahara Africa using RS-derived data from many satellite websites to develop a model and simulate malaria risk infection.

In the context of West Africa, the Normalized Difference Vegetation Index (NDVI) has been utilized for modeling and predicting the incidence of malaria, as highlighted in previous studies by Gaudart and M'Bra (Gaudart *et al.*, 2006, p.1; Gaudart, 2009, p.1; M'Bra *et al.*, 2018, p.11). However, caution must be exercised in the use of NDVI due to its limitations. While NDVI serves as an indicator of biomass greenness and the presence or absence of water, it is important to note that its interpretation should be approached with care. The NDVI, which ranges between -1 and +1, offers insights into the environmental conditions (Ofosu Anim et al., 2013, p.168). However, it is not always a reliable indicator of malaria transmission. Several studies conducted in West Africa have arrived at different conclusions, as demonstrated by Moiroux , Gemperli , and Gosoniu (Moiroux *et al.*, 2012, p.1). Notably, a comprehensive study encompassing West Africa revealed that NDVI was not significantly associated with malaria transmission. Similarly, in Mali, specific studies indicated no statistical relationship between NDVI and the entomological inoculation rate (EIR)

The EVI can be used as a substitute for NDVI, because it preserves more sensitivity over heavier vegetation; hence, good account of the variation and the change in a rich canopy can be recorded (Matsushita *et al.,* 2007, p. 2636). EVI are considered proxies of vector habitat (Jane Ugwu & Zewotir, 2020, p.309).

Apart from the study doing by (Kogan, 2019, p.1) using the African continent malaria data and Vegetation Condition Index data derived from AVHRR satellite, any study didn't use Vegetation Condition Index data derived from AVHRR satellite to assess the impact of land cover change on malaria transmission. Greenness of vegetation and surface temperature are two significant characteristics that characterise mosquito habitat and influence their activity (Kogan, 2019, p.1). Greener and warmer (but not hot) vegetation is thought to improve mosquito survivability and activity conditions, while less green and colder vegetation surface in malaria endemic areas is thought to provide poorer conditions. For example, if the greenness of vegetation increases in response to planet-warming, the activities of mosquito in the transmission of malaria should rise. However, if the temperature in malaria endemic areas rises too quickly (owing to strong thermal drought) as a result of global warming, mosquito environmental conditions might worsen. Therefore, further discussion will present data of satellite-based greenness (estimated from no noise NDVI (SMN)) and radiative temperature trends using no noise Brightness Temperature (SMT)(Kogan *et al.,* 2008, p.3).

Several satellite websites have been used in West Africa to model and predict the transmission of the prevalence of malaria. The main satellite websites used are NOAA AVHRR (Advanced Very High Resolution Radiometer) satellite (Kleinschmidt *et al.,* 2000, p.355; Gaudart *et al.*, 2006, p.1; Gemperli *et al.,* 2006, p.1 ; Gosoniu *et al.,* 2006, p.127; Gosoniu *et al.*, 2013, p.1), Moderate Resolution Imaging Spectro-radiometer (MODIS) (Raso *et al.,* 2012, p.6; Gaudart, 2009, p.1 ; Kleinschmidt *et al.,* 2000, p.355; Giardina, 2012, p.1; Raso *et al.,* 2012, p.6; Kasasa *et al.*, 2013, p.4; Taconet *et al.*, 2021, p.9; Moiroux *et al.*, 2013, p.1; M'Bra *et al.*, 2018, p.11), 3B42 Version 6 Satellite Pour l'Observation de la Terre (SPOT) *(*Moiroux *et al., 2012, p.1*; Machault *et al.*, 2012, p.1), National Aeronautics and Space Administration (NASA) Earth Observing System Data and Information System (EOSDIS), USGS (Gouzile *et al.,* 2022, p.248), USGS-DEM (Giardina, 2012, p.1; Raso *et al.,* 2012, p.6), National Aeronautics and Space Administration (NASA) (Ateba et al., 2020, p.1; Gemperli *et al.*, 2006, p.1; Gosoniu *et al.*, 2006, p.127) and Earth Observing System Data and Information System (EOSDIS) (Ateba *et al.*, 2020, p.1). Among these satelites websites, NOAA AVHRR provide NDVI that is as a suitable malaria predictor in Western Africa (Ebhuoma & Gebreslasie, 2016, p.8b).

This review show that RS could be a good tool to identified the potential risk factor of malaria, to predict or to forecast (Early Warning System) the prevalence of malaria in Western Africa. In developing countries like Benin where the obtention of relevant environmental data is a big challenge, with RS, several environmental data can be downloaded through satellite websites. In the Northern part of Benin, the availability of meteorological data in some provinces (Donga, Borgou Atacora and Alibori) and some districts is a big challenge. Rainfall and temperature can be considered the major natural risk factors affecting mosquito life cycle and breeding habits (Kogan *et al.*, 2019, p.1).So, in the area where access to these data is challenging, RS-derived data can be used to predict the prevalence of malaria and identify potential factors of malaria transmission. The use of the thermal condition (TCI), moisture condition (VCI) and vegetation Greenness (VHI) derived from AVHRR satellite could help to assess the impact of land covers changes on malaria transmission in West Africa especially in Benin

II3.4. Statistic methodologies used in malaria risk modelling and prediction

To predict or forecast the risk of malaria, the incidence of malaria, or identify the potential risk factors of malaria at local, national and regional level, the statistical approach used should accommodate processes that are appropriate for the context and situation. In West Africa many statistical methods (table1) have been used to develop, predict or forecast the incidence or the transmission risk of malaria. The analysis of the various methods used reveals that generalised linear models (logistic regression, linear regression, and Poisson regression) are the most commonly used in malaria transmission simulation. On the other hand, studies conducted in South Asia (Bangladesh) (Rahman *et al.*, 2010, p.1007) ,India and Central Africa in which a multivariate analysis was carried out showed that this approach is relevant in evaluating the relationships between georeferenced environmental variables and prevalence data, identifying potential risk factor(s)/predictor variable(s), explaining the observed variable(s) and forecasting prevalence at unsampled locations. It is was also illustrate that principal component regression approach predict very well the prevalence of malaria using AVHRR data (F. Kogan *et al.*, 2013, p. 112). The use of any approach should be based on the evaluation of the accuracy of the model to predict. The principal Component Regression approach and multivariate analysis approach are the best statistical methods to predict malaria using environmental data.

Conclusion

In this chapter, the various concepts related to the research were elucidated. A comprehensive overview of the socio-economic and environmental determinants influencing the transmission of malaria in West Africa was conducted. Additionally, the different environment and climatic data obtained via satellite website to model the incidence of malaria in the West African region were reviewed, along with the statistical methods employed in the modelling of malaria risk.

CHAPTER THREE: DESCRIPTION OF THE STUDY AREA AND RESEARCH METHODOLOGY

Chapter three: Description of the study area and research methodology

Introduction

Malaria is an urgent health issue in Sub-Saharan Africa, and Benin is no exception. It is a mosquito-borne disease caused by *Plasmodium* parasites that results from the infection of red blood cells by Plasmodium genus protozoan parasites (WHO, 2021, pxix). Human infection occurs when these parasites get into the body by the bite of a *Plasmodium-infected mosquito species*. *Plasmodium falciparum, Plasmodium vivax, Plasmodium malariae, and Plasmodium oval* are malaria parasites. Plasmodium falciparum, which is carried by *Anopheles mosquitos*, is the leading cause of malaria in Africa. It is to blame for the vast majority of severe instances and deaths related with the condition, and it has shown resistance to therapy (Djègbè *et al.*, 2011, p.2; Sominahouin *et al.*, 2018, p.9).

Despite the sustained efforts made by the government of Benin over the years, malaria continues to pose a significant burden in terms of both morbidity and mortality, accounting for a staggering 95% of deaths. In 2021, the reported annual figures are 3,163,648 malaria cases with a slight increase of 1.4% between 2020 and 2021 and 2,956 deaths (ALMA Report, 2022, p.1). The provinces of Couffo, Atacora, Donga, and Borgou belonging to the northern region exhibit the highest levels of malaria prevalence, with cases of 51%, 50%, 47%, and 45% respectively(EBSBV, 2019a, p.2). Understanding the vulnerabilities specific to this region is essential for the creation and implementation of effective control and prevention strategies.

This chapter primarily focuses on the characteristics of the study areas and the methodologies employed to conduct the research.

III1. Description of the study area

3.1.1. Study area

Located on the Gulf of Guinea coast, the Republic of Benin is around 114,763 square kilometres in size, with latitude and longitude coordinates spanning from 6°30' to 12°30' N and 1° to 3°40' E, respectively. The Atlantic Ocean borders the nation on the south, Togo on the west, Burkina Faso on the northwest, Niger on the north, and Nigeria on the east (Figure 7). According to (Adam, K.S., and Boko, 1993, p.12) , Benin has a hot and humid climate. As of 2022, the country's population is projected to be 13,352,864 (The World Bank, 2023b).

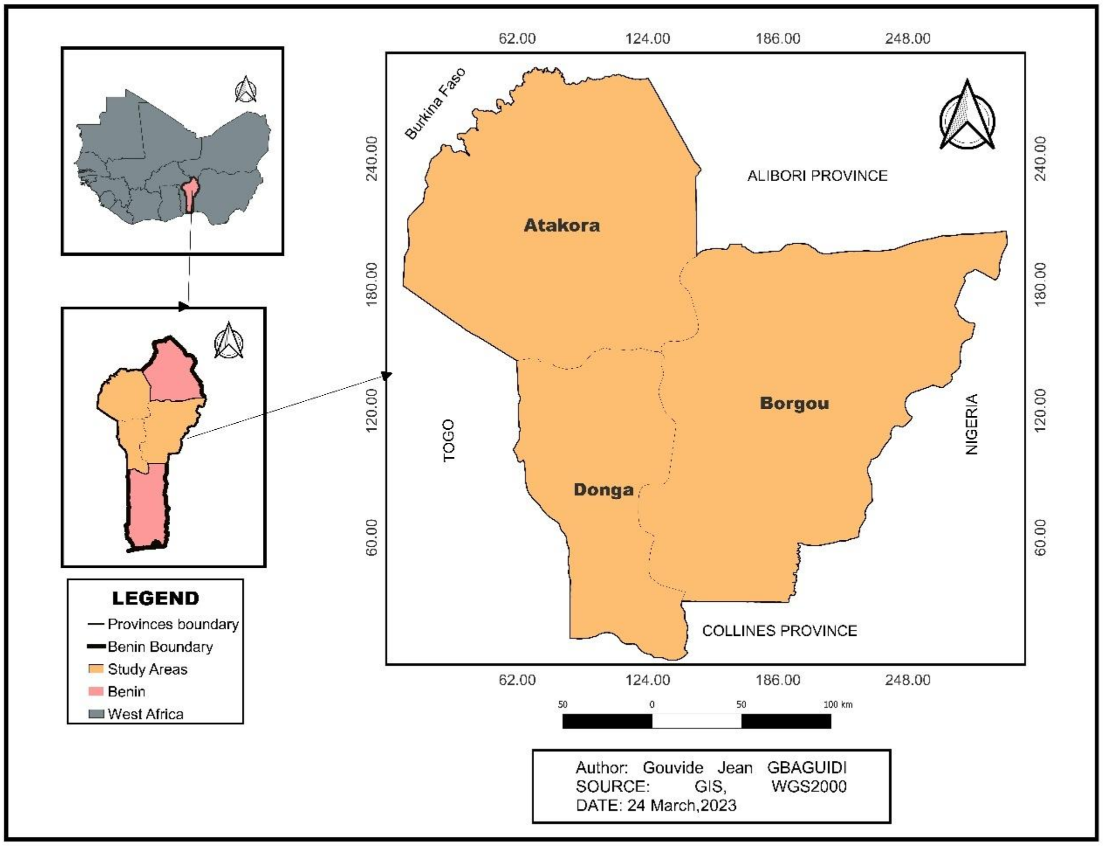


Figure 7: Map of the provinces of the study area

The provinces of Atacora, Donga, and Borgou are included in the northern Benin region under investigation. (Figure8). The province of Borgou covers an area of 25,856 km² (23% of the national territory) of which 13,962 km² is arable land (54% of the total area of the department). It is subdivided into eight (8) districts such as Kalalè, N'dali, Pèrèrè, Nikki, Sinendé, Bembèrèkè, Parakou and Tchaourou. Atacora covers an area of 20,499 km^2. It is the third-largest department after Alibori (26,242 km2) and Borgou (25,856 km2) and is ranked among the least populated in the country. Atacora is subdivided into nine (9) communes and Natitingou is considered the chief town. The other districts are Kérou, Kouandé, Péhunco, Cobly, Boukoumbé, Matéri, Toucountouna, and Tanguiéta. Its population is estimated at 772,262 inhabitants with a growth rate of 3.04 between 2002 and 2013. The Atacora mountain range has an average altitude of 700 meters, with a summit located at Boukoumbé (835 m). The province of Donga covers an area of 11,126 km^2. It is subdivided into four (4) districts such as Djougou (capital of the department), Bassila, Copargo and Ouaké. Donga population is estimated at 543,130 inhabitants according to the fourth General Census of Population and Housing (RGPH4). The soils are made of crude mineral types, tropical ferruginous and hydromorphic. The vegetation is dense along the watercourses and constitutes gallery forests.

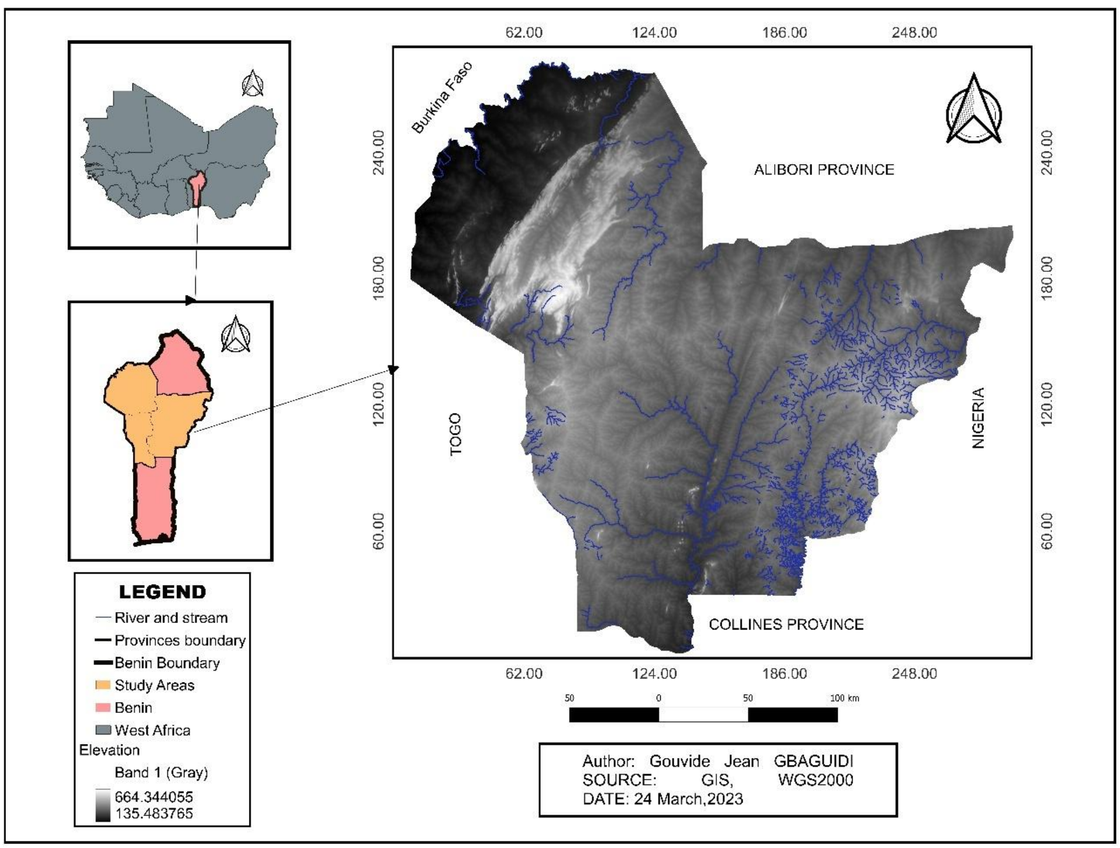


Figure 8: Elevation map of the study area

3.1.2. Population, climate and malaria cases

Benin is a country in West Africa that borders the Gulf of Guinea. Northern and central Benin receives between 200-300 mm of rainfall per month during the height of the rainy season (July-September) (World Bank, 2023).

The Republic of Benin's northern area has a unique climate pattern defined by a noticeable separation between the dry and rainy seasons, which are dictated by the movement of the Inter-Tropical Convergence Zone (ITCZ). May marks the beginning of the wet season, which lasts until October when the ITCZ reaches its northernmost point. The highest monthly precipitation during this time is recorded in August, with an average of 253.61 millimetres, while January has the lowest average rainfall of 1.90 millimetres. The 'Harmattan' winds, which originate in the northeast and bring air from the Sahara Desert, wash in during the dry season, which runs from November to April (Figure 9).

The projected population of the study area in 2021 was 3,606,063 according to the 4th General Population and Housing Census (RGPH4). A small decrease in malaria cases was seen between 2016 and 2017, which underscores the coordinated efforts of the government and its allies to lessen the disease's burden. The Inter-Tropical Convergence Zone's seasonal movement is responsible for the unique climatic patterns that are seen in the northern part of Benin, where the dry and wet seasons are clearly defined. The region's agricultural practices, the management of water resources, and the frequency of climate-sensitive illnesses like malaria may all be significantly impacted by this seasonal fluctuation in precipitation levels, which peaks in August and troughs in January.

(The World Bank, 2023a) reports that the average air temperature across the nation is 27.13 degrees Celsius.

The documented decrease in malaria infections between 2016 and 2017 points to the success of the government's and its partners' efforts in combating this public health emergency.

However, from 2017 to 2021, the number of malaria cases has shown an increasing trend, with the exception of a dip in 2020. Given the growing population size, the corresponding increase in the number of malaria cases is unsurprising, as evidenced by the strong positive correlation (p-value = 4.034e-09, Cor=0.98).

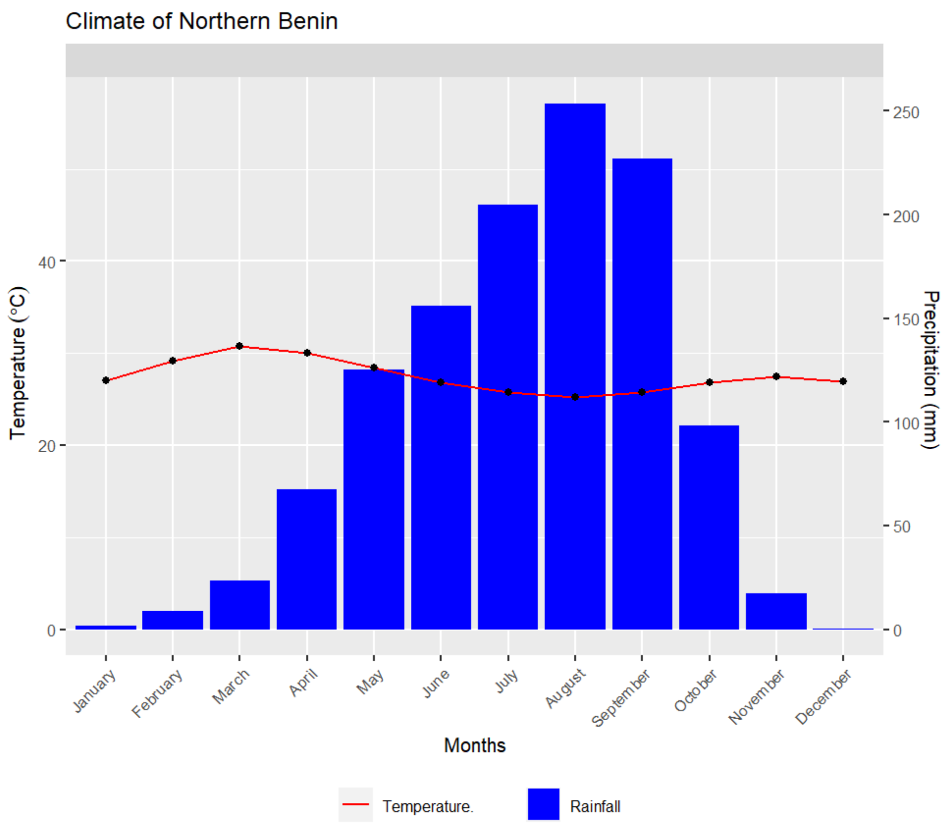


Figure 9:Climate of northern Benin, West Africa

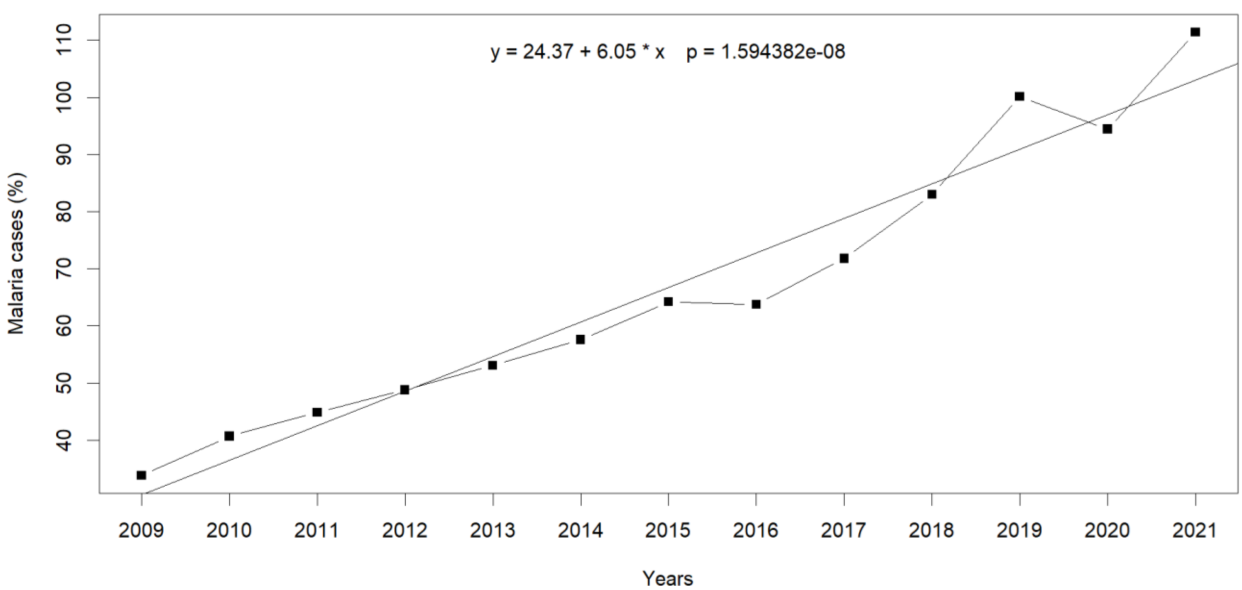


Figure 10: Time series of malaria cases over 2009 to 2021 period

III2. Research methodology

3.2.1. Effects of climate change on the spread of malaria in northern Benin, West Africa

3.2.1.1. Data collection

3.2.1.1.1. Clinical data

The monthly malaria case data for the 2009-2021 period were obtained from the Benin Ministry of Health. This comprehensive dataset encompasses the total confirmed malaria-infected population across the various districts within the study area. A patient is declared to have malaria when the disease is confirmed at a laboratory by microscopy or rapid diagnosis (WHO, 2021, pxix)

3.2.1.1.2. Climatic data

The National Meteorological Agency of Benin operates the Natitingou and Parakou airport meteorological stations, from which monthly weather data were gathered. This dataset encompasses temperature, wind speed, and relative humidity recordings spanning the 1991 to 2021 period. Furthermore, monthly precipitation data were extracted from nine rain gauge stations, with the selection of these stations based on the districts exhibiting the highest, medium, and lowest incidences of malaria within the study area (Table 2).

Table II: Location of rain gauge and meteorological stations

Stations	**Longitude DEG.FRAG**	**Latitude DEG.FRAG**
TANGUIETA	1.26656	10.6171
NATITINGOU	1.38333	10.3166
BEMBEREKE	2.66666	10.2
BOUKOUMBE	1.1	10.16667
NIKKI	3.2	9.933333
BASSILA	1.665544	9.022698
NATITINGOU_PEPORIYAKOU	1.358889	10.37833
PARAKOU_AEROPORT	2.6	9.35

3.2.1.2. Data processing

To investigate the differences in precipitation patterns throughout the study region, we calculated the precipitation concentration index (PCI). Trends in precipitation and temperature were assessed using Sen's slope estimates, and the significance of trends was estimated using the Mann Kendall (MK) test (Salman *et al.,* 2019, p.429) over the period 1991-2021. Pettitt's test was used to assess the degree of homogeneity in the data. The PCI values were computed, as given by (Oliver, 1980, p.302) and modified by (De Luis et al., 2011, p.1260), as:

$$PCI_{annual} = \frac{\sum_{i=1}^{12} P_i^2}{\left(\sum_{i=1}^{12} P_i\right)^2} * 100 \quad \text{(Eq 1)}$$

where Pi = the rainfall amount of the i^{th} month. According to(Oliver, 1980), the MK test statistic ‘S’ is calculated based on (Kendall, 1948) using the formula:

$$S = \sum_{k=1}^{n-1} \sum_{i=k+1}^{n} \text{sign}(x_i - x_k)$$

Where

$$\text{sign}(x_i - x_k) = \begin{cases} +1 & When\ (x_i - x_k) > 0 \\ 0 & When\ (x_i - x_k) = 0 \\ -1 & When\ (x_i - x_k) < 0 \end{cases}$$

Z statistic is used to compute trend significance (Equation2).

$$Z = \begin{cases} \frac{S-1}{\sqrt{Var(S)}} & When\ S > 0 \\ 0 & When\ S = 0 \\ \frac{S-1}{\sqrt{Var(S)}} & When\ S < 0 \end{cases} \quad \text{(Eq.3)}$$

Where Var (S) is the variance, and it is calculated as

$$Var(S) = \left(n(n-1)(2n+5) - \sum_{i=1}^{m} t_i(t_i - 1)(2t_i + 5)\right)/18$$

Sen's slope was calculated using the subsequent relationship:

$$Sen's\,slope = \begin{cases} Q_{|n+1/2|} & \text{When n is odd} \\ Q_{\frac{n}{2}} + Q_{\frac{n}{2}} & \text{When n is even} \end{cases} \quad \text{(Eq.3)}$$

n is the total number of slopes, and Q is the slope between two successive spots.

The study used principal component analysis (PCA) and Pearson correlation tests to assess the association between malaria incidence and climatic factors. The covariance matrix was computed after a matrix including regions and indicators was generated. Each eigenvalue's importance was evaluated, and the slope between any two spots as well as the total number of slopes were computed. R software version 4.1.3 was used to process the data.

3.2.2. Towards an intelligent system for detecting and alerting people to malaria epidemics in the northern part of Benin, West Africa

3.2.2.1. Data collection

3.2.2.1.1. Dependent variables

Data regarding monthly incidences of malaria in every district of the Republic of Benin, spanning the years 2009 to 2021, was sourced from the Benin Ministry of Health. The whole confirmed infected population with confirmed malaria diagnoses nationwide is included in this comprehensive dataset. A patient is declared to have malaria when the disease is confirmed at a laboratory by microscopy or rapid diagnosis (WHO, 2021, pxix)

3.2.2.1.2. Independent variables

The study used monthly weather data from the National Meteorological Agency of Benin's Parakou Airport and Natitingou meteorological stations, which are operational from 1991 to 2021. The data included temperature, wind speed, and relative humidity. In addition, monthly precipitation data were retrieved from nine rain gauge stations. The stations were chosen based on which districts in the research region had the highest, medium, and lowest rates of malaria (Table 3).

Table III: locations of meteorological stations and rain gauges

Station	Longitude DEG.FRAG	Latitude DEG.FRAG
BIRNI	1.529987	9.990087
PENESSOULOU	1.551297	9.239867
TANGUIETA	1.266561	10.61712
KOUANDE	1.692409	10.33185
NATITINGOU	1.383333	10.31667
KALALE	3.381675	10.29007
BEMBEREKE	2.66666	10.2
BOUKOUMBE	1.10	10.16667
NIKKI	3.20	9.933333
BASSILA	1.66554	9.022698
MATERI	1.012	10.73
COPARGO		
PEHUNCO	2.003	10.2299
PERERE		
N'DALI	2.7	9.85
PARAKOU_AEROPORT	2.6	9.35
NATITINGOU_PEPORIYAKOU	1.358889	10.37833

3.2.2.2. Data processing

3.2.2.2.1. Analysis of factors

The appropriate meteorological data was matched with the monthly average incidence of malaria. The data's distribution was evaluated using both univariate normality and multivariate tests (Henze-Zirkler and Anderson-Darling) (Gbaguidi *et al.*, 2024b, p.4). The researchers have conducted a thorough suite of studies, including assessments of collinearity, regression, and correlation, using the traditional statistical technique distribution.

3.2.2.2.2. Exploratory factor analysis (EFA)

To find any latent ecological factors that may be impacting the spread of malaria, using the collection of observable environmental variables, exploratory factor analysis (EFA) was used

(Bentler *et al.*, 1980, p.302; Ruscio & Roche, 2012, p.12). The link between the latent components and the observed environmental variables was determined using varimax rotation (Table IV) (Gbaguidi *et al.,* 2024b, p.4).This orthogonal rotation method was used to facilitate the interpretation of the underlying factors influencing malaria infection. The analysis revealed the presence of a variety of unobserved latent factors driving the malaria transmission dynamics within the study area. To develop an initial model, data fitting techniques, correlation and regression analysis, as well as exploratory factor analysis were used (Duo-quan *et al.*, 2013, p.3).

Table IV: The Varimax approach rotated each indicator in the load factor for the two potential components (Gbaguidi *et al.*, 2024b, p.4).

Indicators	Factors	Factor1(F1)	Factor2(F2)
I1	Mean Monthly Precipitation		
I2	Mean Monthly Minimal Temperature		**0.98**
I3	Mean Monthly Maximal Temperature	**-0.82**	
I4	Mean Monthly Relative Humidity	**0.98**	
I5	Mean Monthly Maximal Relative Humidity	**0.94**	
I6	Mean Monthly Wind Speed		0.37
I7	Mean Monthly Malaria Incidence	0.48	

3.2.2.2.3. Confirmatory factor analysis (CFA)

Confirmatory factor analysis's main objective is to use a single latent variable to shed light on the covariances or correlations between a large number of observed variables (Austin, 2013, p.8). In the prior model, seven observed indicators were examined. After 30 iterations, weighted least squares were employed to assess the convergence of the parameters in compliance with the model t rule ($t = p * (p+1)/2 = 7 * 8/2 = 28$) (Modu et al., 2017, p.).

3.2.2.2.4. Structural equation model (SEM)

Structural equation modelling (SEM) was employed to conduct the confirmatory analysis, as outlined by (Bollen, 1989, p.238). This multivariate statistical technique allowed for the examination of the relationships between the variables, irrespective of their latent or observed nature, with the distinction between dependent and independent variables taking precedence (Bentler *et al.*, 1980, p.302).

The covariances between the endogenous variables, or between the endogenous and exogenous variables, were not arbitrarily modified; rather, they were described using the free parameters within the hypothesised model structure. In line with the recommendations of (Yuan & Bentler, 2006, p.304) , the proposed model structure placed the correlations between the independent variables at zero.

The SEM approach is defined by the following system of equations (Eq 4), where the observed variables can be written as a linear combination of the potential components plus residual terms. Accordingly, we offer the subsequent mathematical SEM depictions of Figure 3:

$$\begin{cases} \text{Factor I} = \lambda 1{,}1(\text{Mean relative humidity}) + \lambda 1{,}2(\text{Maximum mean relative humidity}) + \\ \beta 1{,}2(\text{Maximum mean temperature}) + \gamma 1(\text{malaria incidence}) + e1 \\ \text{Factor II} = \lambda 2{,}1(\text{Minimum mean temperature}) + \gamma 2(\text{malaria incidence}) + e2 \end{cases} \quad \text{(Eq 4)}$$

3.2.2.5. Machine learning

3.2.2.5.1. Data processing

"All models are wrong; some models are useful" (Box, 1979, p.1) is an iconic quote attributed to George Box that will be employed to make a reliable prediction of malaria occurrence. To train the model and evaluate its predictive capacity, a random sample technique was used to create the test and training sets. Given the limited number of observations available, 90% of the data were randomly selected for the training phase, while the remaining 10% were reserved to examine the predictive model. Three distinct machine learning techniques were utilised to develop the malaria outbreak warning model: support vector machine (SVM), linear regression (LR), and negative binomial regression (NBR) (Gupta *et al.*, 2021, p.6).

3.2.3.2.5. An intelligent outbreak malaria early warning application

A web application was developed for the Malaria Outbreak Warning. It uses the built malaria outbreak warning model.

The application works in three steps: The weather forecasting data from Meteostat will be pre-processed; the data will be processed by applying it to the best algorithm and implementing the model's interface; the prediction data will be post-processed and presented on the app's UI front layer. The application will support both automatic and manual data input. When a city is selected, the tool predicts the likelihood of a malaria outbreak based on the last month's data up to the current hour. The current outbreak predictions and matching status are displayed. Users can manually enter a set of climatic variables and get a prediction that shows up alongside the status.

The web application will be built using the Streamlit framework and is responsive and compatible with all navigators. The weather forecasting data is powered by Meteostat, an online weather data service provider. Meteostat offers a Python library for querying forecasting data using coordinates (referred to as points). This interface reduces complexity for users as it does not require knowledge about the available weather stations. Instead, data can be retrieved directly. Additionally, HyperText Markup Language (HTML) and Cascading Style Sheets (CSS) will used for the front-end. The application will be online and travellers and local communities can use it to be informed about the risk of malaria (malaria incidence) in any district of the province of Borgou, Atacora, Donga and Alibori in northern Benin. Public health policymakers of Benin will use this to plan the different malaria program activities.

3.2.4. Modelling and forecasting malaria in northern Benin, West Africa, using Vegetation Health Indexes based on Advanced Very High-Resolution Radiometers (AVHRR)

3.2.4.1. Data collection

3.2.4.1.1. Dependent variable

The monthly malaria case data for each district were obtained from Benin's Ministry of Health, covering the period from 2009 to 2021. This comprehensive dataset includes the total confirmed population infected by malaria within the study area. When malaria is identified in a patient through the use of rapid diagnostic tests or microscopic examination of blood samples in a laboratory setting, the diagnosis is confirmed (WHO, 2021, p.117).

3.2.4.1.2. Independent variables

Vegetation health conditions were evaluated using data from remote sensing to evaluate the effects of land cover change. From 2009 through 2021, the weekly brightness temperature (BT), Normalised Difference, and Vegetative Index (NDVI) were determined using the Advanced Variability Harvesting Radiometer (AVHRR) aboard the National Oceanic and Atmospheric Administration (NOAA) family of satellites. The Temperature Condition Index (TCI), Vegetation Condition Index (VHI), and Vegetation Condition Index (VCI), which are helpful indicators for monitoring malaria and estimating the condition of the vegetation, were created using BT.

3.2.4.2. Data processing

3.2.4.2.1. Public health data

Malaria transmission and consequences are influenced by climate and environmental factors (Kasasa *et al.*, 2013). The time series data have been partitioned into two distinct components such as deterministic (Ysp) and Random (Yw): Ysp represents factors related to socioeconomic conditions and policy decisions and Yw is influenced by variations in weather patterns, which determine the proportion of malaria cases. In other words, the malaria incidence data can be decomposed into a deterministic component influenced by socioeconomic and policy factors, and a random component driven by fluctuations in weather conditions. This disaggregation of the time series data facilitates a more nuanced analysis of the underlying drivers of malaria transmission in the study region.The observed malaria cases in northern Benin can be expressed by $DY = Yw + Ysp\ (Eq\ 5)$.

To show the interannual fluctuation in malaria prevalence, the percentage of instances' time series was used to generate a linear trend. This interannual variation is likely to be, at least in part, attributable to fluctuations in weather patterns over the same period. As a ratio of the actual malaria cases to the estimated trend, the weather-related variability around the trend was expressed (Eq 6) $Yw = (Ysp * 100)/Yt$ (2) (Nizamuddin *et al.*, 2013, p.110; Rahman *et al.*, 2010, p.1007). Due to fluctuations in weather patterns on an annual and seasonal basis, malaria episodes' deviation (anomaly) from the general trend is represented by the Yw component. Yw is a useful comparison measure of malaria case counts. In 2009, the Yw value was 33.82%, while in 2021 it reached 111.40%, corresponding to the fewest malaria case year and the worst malaria outbreak, respectively (Figure 11).

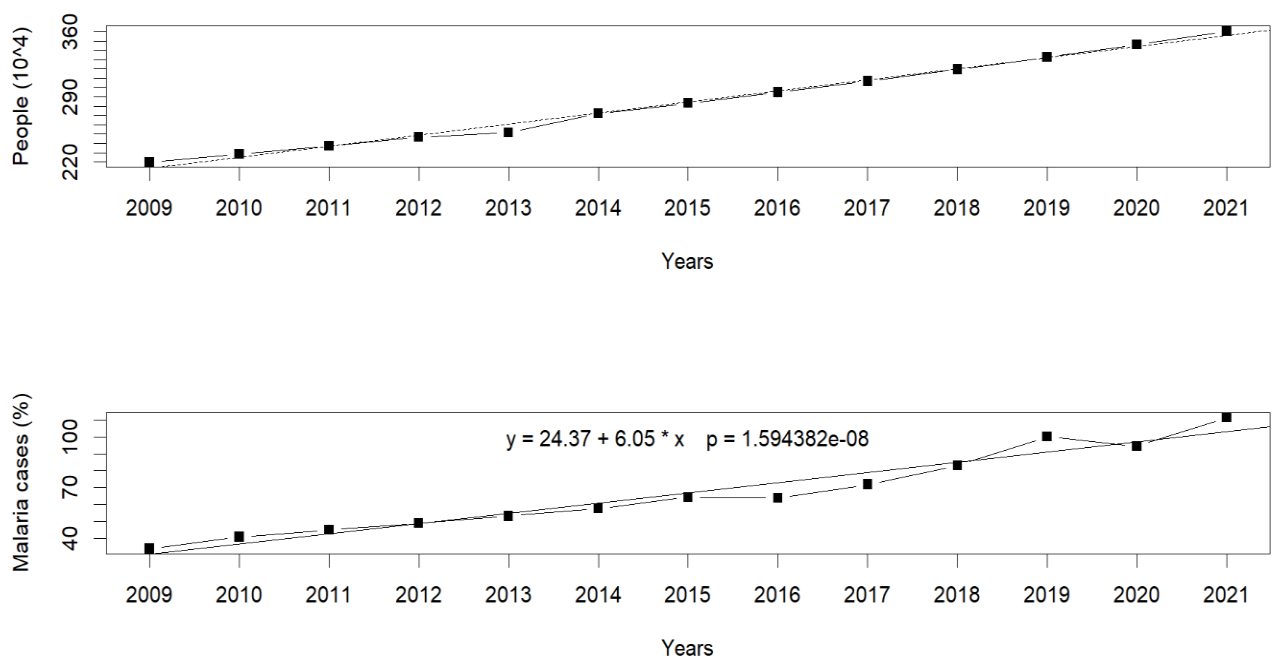


Figure 11:Time series for the population and the malaria cases

3.2.4.2.2. Satellites data: vegetation health indices

The aim is to employ operational satellite technology to detect early environmental conditions that facilitate mosquito growth and the subsequent transmission of malaria. The concept of Vegetation Health (VH) indices is predicated on the capacity of healthy green vegetation to either reflect or emit solar energy across the visible (VIS), near-infrared (NIR), and infrared (IR) wavelength spectra.

Specifically, healthy vegetation exhibits minimal reflection of radiation in the visible spectrum due to the strong absorption of solar energy by chlorophyll. Conversely, a substantial amount of NIR radiation is reflected, owing to light scattering by the internal tissues of the leaves, as well as reduced absorption by pigments, water, and other leaf components. This interplay results in a high Normalised Difference Vegetation Index (NDVI).The global vegetation index (GVI) was developed from the reflectance/emission observed by the Advanced Very High-Resolution Radiometers (AVHRR) of the NOAA polar-orbiting satellite in the visible (VIS), near-infrared (NIR) and infrared (IR) wavelengths (Kogan, 2019, p.1). In developing the GVI, the measurements were spatially sampled from 16 km² (National Area Coverage–NAC) to 16 km² and from daily observations to a seven-day composite (Kogan, 1995, p.276). Pre- and post-launch calibrations of the VIS and NIR reflectance were performed, and the NDVI was computed using the relation $NDVI = \frac{NIR - VIS}{NIR - VIS}$ $(Eq7)$. The infrared observations at 10–11 µm wavelengths will be translated to blackbody. The high-frequency noise of the NDVI and BT related to variable transparency of the atmosphere, bidirectional reflectance, orbital drift, randomness, and others was already removed from the data by statistical techniques (Kogan et al., 2018, p.59). Weekly data on the Normalised Difference Vegetation Index (NDVI) and Brightness Temperature (BT) were collated for each 16 km² pixel within the study site, located in Northern region of Benin, spanning the period from 2009 to 2021.

Lastly, throughout the studied timeframe, the weekly minimum and maximum values of BT and NDVI were calculated. From the values of the NDVI and BT, we calculated three indices (Eq 8, Eq 9, Eq 10 and equation 6): the Vegetation Condition Index (VCI) characterizing moisture, the thermal condition index (TCI) characterizing the soil temperature and the Vegetation Health Index (VHI). $VCI = 100 * \frac{NDVI - NDVImin}{NDVImax - NDVImin}$ $(Eq\ 8)$ $TCI = 100 * \frac{BTmax - BT}{BTmax - BTmin}$ $(Eq. 9)$

$$VHI = a * VCI + (1 - a) * TCI \ (10)$$

where NDVI, NDVImax, and NDVImin (BT, BTmax, and BTmin) are the no noise monthly NDVI and BT, their multi-year absolute maximum and minimum, respectively. The coefficient 'a' measures the contribution of the Vegetation Condition Index (VCI) and Temperature Condition Index (TCI) to overall Vegetation Health (VH), with a value of 0.5 assumed (Jensen R, 2000). This study uses Pearson correlation and regression analysis to investigate the connection between malaria occurrence and vegetation health, using Vegetation Health (VH), Vegetation Condition Index (VCI), and Temperature Condition Index (TCI) scaled to 0-100, corresponding to weather conditions.

3.2.4.3. Machine learning

To create a set of training data and a test set, along with instructing the model and assessing the accuracy with which it predicts, a method of random sampling was utilised. Due to the limited number of observations available, 90% of the data was randomly selected for the training set, while the remaining 10% was reserved for testing the predictive model.

Three techniques, denoted by Equations 11, 12, and 13, were utilised in the construction of the malaria outbreak warning model: Principal Component Regression (PCR), Ordinary Least Squares (OLS), and Support Vector Machine (SVM) (Gbaguidi *et al.*, 2024b, p.4).

To find out how different vegetation health indices affect the prevalence of malaria, the SVM and OLS algorithms were utilised. Using SVM, OLS, and PCR, it was possible to look at how different vegetation health indices affected malaria incidence.

$Malari\ a\ incidence = \alpha + \beta 1 * \mathrm{VCI} + \beta 2 * \mathrm{TCI} + \beta 3 * \mathrm{VHI}\ Eq\ 11$, *with α representing the intercept, and β1, β2, and β3 are the coefficients associated with the independent variables VCI, TCI, and VHI, respectively.*

$Malari\ a\ incidence = \alpha + \beta 1 * VCI + \beta 2 * TCI + \beta 3 * VHI\ Eq\ 12$, *where α is the intercept, and β1, β2, and β3 are the coefficients associated with the independent variables VCI, TCI, and VHI, respectively.*

$\mathrm{Malaria\ incidence} = \alpha + \beta 1 * \mathrm{PC1} + \beta 2 * \mathrm{PC2} + \beta 3 * \mathrm{PC3}\ \mathrm{Eq}\ 13$, *where α is the intercept and β1, β2, and β3 are the coefficients corresponding to PC1, PC2, and PC3, respectively, of the principal components.*

To identify the optimum forecasting algorithm (Gupta et al., 2021, p.6), we computed the mean absolute error (MAE), mean square error (MSE), root mean square error (RMSE) and R-squared value on a validation dataset through random sampling of the proposed models (SVM, OLS, and PCR) for the prediction of malaria incidence. The metrics of bias and standard deviation were used to assess the accuracy of the top-performing models. These metrics were calculated by comparing the observed malaria incidence values with the corresponding predicted incidence values.

3.2.5. Assessing the socio-economic and environmental vulnerability to malaria in the context of changes in climate in northern Benin

3.2.5.1. Indicators selection

Following an extensive literature review on the socioeconomic and environmental determinants of malaria in West Africa, we have carefully selected twenty-four (24) indices for assessing the vulnerability to malaria in the Northern region of Benin.

Table V summarises the various indicators and the rationale for their inclusion in accordance with this criterion.

Table V: Selection and explanation of indicators

Evaluation Items	Indicator	Justification	Sign[a]
Exp_1	Number of household members	Larger families with more people have a higher potential host pool for malaria vectors, increasing indoor exposure risk.	+
Exp_2	Number of Children under 5	Malaria primarily affects children under five years old. More children are in the household, larger will be the vulnerability	+
Exp_3	Number of people visiting a household	More visitors increase the risk of malaria by spreading disease or vectors into dwellings, likely from places with variable levels of transmission.	+
Exp_4	Thermal condition (TCI_Mean)	Soil temperature conditions significantly influence malaria transmission dynamics by assessing environmental suitability for vector breeding and parasite development.	-
Exp_5	Vegetation Condition(VCI_Mean)	The Vegetation Condition Index (VCI) helps identify breeding sites for malaria vectors by indicating suitable environmental conditions for mosquito breeding, such as high vegetation density and moisture.	+
Sus_1	Number of people sleeping under ever mosquito bed nets	Mosquito bed nets are an effective tool for preventing malaria transmission by reducing the contact between mosquitoes and humans.	-
Sus_2	Number of population sleeping under ITN	Insecticide-treated bed nets (ITNs) are more effective than untreated bed nets in preventing malaria transmission.	-
Sus_3	Number of population sleeping under LLIN	The control of malaria is greatly aided by long-lasting insecticidal nets (LLINs), a type of ITN that is developed to be effective for several years.	-
LoR_1	Number of population with education	Education significantly predicts malaria transmission and improves public health (Olukosi et al., 2020).	-
LoR_2	Number of households with protected and hygienic sewage disposal	Proper sewage disposal is crucial for preventing malaria transmission by preventing mosquito reproduction and preventing stagnant water build-up.	-
LoR_3	Number of population without health insurance (Mutual; community organisation, Insurance)	Ensuring healthcare access is crucial for maintaining health insurance coverage, as lack may limit essential medical care and increase malaria susceptibility.	+
LoR_4	Number of Population with no access to credit	Access to credits aids malaria resistance by enabling people to invest in preventive measures, such as bed nets and medical attention, while financial constraints restrict resources and increase risk.	+
LoR_5	Number of Population with access to land usable for agriculture	Population's ability to support lifestyles through agriculture depends on land availability, a key socioeconomic indicator. Lack of land for agriculture may indicate vulnerability to malaria as a lack of resilience.	+
LoR_6	Number of population with radio	Radios aid in disseminating health-related information, including malaria prevention strategies, by providing access to healthcare services and updates on outbreaks.	-

Evaluation Items	Indicator	Justification	Sign[a]
LoR_7	Number of population with television	Television broadcasts effectively educate communities on malaria prevention, treatment, and vector control, reaching a large audience and promoting awareness.	-
LoR_8	Number of population with mobile phone	Mobile phones enable health messages, apps, and communication with healthcare providers.	-
LoR_9	Number of Population with motorcycle	Motorcycles enhance malaria-endemic areas' adaptation capacity, improving healthcare access and mobility, ensuring timely diagnosis and treatment.	-
LoR_10	Dwelling has been sprayed against mosquitoes the last 12 months	Indoor residual spraying (IRS) involves insecticides on dwelling walls and ceilings to kill mosquitoes, assessing vector control effectiveness and malaria protection among populations.	-
LoR_11	Number of population without literacy level	Education impacts people's ability to read and understand anti-malarial drug instructions, impacting preventive and treatment-seeking behaviors (Eteng et al., 2014, p.7; Anyanwu et al., 2017, p.7).	+
LoR_12	Number of population Owns livestock (birds or farm animals)	Income level impacts malaria treatment and diagnostic test usage (Anyanwu et al., 2017, p.7; Okebe et al., 2014, p.1).	-
LoR_13	Number of the population with no a bank account	Bank accounts offer secure savings for healthcare expenses, malaria prevention, and access to credit and loans for income-generating activities.	+
LoR_14	Number of population with an Internet connection	Internet access provides essential knowledge, resources, and skills for adapting to threats and pressures.	-
LoR_15	Population with no access to potable water	In scarce water sources, communities store water in open containers, facilitating mosquito breeding and increasing malaria transmission risk. Malaria control programs rely on water-related interventions, but lack of potable water may hinder their implementation, exacerbating vulnerability.	+
LoR_16	Number of population using Natural gas as cooking fuel	Natural gas offers sustainable, environmentally friendly cooking fuel alternative.	-

[a]Sign indicates if high indicator values increase (+) or decrease (−) vulnerability;
Exp=Exposure, Sus= Susceptibility (or fragility) and LoR= Lack of resilience

3.2.5.2. Data collection

3.2.5.2.1. Primary data-field survey

3.2.5.2.2. Study population

The household leader is the target population. Without any doubt, he or she is the ideal individual to supply precise facts about the household. In our study, a household is represented by a married man, his wife (wives), or child along with any other residents (adopted children, family members), or by an adult unmarried woman who is acknowledged as the head of the household.

3.2.5.2.3. Remote sensed data

The challenge of developing accurate modelling frameworks for infectious disease dynamics and climate projections in West Africa, particularly Benin, is addressed by using proxy data from remote sensing satellites. This approach could overcome the lack of ground-based meteorological observations and create more reliable models.

Weekly AVHRR data from the NOAA satellite website were acquired for the entirety of 2022. A graphical modeller was devised to execute several essential tasks including data clipping, reprojection to match the coordinate system of the study areas, and computation of the yearly average values for both the Thermal Condition Index (TCI) and the Vegetation Condition Index (VCI) using the zonal calculation function in QGIS (Figure 12). This systematic approach facilitated the extraction and analysis of the desired information from the satellite data.

The ability of green vegetation to either emit or reflect solar radiation throughout the visible (VIS), near-infrared (NIR), and infrared (IR) wavelengths provides the foundation for the creation of Vegetation Health (VH) indices. In the case of healthy vegetation, there is a substantial absorption of solar radiation in the visible range (primarily due to the high absorption of chlorophyll), coupled with a considerable reflection in the near-infrared range (resulting from light scattering by internal leaf tissues and minimal .absorption by water, pigments, and other components of leaves). This behavior manifests in elevated values of the Normalized Difference Vegetation Index (NDVI), indicative of robust vegetation health (Refer to section 2.4.3. 2. For more detail).

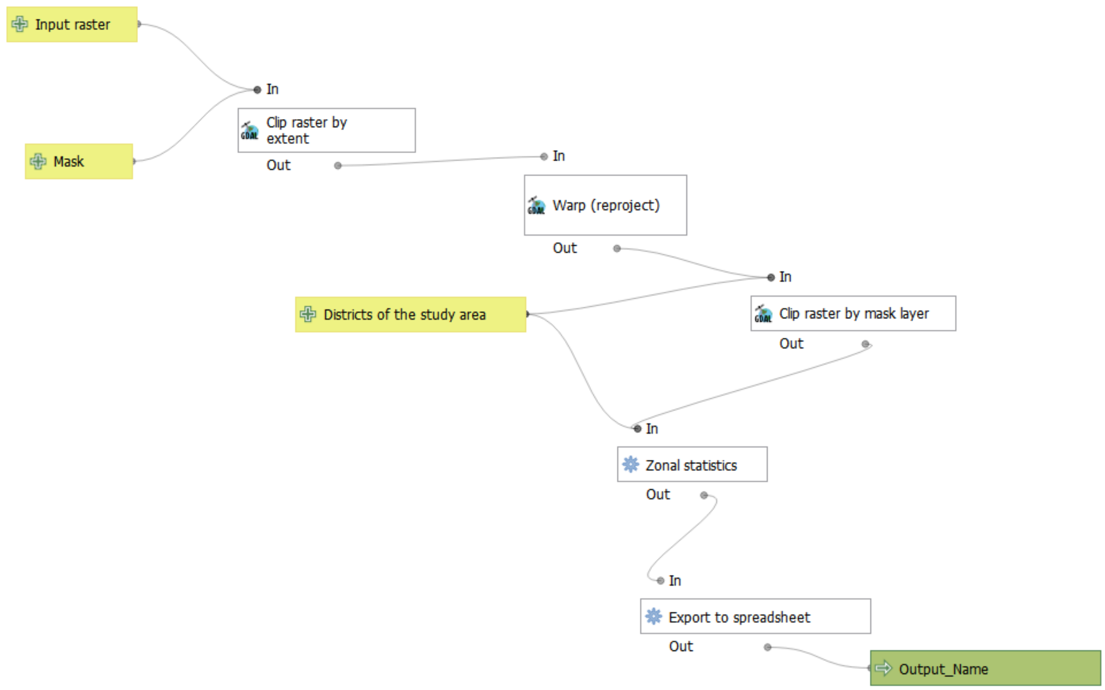


Figure 12: Model for extracting yearly average values of the thermal condition index (TCI) and Vegetation Condition Index (VCI) from NOAA satellite data

3.2.5.2.4. Field survey

The research emphasised community vulnerability while also determining how the community perceives its susceptibility to malaria and the relevance of several factors. After evaluating the literature on socioeconomic and environmental variables influencing malaria in West Africa, the researchers established twenty-four (24) valid indices for assessing malaria vulnerability in Northern Benin. The survey was conducted among households in the districts of Atacora (Kerou, Kouande, Péhunco, Cobly, Boukoumbe, Materi, Toucountouna, Tanguieta), Borgou (Kalale, N'dali, Perere, Nikki, Sinende, Bembereke, Parakou, and Tchaourou), and Donga (Djougou, Bassila, Copargo, and Ouake). To provide a gender-balanced representation, a sample of 5,864 households was selected using the Schwaz algorithm (Eq 14). Table VI shows the distribution of survey households per district in each province.

$$n = \frac{\varepsilon^2 * p * q}{i^2} \quad \text{(Eq 14)}$$

ε: Reduced deviation corresponding to the risk of error α at 5%, $\varepsilon = 1.96$

n: sample size,

p: Prevalence of malaria

q=1-p

i: Level of accuracy or margin of error(i=0,05)

Table VI: Sampling size of the survey household

Provinces	**Districts**	**Sample**	**Male**	**Female**
Atacora	Boukoumbe	370	185	185
	Cobly	352	176	176
	Kerou	234	117	117
	Kouande	206	103	103
	Materi	340	170	170
	Natitingou	310	155	155
	Pehunco	222	111	111
	Tanguieta	300	150	150
	Toucountouna	284	142	142
Borgou	Bembereke	362	181	181
	Kalale	226	113	113
	N'dali	250	125	125
	Nikki	288	144	144
	Parakou	164	82	82
	Perere	280	140	140
	Sinende	382	191	191
	Tchaourou	206	103	103
Donga	Bassila	324	162	162
	Copargo	238	119	119
	Djougou	286	143	143
	Ouake	240	120	120
	Total	**5864**	**2932**	**2932**

3.2.5.3. Data processing

3.2.5.3.1. Normalization

We used the UNDP's Human Development Index (HDI) methodology to normalise the data (UNDP, 2006, p.5). The normalised indicators are in the 0–1 range. We discovered a functional link between vulnerability and indications prior to normalisation. There are two types of functional interactions: vulnerability increases or decreases proportionally to indicator levels. The normalised score is determined using the following formula (Eq. 15) when the factors raise the vulnerability:

$$x_{ij} = \frac{X_{ij} - Min_{i}\{X_{ij}\}}{Max_{i}\{X_{ij}\} - Min_{i}\{X_{ij}\}} \quad (Eq.15)$$

When the variables decrease the vulnerability, the normalised score is computed using the formula (Eq 16):

$$x_{ij} = \frac{Min_{i}\{X_{ij}\} - X_{ij}}{Max_{i}\{X_{ij}\} - Min_{i}\{X_{ij}\}} \quad (Eq.16)$$

Where X_{ij} is the variable, Max{ X_{ij}} and Mi{ X_{ij}} are the maximum and minimum variables.

3.2.5.3.2. Construction of vulnerability index

Vulnerability is defined by the Intergovernmental Panel on Climate Change (IPCC) as the tendency to be adversely affected. Within the particular context of this study, it includes a variety of ideas and aspects, such as sensitivity or susceptibility to damage and the inability to cope with and adapt to malaria infection (IPCC, 2022a, p.3).

It is possible to compute the Vulnerability Index (VI) with equal or unequal weighting for the indicators. On the other hand, imbalances can result from techniques such as the Simple Average Method and Patnaik and Narain, which might reflect the relative relevance of indicators incorrectly (Patnaik, 2005). A number of writers concurred that techniques with uneven weight appear to be the most accurate way to give indications weight (Gbetibouo G.A and Ringler. C., 2009, p.1; Iyengar, 1992, p.2.

The Principal Component Analysis (PCA) approach was used in this work to evaluate and quantify the study area's malariavulnerability.

Principal component analysis, or PCA, is a powerful method for identifying patterns in high-dimensional datasets. PCA decreases the number of dimensions and shows underlying patterns while conserving a significant amount of data, enabling data reduction. PCA involves several procedures in order to extract meaningful information from the data. We create a matrix X, with rows representing districts/regions (M) and columns representing indicators (K). As a result, matrix X's dimension is M x K. The mean of each variable across all recordings is then computed and subtracted from each observation. A new matrix, X - X, is produced as a consequence of this procedure, and each column's total element count is zero. The formula (X - X)^T(X - X)/m is used to compute the covariance matrix (ω). The diagonal members in this covariance matrix reflect the variances of the variables, correspondingly, while the off-diagonal entries show the covariances between the variables.

To assess each eigenvalue's importance, they are ranked from lowest to highest ($\lambda_1 < \lambda_2 \geqq \ldots \leq \lambda_n$). Finding the most significant principle components is made simpler by this order. First principle component loadings are used to construct the vulnerability indicator weights. For each indication i($1 \leq i < n$), the corresponding eigenvector (loading) vi is extracted using the eigenvector matrix v. The weight of the indicator is then determined using the formula Weight = (vi / prod(vi))2, which is based on the squared normalised loading. The weights assigned to each signal indicate its relative importance in identifying vulnerabilities.

Equation 17 is then employed to provide a thorough vulnerability index for every district based on the assigned weights (Filmer & Pritchett, 2001, p.117).

$VI = k = 0 n$ bi aij − xi si $(Eq\ 17)$

With a mean of 0 and a standard deviation of 1, the eigenvalue is a metric for standardised variance. Every standardised variable, which includes the 19 indicators in this case, adds at least one variance to the main component extraction procedure. Following the Kaiser criterion, any main component with a standardised variance of 1 or above that is unable to extract a variance amount equivalent to or more than one of the original variables should be eliminated from additional analysis Filmer & Pritchett, 2001, p.117).

In the aforementioned formula, v represents the vulnerability index, a represents the indicator value, x represents the mean indicator value, and s represents the standard deviation of the indicators. The weight is calculated from the first main component produced using PCA. GIS is used for visualising the findings to enhance comprehension. Pearson correlation analysis is used to examine correlations between VI and other indicators in order to identify relevant vulnerability factors.

Conclusions

Several statistical techniques were used to carry out this investigation. Pearson correlation, Principal Component Analysis (PCA), Mann-Kendall test, and Sen's slope were used to evaluate the possible impact of climate change on malaria transmission. To develop a model to forecast the prevalence of malaria in Nord Benin, the Structural Equation Model (SEM), multiple linear regression, negative binomial regression, and support vector machine (SVM) were utilised. The Streamlit framework was used to create an online malaria early warning system. An effect analysis of vegetation health indices was conducted, and a malaria forecast model was constructed with the use of these data. Socioeconomic and environmental variables are used to evaluate the community's susceptibility. The weight of each indicator was calculated using PCA.

CHAPTER FOUR: RESULTS AND DISCUSSION

Chapter four: Results and discussion

Introduction

Malaria is a big public health challenge in Benin. Despite the government's consistent efforts over the years, malaria remains a serious burden in terms of both morbidity and mortality. Climate change will have an impact on human health and well-being through diverse direct and indirect pathways, which are contingent upon exposure to hazards and vulnerabilities(Leal Filho, W. *et al.*, 2022) These hazards and vulnerabilities exhibit heterogeneity and variation within societies and are influenced by social, economic, and geographical factors.

Modelling the relationship between environmental and climatic factors with malaria incidence can contribute to a better understanding of this association. Such an understanding is essential for providing information on disease patterns, emergence, and potential control strategies, which can aid policymakers in developing effective interventions (IPCC, 2022, p.51).

Early warning systems can play a valuable role in adapting to climate-related risks associated with infectious diseases if they rely on high-skill forecasting and if there are timely and effective responses aligned with the forecasted timeframe (Leal Filho, W. *et al.,* 2023; p.51 IPCC, 2022, p.3). Proactive and timely adaptation measures can significantly reduce health risks and improve well-being. Investigating the relationship between vegetation health indicators and the prevalence of malaria within the study region and developing seasonal weather predictions using NOAA/AVHRR environmental satellite data that may be used in place of forecasts for malaria epidemics. Assessing malaria vulnerability will allow good decision-making in high-risk areas for the development of effective control actions (Kogan, 2019, p.1).Combined with the vulnerability indicators, the transmission risks and the early detection indicators from health facilities can be a good tool to confirm the beginning of a malaria outbreak, especially in districts where sentinel health surveillance and early warning systems are lacking (Leal Filho, W. *et al.,* 2019, p.2).

This chapter presents the various findings of the study and suggests essential adaptations to mitigate climate change's implications on human health, particularly regarding the transmission of malaria in Benin.

IV-1. Potential impacts of climate change on malaria transmission in northern Benin, West Africa

4.1.1- Characterisation of the climate in northern Benin

4.1.1.1. Trends in total precipitation

Table VII displays the trends of the total precipitation. The analysis of this table reveals that Mann-Kendall (MK) statistical test results show that the precipitation patterns at the meteorological station in Bassila exhibit statistically significant trends (p-value < 0.05).

Furthermore, with a slope value of -195, Sen's slope analysis using a non-parametric technique for determining the trend's magnitude reveals a tendency towards decreasing precipitation at the Bassila station. At this specific site, the quantitative evaluation shows a decrease tendency in precipitation levels across the research period.

Table VII: Total precipitation trends using the Mann-Kendall test in northern Benin

Stations	z	p-value	Sen's slope
Bassila	-3.30	**0.00**	-195
Copargo	-0.30	0.76	-19
Djougou	0.17	0.87	11
Natitingou	-1.50	0.13	-89
Boukoumbe	-0.32	0.75	-20
Tanguieta	-0.73	0.46	-44
Parakou	00	1	-1
Nikki	-1.77	0.08	-105
Bembereke	-1.33	0.18	-79

However, the trend analysis did not detect any statistically significant patterns in the total amount of precipitation at the other weather stations, as shown in Table VII.

The Sen's slope analysis, which estimates the magnitude of trends, revealed negative slope values at all stations, with the exception of the Djougou station. Based on these findings, it is plausible to conclude that there is a non-significant decreasing trend in precipitation levels observed across Northern Benin, although the magnitude and significance of these trends vary between the individual monitoring locations.

4.1.1.2. Trends in monthly and annual temperatures

The Mann-Kendall (MK) statistical test findings for the monthly maximum temperature data at the Natitingou meteorological station are shown in Table VIII. The maximum temperatures for the months of May (Z-score = 174), June (Z-score = 114), July (Z-score = 133), October (Z-score = 119), and November (Z-score = 149) show statistically significant positive trends, according to the MK test.

Moreover, a noteworthy rise in the maximum temperature at the Natitingou station during these months is verified by the Sen's slope analysis, a non-parametric technique for determining the amplitude of trends. The research shows that the maximum temperatures for May, June, July, October, and November will climb by 2.96°C, 1.93°C, 2.25°C, 2.01°C, and 2.52°C, respectively.

Table VIII: Monthly maximum temperature Mann-Kendall Test

Station of Parakou-Airport				**Station of Natitingou**		
Months	Z	P-value	S	z	P-value	S
January	1.32	0.19	75	1.33	0.18	79
February	1.61	0.12	91	0.31	0.76	19
March	2.35	**0.02**	132	1.28	0.20	76
April	1.61	0.11	91	1.21	0.23	72
May	1.64	0.10	93	2.96	**0.00**	174
June	1.90	**0.06**	107	1.93	**0.05**	114
July	1.90	**0.06**	107	2.25	**0.02**	133
August	1.02	0.31	58	1.31	0.19	78
September	0.68	0.50	39	1.40	0.16	83
October	0.70	0.48	40	2.01	**0.04**	119
November	1.29	0.20	73	2.52	**0.01**	149
December	0.68	0.50	39	1.32	0.19	78

Significance: P-value<=0.05

Temperature trends in northern Benin are analysed, and the results show that there is a noticeable tendency of temperature increase over time as well as noteworthy variability in the area. This observed rise in temperature has the potential to impact mosquito development and reduce their activity in transmitting infections to humans.

Figure 13 shows the yearly trend evolution of the maximum temperature at the Parakou Airport station (Graph b) and the Natitingou meteorological station (Graph a). The study of this figure reveals a noticeable break in the temperature trend at the Natitingou station in 2005.

From 2005 to 2021, the maximum temperatures at the Natitingou station are expected to climb as a result of this structural break in the trend.

At the Parakou Airport station, however, no such breakpoint in the temperature trend was noted between 1991 and 2021. The maximum temperature data from the Parakou Airport station does, however, show an increased trend from 2012 to 2021, along with an unusual spike in temperature in 2008. Similarly, there are notable positive trends in the maximum temperature data from the Parakou airport station for the months of March (Z-score = 132), June (Z-score = 107), and July (Z-score = 107) according to the MK test. At the Parakou airport station, the corresponding Sen's slope values of 2.35°C, 1.90°C, and 1.90°C, respectively, show significant rises in the maximum temperature for the months of March, June, and July.

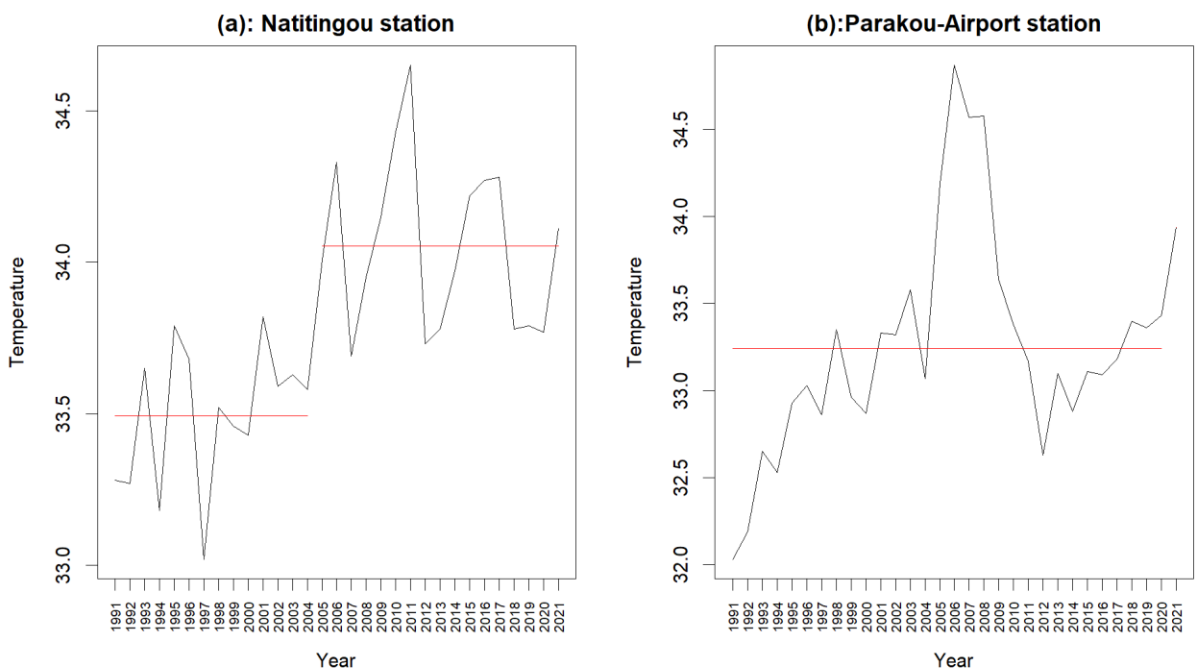


Figure 13:The yearly maximum temperature evolution trend at the Natitingou and Parakou Airport stations

The analysis of temperature patterns in the northern region of Benin leads to the conclusion that temperatures are exhibiting significant variability and an overall upward trend over time. This observed rise in temperatures has the potential to impact the development and activity of mosquito populations, which could in turn influence their capacity to transmit infections to humans.

4.1.1.3. Precipitation Concentration Index (PCI)

For a number of meteorological stations in Northern Benin, including Boukoumbe, Natitingou, Tanguieta, Parakou-Airport, Bembèrèkè, Nikki, Djougou, Copargo, and Bassila, Figure 14 shows the precipitation concentration index graphics. The regression trend is shown by the blue line, while the evolution trend is represented by the black line.

These numbers' analysis reveals significant regional variability in precipitation concentration patterns. A non-significant declining trend in precipitation intensity (P-value>0.05) is seen in graphs d, e, and f, which correspond to the Boukoumbe station (R=-0.21, P-value=0.27), Natitingou station (R=-0.21, P-value=0.27), and Tanguieta station (R=-0.053, P-value=0.78) in the Atacora province. For these locations, the precipitation Concentration Index (PCI) indicates a change in favour of a moderate precipitation concentration (Gbaguidi et al., 2024a, p. 7, p. 7).

A non-significant declining trend in precipitation intensity is also shown in graphs h and j, which correspond to the Parakou-Airport district (R = -0.022, P = 0.91) and the Nikki district (R = -0.26, P = 0.17) in the Borgou province, respectively. The overall trend in the Borgou province points to a falling precipitation concentration, while the Bemberekè station (R = 0.14, P-value = 0.45) shows a minor rise in precipitation concentration (Gbaguidi *et al.*, 2024a, p. 7).

The districts shown in graphs a and b, Djougou (R=-0.17, P-value=0.37) and Copargo (R=-0.16, P-value=0.41), show a drop in precipitation intensity, which is not statistically significant (P-value>0.05). In contrast, Graph c shows a somewhat higher concentration of rainfall at the Bassila station (R = 0.1, P-value = 0.59). Additionally, there is no statistically significant difference in the intensity of rainfall in the province of Donga (P-value > 0.05).

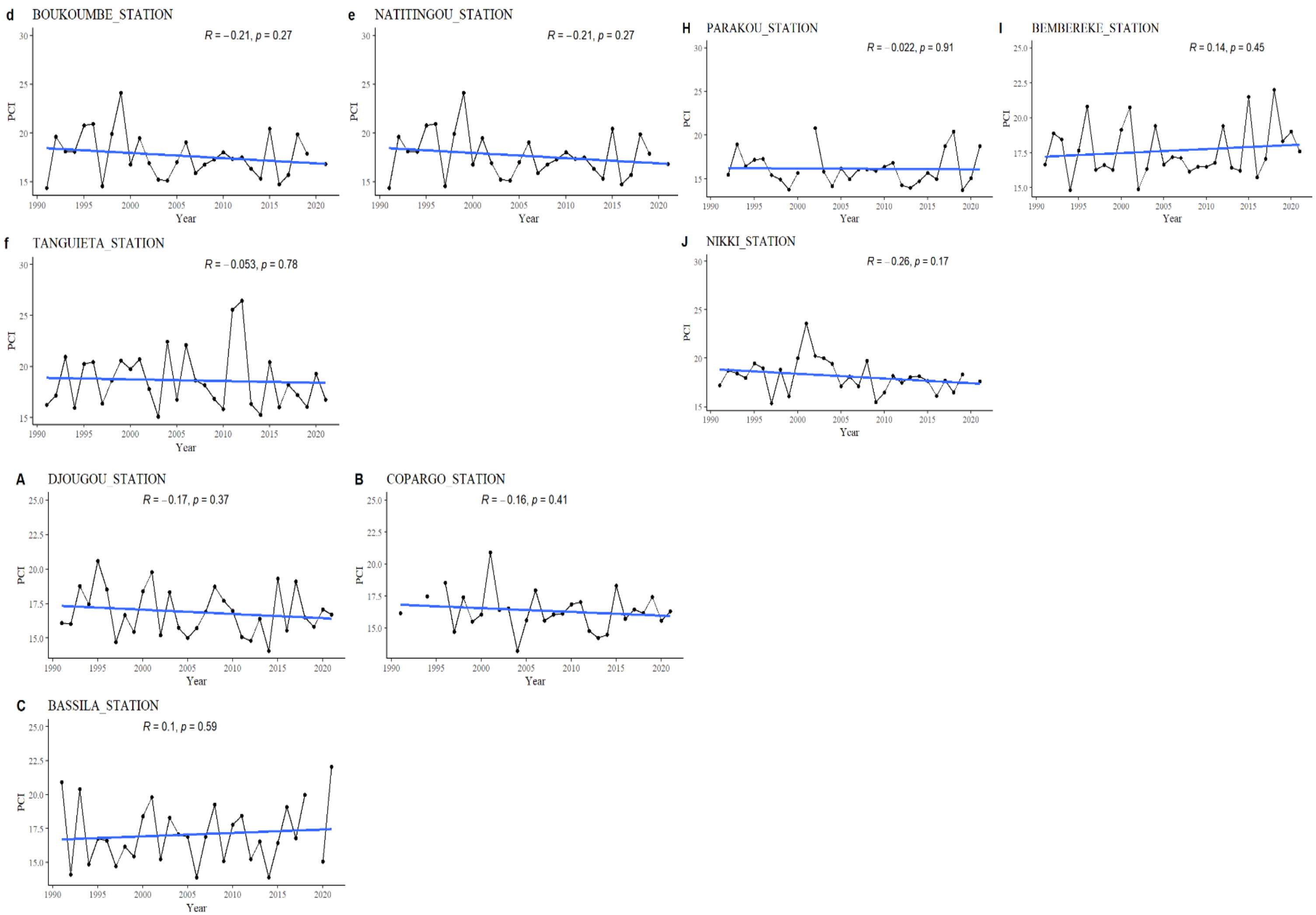


Figure 14: Precipitation concentration index in the Northern part of Benin.

A careful examination of the presented graphs reveals a non-significant decreasing trend in rainfall intensity observed in the northern region of Benin.

4.1.1.4. Description of the climatic season

The climate of northern Benin is depicted in Figure 15, which further illustrates the distinctive weather patterns that are typical of the area. Upon closer inspection, this chart reveals that the northern region of Benin has a unique seasonal pattern, with two main seasons: the rainy season and the dry season.

In northern Benin, the dry season runs from November to April, and the rainy season begins in May and lasts until October. The region's climate is known for having this bimodal pattern of precipitation.

It is essential to recognise that the variability observed in the rainy and dry seasons within the research regions is significantly impacted by climate change. The usual seasonal features that have traditionally defined the climate of northern Benin have undergone considerable changes and alterations due to the effect of climate change (Amouzou *et al.*, 2019, p.105; The World Bank, 2023a).

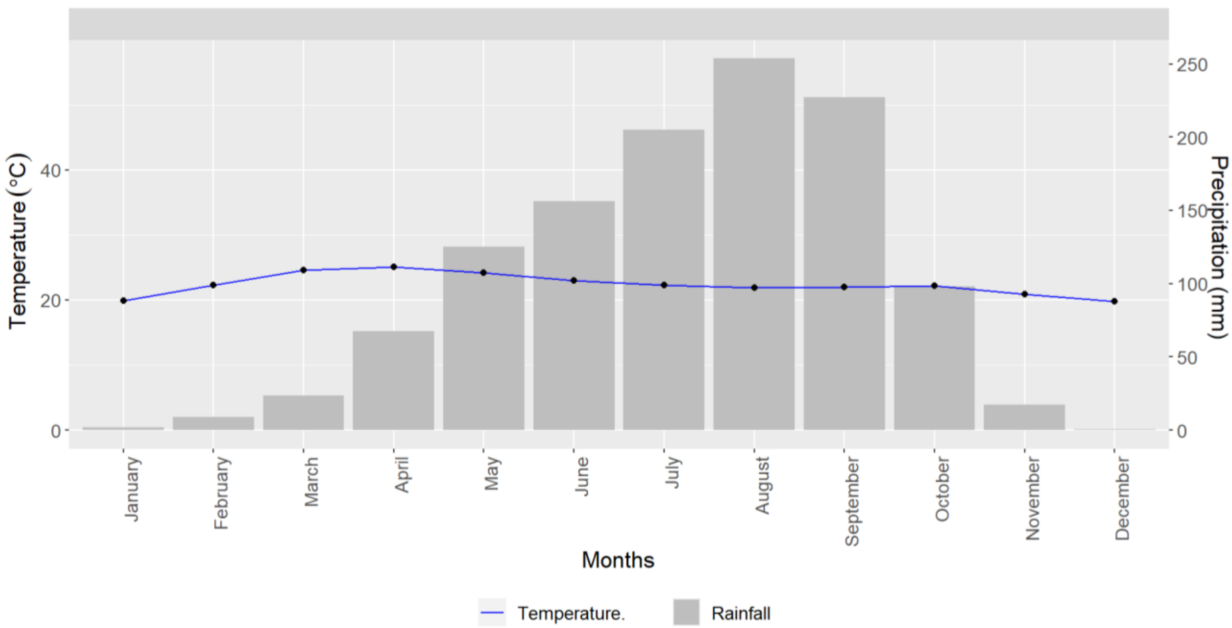


Figure 15: Climatographic in northern Benin

This fluctuation in climate patterns can pose challenges to the effective control of malaria transmission within these regions (Padonou *et al.*, 2018, p.40, Sominahouin *et al.*, 2018, p.9).

4.1.2. Climate change and malaria in northern Benin

4.1.2.1. Relationship between malaria incidence and precipitation

The association between the climatic factors and the prevalence of malaria in the districts of Parakou, Nikki, Bembereke, Natitingou, Boukoumbe, Tanguieta, Bassila, Djougou, and Copargo was investigated using the Pearson correlation analysis shown in Table IX (see the annexes). As indicated by the stated p-value (pvalue < 0.05), the statistical analysis's results showed a statistically significant and positive association between the incidence of malaria and precipitation. This result implies that within the districts under investigation, greater precipitation levels are linked to a higher malaria prevalence.

It is noteworthy, therefore, that the lack of statistically significant associations in other districts suggests that variables other than climate may be relevant in determining the frequency and transmission of malaria. These variables could include, but are not restricted to, socioeconomic circumstances in the different districts, healthcare infrastructure accessibility and quality, and vector control strategies.

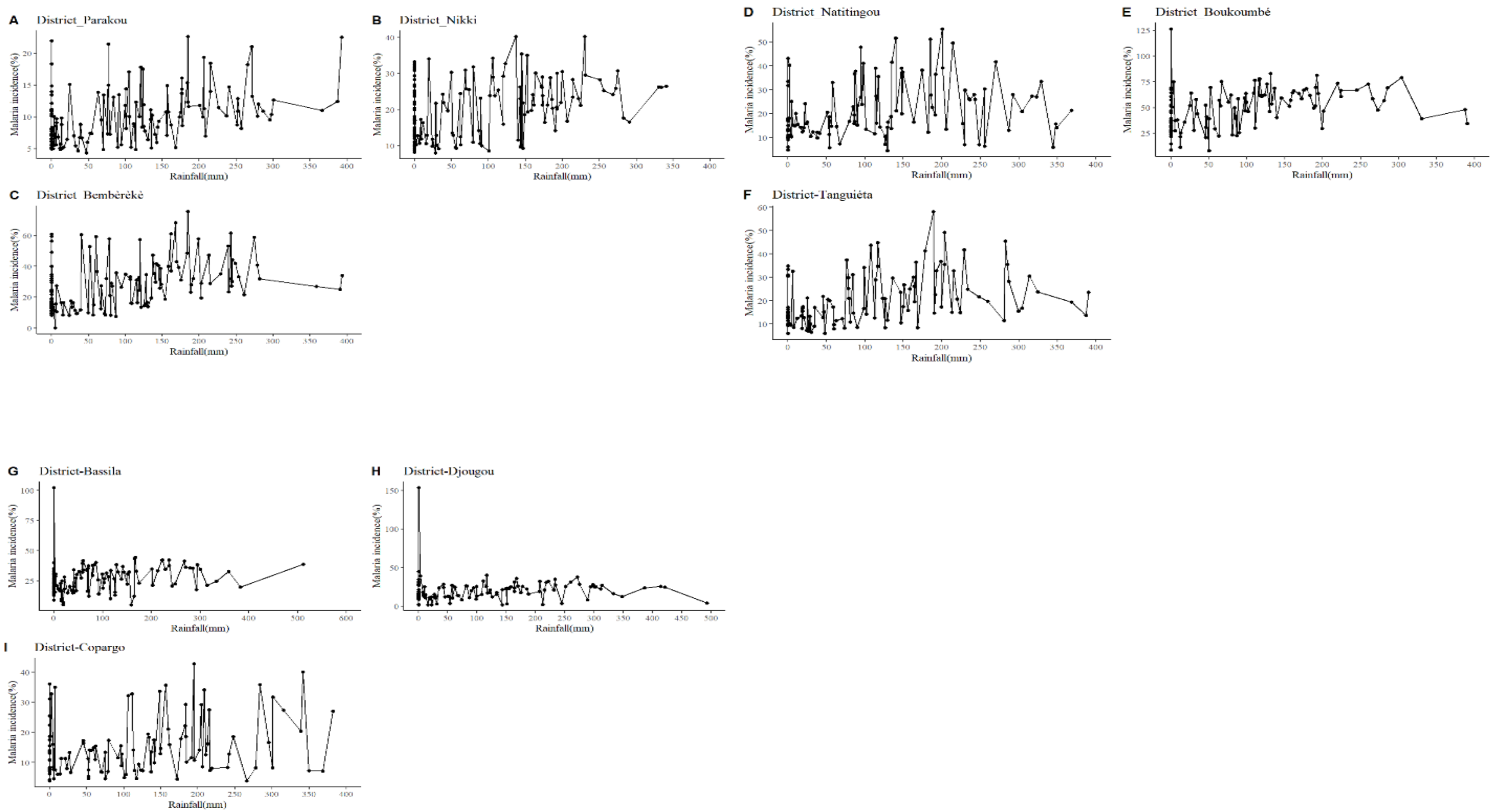


Figure 16:Link between malaria incidence and rainfall in northern Benin

The results of this study show that, in northern Benin, there is a significant positive association between monthly precipitation levels and monthly incidence of malaria. As Figure 16 makes abundantly evident, the study shows that an average precipitation range from 40 to 215 mm is linked to a significant rise in malaria incidence (Gbaguidi *et al.*, 2024a, p. 7).

These precipitation values directly correspond with the highest recorded incidence of malaria across all the examined districts. This observation underscores the significant role that precipitation plays in the epidemiology of malaria in the northern part of Benin.

4.1.2.2. Association between temperatures and malaria incidence

Regarding the districts of Parakou, Nikki, and Bembereke (Borgou province), Natitingou, Boukoumbe, and Tanguieta (Atacora province), as well as Bassila, Djougou, and Copargo (Donga province), a Pearson correlation analysis was performed to investigate the relationship between different climate variables and the incidence of malaria (Table IX).

Significant negative associations between the highest and average temperatures and the prevalence of malaria in the areas under investigation are shown by the statistical analysis's findings. As shown in Figure 17, the results show that most cases of malaria are found in the provinces of Borgou, Atacora, and Donga, with average temperature ranges of 25-35°C, 23-28°C, and 25-29°C, respectively (Gbaguidi *et al.*, 2024a, p. 7).

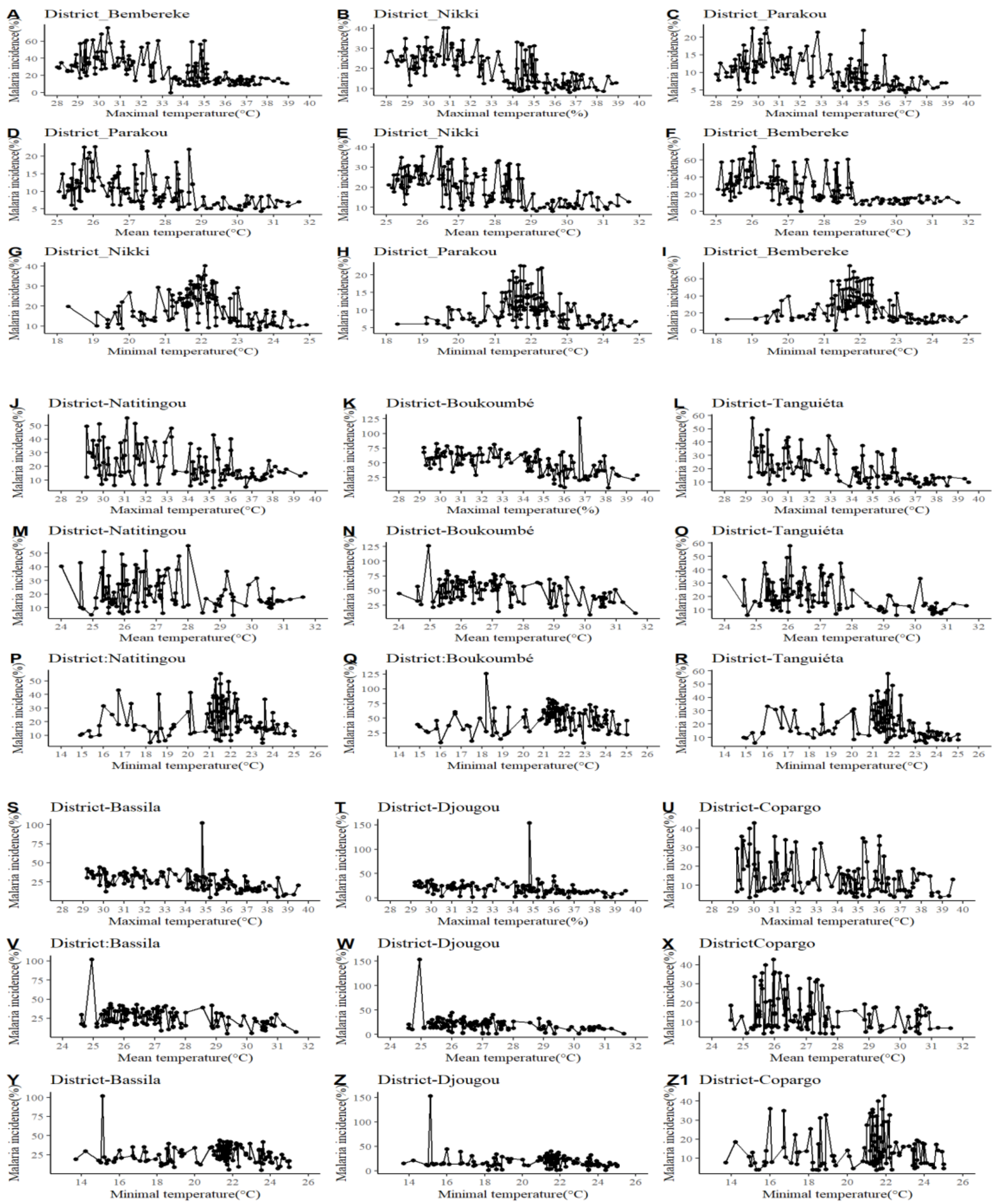


Figure 17:Link between temperatures and malaria incidence in northern Benin

This observation suggests that moderate temperature conditions (24 to 33°C,) within these observed ranges, are more conducive to the transmission and proliferation of malaria in the northern regions of Benin. The negative correlations between temperature and malaria incidence underscore the complex interplay between climatic factors and the epidemiology of the disease in these geographical areas.

4.1.2.3. Link with relative humidity and malaria incidence and

The association between several meteorological factors and the prevalence of malaria in the districts of Parakou, Nikki, Bembereke, Natitingou, Boukoumbe, Tanguieta, Bassila, Djougou, and Copargo was investigated using the Pearson correlation analysis Table IX (see the annexes).

The statistical analysis's findings show a substantial positive correlation between the lowest, maximum, and average relative humidity levels in the areas under investigation and the monthly incidence of malaria (Gbaguidi *et al.*, 2024a, p. 7). In addition, Figure 18's study shows that the northern part of Benin relies heavily on an average relative humidity range of 45% to 85% for modelling and controlling malaria transmission.

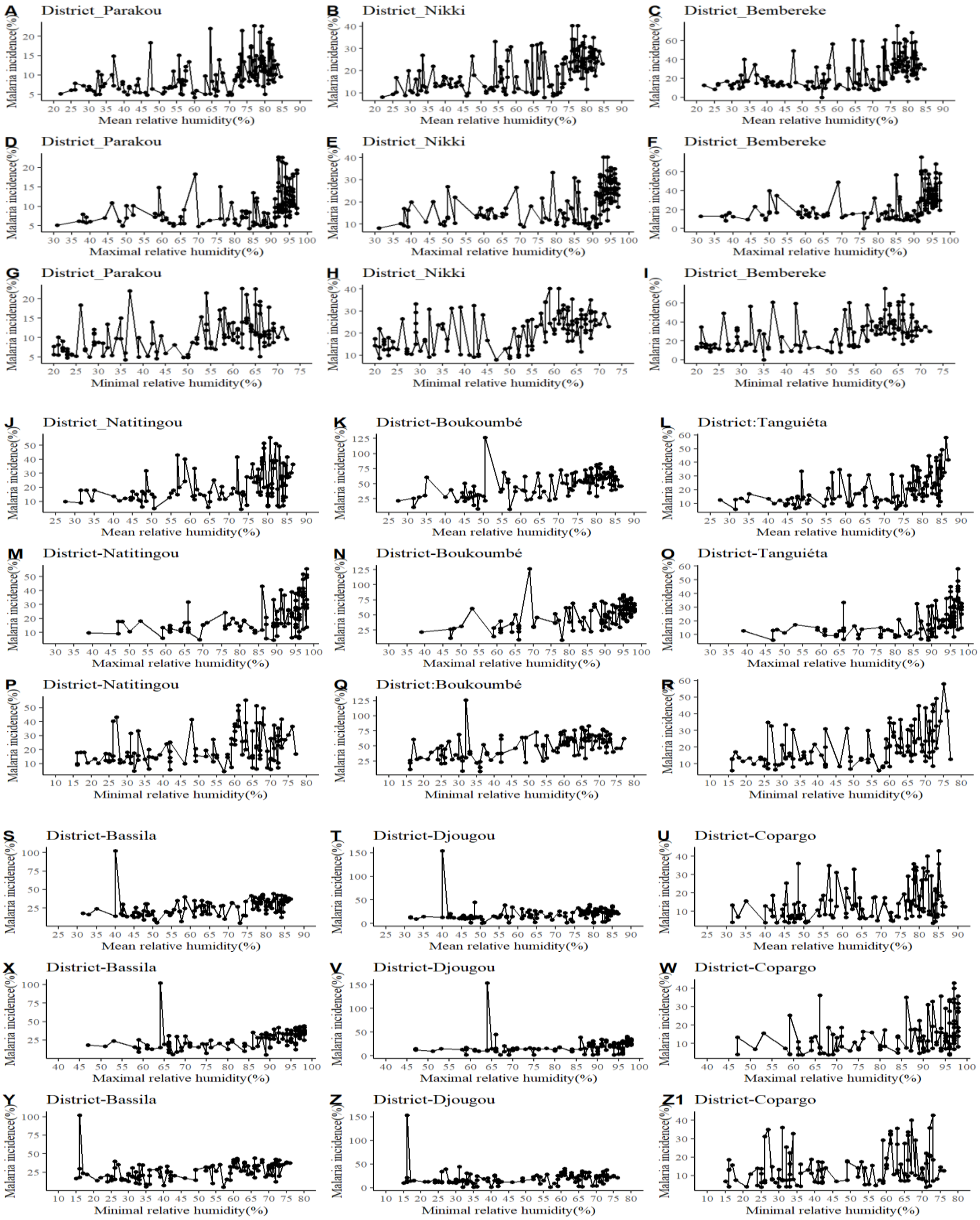


Figure 18: Association between malaria incidence and relative humidity in Northern Benin

This finding suggests that moderately high levels of humidity, falling within this identified range, are conducive to the proliferation and transmission of malaria in the study area. The positive correlation between relative humidity and malaria incidence underscores the importance of considering atmospheric moisture as a key climatic determinant of malaria epidemiology in this region.

4.1.2.4. Relationship between malaria incidence and wind speed

The districts of Parakou, Nikki, Bembereke, Natitingou, Boukoumbe, Tanguieta, Bassila, Djougou, and Copargo underwent a Pearson correlation analysis to investigate the association between the prevalence of malaria and wind speed (Table IX in the annexes). As a consequence of the statistical investigation, the districts of Parakou, Nikki, and Bembereke have a statistically significant negative correlation between wind speed and malaria incidence. Specifically, the analysis presented in Graphics J, K, and L of Figure 19 indicates that the highest incidence of malaria in the districts of Parakou, Nikki, and Bembereke is associated with wind speed ranges of 1.8-2.26 m/s, 1.5-2.6 m/s, and 1.8-2.7 m/s, respectively (Gbaguidi *et al.*, 2024a, p. 7).

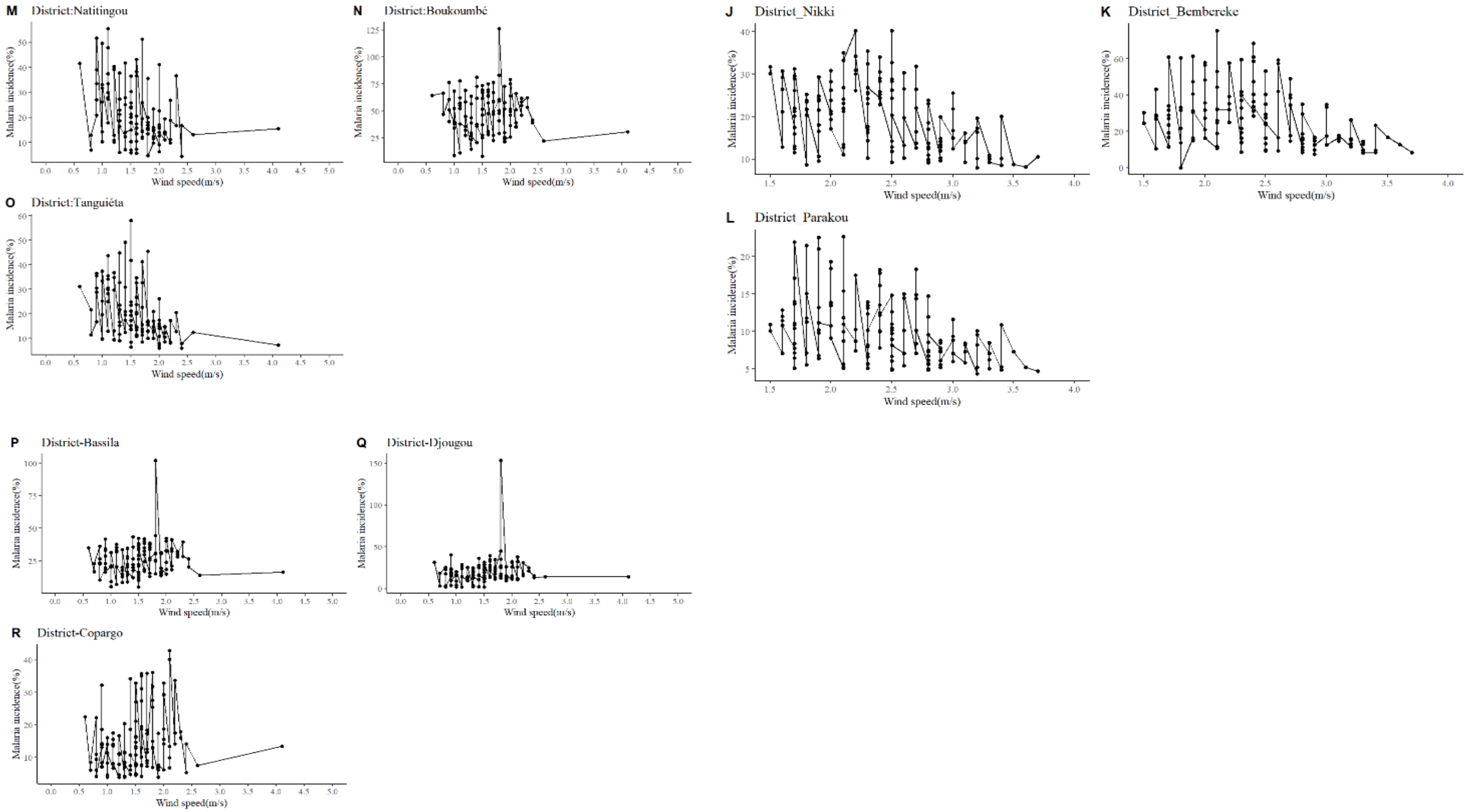


Figure 19: Link between malaria incidence and wind speed

These results imply that although wind speed may not consistently be useful in preventing the spread of malaria across Benin's northern region, it has a great deal of potential as a malaria control strategy in the province of Borgou (Gbaguidi *et al.*, 2024a, p. 7).

4.1.2.5. Potential climatic factors influencing the incidence of malaria

Figure 20 shows the results of principal component analysis (PCA) analysing the effects of climate on malaria incidence in northern Benin. The results indicate that the second principal component (PC) accounts for 22.70% of the overall fluctuation in malaria incidence. Conversely, the first PC and second PC explain 47.52% and 12.12% of the variance, respectively.

The first two main components together account for 70.2% of the variation in malaria incidence overall. Moreover, the first three PCs together account for 82.3% of the total variance in malaria incidence within the study region (Figure 20) (Gbaguidi *et al.*, 2024a, p. 7).

The findings show a substantial correlation between the first PC (Dim. 1) and mean relative humidity, maximum relative humidity, and minimal relative humidity. A strong positive correlation exists between the second PC (Dim. 2) and the wind speed, mean temperature, and minimum temperature. Moreover, there is a significant inverse relationship between the maximum temperature and the second PC. Only precipitation has a significant positive connection with the third PC (Dim. 3) refer to table X in the annexes.

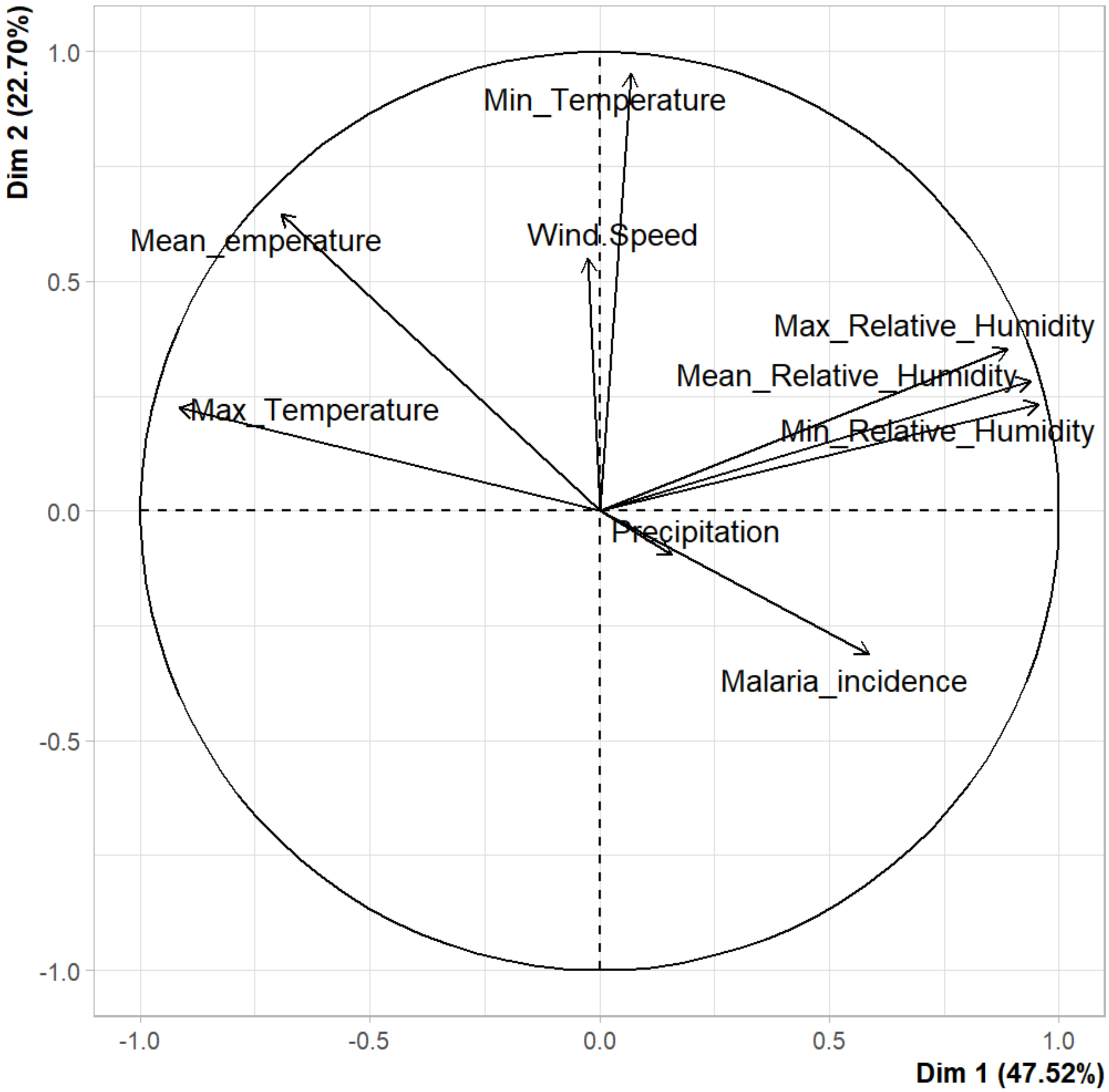


Figure 20: Principal component analysis of the meteorological variables influencing malaria incidence

Furthermore, the figure shows a positive correlation between the first principal component (PC) and the incidence of malaria. Conversely, malaria incidence exhibits a negative association with the second and third principal components.

This pattern of correlations suggests that relative humidity and maximum temperature are the climatic parameters that exert a significant influence on the transmission dynamics of malaria in the studied areas.

4.1.2.6. Seasonal variation in malaria incidence

The seasonal trends in malaria incidence within the Borgou province depicted in Figure 21, warrant further examination. The analysis reveals that malaria incidence exhibits a distinct pattern of variability throughout the year.

During the months of May through October, the incidence of malaria is observed to be elevated. Conversely, the incidence of the disease declines markedly from November through April (Gbaguidi *et al.*, 2024a, p. 7).

This seasonal fluctuation in malaria prevalence aligns with the climatic conditions in the northern region of Benin. The high incidence period corresponds with the wet season, which spans from May to October, while the low incidence period coincides with the dry season, from November to April (Figure21).

Figure 21 : Seasonal variation of malaria incidence in Northern Benin

[redacted]

Infections with malaria are less common in the northern region of Benin during the dry season, but they are more prevalent during the rainy season.

Discussion

To gain a comprehensive understanding of malaria epidemiology, it is critical to closely examine the trends in climatic variables. In the northern region of Benin, the analysis of fluctuations in annual total precipitation reveals a correlation with a decreasing precipitation pattern. This finding is consistent with the results of (Ahokpossi, 2018), who reported a significant decrease (95% significance) in rainfall between 1940 and 1970. Similarly, no significant trend in annual rainfall total was observed in Ethiopia from 1965 to 2002 (Seleshi & Zanke, 2004, p.980). (Kouman *et al.*, 2022) demonstrated a decreasing trend in annual total precipitation (112.37 mm) and daily precipitation intensity indices in the northeast region of Côte d'Ivoire from 1981 to 2020. Conversely, Akinsanola found both decreasing and increasing trends in mean annual precipitation in Nigeria from 1971 to 2000 (Akinsanola *et al.*, 2014, p.4).

The analysis of temperature patterns in the northern region of Benin reveals a concerning trend of increasing maximum, minimum, and average temperatures. A study conducted by Kouman reached a similar conclusion in the northeast region of Côte d'Ivoire from 1981 to 2020 (Kouman *et al.,* 2022). Our results also align with Akinsanola, who found both decreasing and increasing trends in air temperature in Nigeria from 1971 to 2000(Akinsanola *et al.*,2014, p.3).

Climate conditions, such as temperature and rainfall, are the primary drivers of malaria transmission. The northern region of Benin exhibits a strong positive correlation between monthly precipitation levels and monthly malaria incidence.

An average monthly precipitation range of 40 to 215 millimeters is linked to the greatest prevalence of malaria. However, when precipitation exceeds 300 millimeters, the incidence of malaria tends to decrease. This relationship suggests that an optimal range of rainfall is conducive to the proliferation of mosquito vectors and the subsequent transmission of the malaria parasite.

Heavy rainfall events can have the opposite effect, as they may wash away mosquito larvae from their breeding sites. This disruption to the mosquito life cycle can lead to a decline in vector populations and, consequently, a reduction in malaria incidence. M'Bra agrees that the duration of the rainfall season is also crucial in malaria transmission in Northern Côte d'Ivoire (M'Bra *et al.*, 2018, p.11).

For malaria vectors to thrive and reproduce, an average temperature range of 24 to 33 degrees Celsius is quite favourable. It has been shown that this ideal temperature range is where malaria incidence is maximum. Conversely, temperatures exceeding 35 degrees Celsius are found to be unfavourable for mosquito development and breeding. Sissoko found similar results in a suburban area along the Niger River, where high temperatures limited malaria incidence (Sissoko *et al.*, 2017). Kasasa reported that temperatures close to 40°C reduce mosquito survival and density in northern Ghana (Kasasa *et al.*, 2013, p.4).

Our findings align with the results of the study of Donovan and Rouamba, who found a positive and significant association between malaria incidence and rainfall and temperature in Nanoro, Burkina Faso (Donovan *et al.*, Kasasa *et al.*, 2013, p.4; Rouamba *et al.*, 2014, p.1).

The positive association between the highest incidence of malaria and an average relative humidity range of 45% to 85% in the northern region of Benin suggests that the prevailing moisture levels within this humidity range provide favourable conditions for the development and breeding of mosquito vectors, which are the primary transmitters of the malaria parasite. Segun and Ateba support our findings, stating that a relative humidity between 60% and 86% is the most suitable threshold for the development of Anopheles mosquitoes (Ateba *et al.*, 2020, p.1). Research carried out by Donnees also emphasized the dominant role of relative humidity in malaria prevalence, with rainfall directly affecting relative humidity by creating water points and surface wastewater (Donnees *et al.*, 2010, p.6).

Even though there is no statistically significant correlation between wind speed and monthly malaria incidence, the analysis suggests that wind speed nonetheless plays a pivotal role in the transmission dynamics of malaria in the northern region of Benin. A wind speed range of 1.7 to 2.7 m.s^{-1} is identified as highly favourable for malaria transmission. Within this optimal range, mosquitoes are capable of covering distances exceeding 10 kilometres, enabling them to infect neighbouring areas and populations. However, when wind speeds exceed 2.7 metres per second, mosquito activity and mobility become notably diminished. Intense wind conditions can even render mosquitoes inactive by causing physical damage to their wings, disrupting their ability to fly and transmit the malaria parasite effectively. In 2020, Ateba similarly found that a mean wind speed below 1.8 m/s is associated with a high incidence of malaria malaria (Ateba *et al.*, 2020, p.1). However, Thomas and Ouedraogo's findings confirmed that there is no significant relationship between malaria incidence and wind speed (Thomas *et al.,* 2021, p.1; Ouedraogo *et al.,* 2018, p.5).

The wet season in the northern region of Benin is when the highest malaria incidence is recorded. This finding is supported by the results of Djègbè, who demonstrated that the rainy season is the optimal time for mosquito proliferation in the same study area (Djègbè *et al.,* 2020, p.2). Salako's study confirmed higher biting rates of An. Gambiae in the rainy season compared to the dry season in the province of Alibori (Salako *et al.,* 2018, p.8). Warmer temperatures have the effect of decreasing mosquito activity and population dynamics, which explains why the incidence of malaria during the dry season is usually lower. This finding is consistent with the research conducted by (Sominahouin *et al.,* 2018, p.9), which also found that an increase in temperature leads to a decrease in the number of malaria cases. In contrast, the rainy season is characterised by the availability of various water bodies and breeding sites, which facilitate the proliferation of mosquito populations. This increased mosquito abundance during the wet season is a contributing factor to the higher malaria incidence observed in the northern Benin region.The study conducted by Subtil in South Benin confirmed that rainfall ensures the persistence of peri-domestic larval sites in villages with continuous vector biting rates (Subtil *et al.,* 2014, p.237). The rainy season in northern Benin poses an extremely high risk of malaria infection, and it is crucial to prioritize malaria control actions during this period according to (Govoetchan *et al.*, 2014, p.8).

The observed increase in malaria incidence within the study areas during the months of November and December may be linked to the high-level precipitation patterns that occur throughout the rainy season. The analysis indicates that the prolonged period of intense rainfall, typically occurring from July to October, is the primary driver behind the surge in malaria cases observed in the later months of the year. Intense precipitation can destroy mosquito breeding, developmental, and resting sites, as demonstrated by Hunter in a study conducted in Malawi (Hunter.PR, 2003, p.37). Our findings align with the results of the work of Ayanlade, who reported that heavy rainfall or storms can destroy existing breeding sites, interrupt the development of mosquito eggs or larvae, or flush them out of pools (Ayanlade *et al*., 2013, p.16).

Controlling malaria infection in the research region is expected to become a more difficult task in the upcoming years due to the reported alterations in the climate. The analysis indicates that since

2021, there has been a notable increase in malaria incidence during November and December in Northern Benin (Gbaguidi *et al.*, 2024a, p. 7).

IV.2. Towards an intelligent malaria outbreak warning system for northern Benin, West Africa

4.2.1. Modelling the effects of climate change on the transmission of malaria in northern Benin

4.2.1.1. Exploratory Factor analysis (EFA)

The analysis has identified two latent factors that contribute to the prevalence of malaria in the study area: Average mean relative humidity, average maximum relative humidity, and average maximal temperature are all correlated with factor 1. The average minimum temperature is correlated with factor 2. The chi-square statistic (φ2) is 18.56 with 8 degrees of freedom (df) and a p-value of 0.017 at a 5% level of significance. Sixty-seven percent of the variation in the data is explained by these two factors (Gbaguidi *et al.*, 2024b, p.4). This result provides a sufficient explanation for the malaria frequency that has been reported in the research region. In order to ascertain the proper quantity of components to be recovered, the researchers have examined the Guttman-Kaiser and Cattell scree plots (Guttman, 1954; Kaiser, 1960). The precise number of factors in the population correlation matrix (Table IX) is equal to the number of eigenvalues larger than one.

The eigenvalues that have been computed are 2.80, 1.12, 0.29, 0.19, -0.04, -0.09, and -0.20. According to Cattell's scree plot test (Cattell, 1966, p.245), the number of particularly large eigenvalues is correlated with the number of factors used in the study. In this case, the analysis indicates that there are two factors that significantly affect the incidence of malaria (Gbaguidi *et al.*, 2024b, p.4).

Table VIII: Matrix of correlations between malaria incidence and climate factors.

Item	**Mean**	**Std.Dev**	**Average Precipitation**	**Average minimal temperature**	**Average maximal temperature**	**Average mean relative humidity**	**Average maximal relative humidity**	**Average Wind Speed**	**Average Malaria incidence**
Average Precipitation	113.96	71.58	1.00						
Average minimal temperature	21.76	1.40	-0.01	1.00					
Average maximal temperature	33.53	2.25	-0.14	0.16	1				
Average mean relative humidity	65.43	13.03	0.12	0.32	-0.76	1			
Average maximal relative humidity	83.38	11.72	0.06	0.39	-0.67	0.96	1		
Average Wind Speed	2.03	0.37	-0.18	0.36	-0.01	0.04	0.05	1	
Average malaria incidence	28.22	6.10	-0.04	-0.18	-0.48	0.42	0.43	-0.2	1

The proportion of variation explained by the principle components is shown in the scree plot (Figure 22) that results from the analysis of the matrix table (Table IX). The eigenvalues of the first two components in the scree plot are shown by the parallel lines, which fall below the parallel indication. This scree plot corroborates the presence of precisely two latent factors

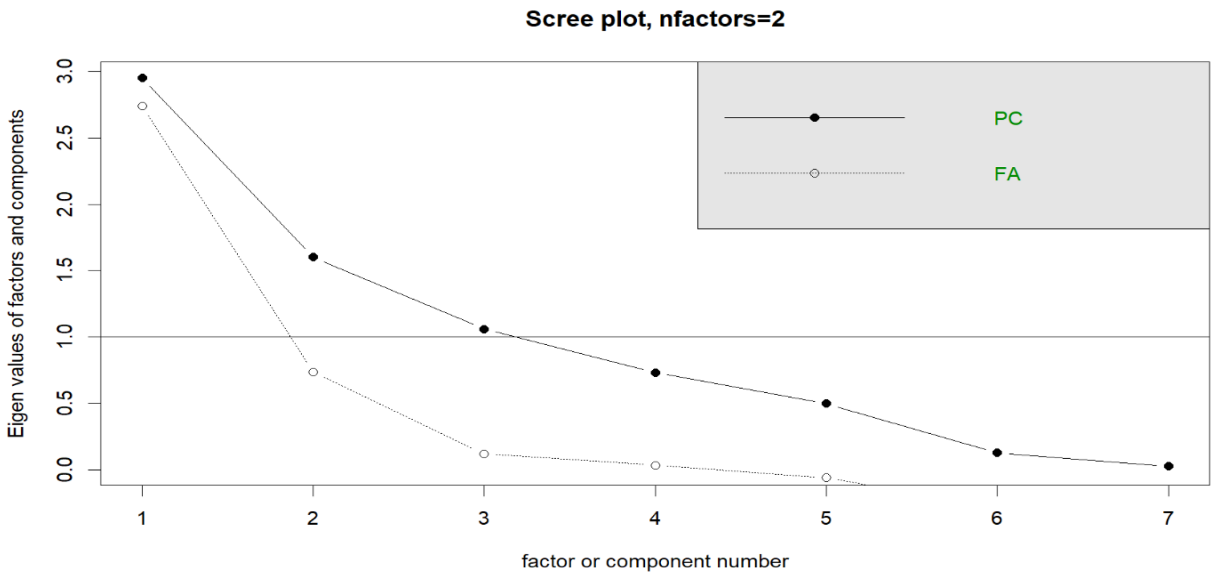


Figure 22: Using data from Table IX, the Cattell scree plot shows the component eigenvalues, which may be used to determine how many climatic factors need to be taken into account.

***4**.2.1.2. Pearson's cross-correlation analysis of ecological variables and malaria prevalence*

Table X displays the Pearson's cross-correlation between ecological factors and malaria prevalence at various lag effects (0–3 months). Lag0, Lag2, and Lag3 (or 0 months, 1 month, and 2 months) illustrate how climatic conditions have a delayed influence on the prevalence of malaria in Northern Benin (Gbaguidi *et al*., 2024b, p.4). Average precipitation, average mean relative humidity, and average maximum relative humidity all have a positive correlation with the incidence of malaria at lag effects of 0 months and 1 month, with respective values of (0.05, 0.423, 0.431) and (0.015, 0.554, 0.576) (Gbaguidi *et al*., 2024b, p.4).

Furthermore, average mean relative humidity, average maximum relative humidity, and wind speed all had positive relationships with malaria incidence at two-month lag effects (0.526, 0.524, and 0.038, respectively).

Table IX: Cross-correlation between malaria incidence and climate factors

Variables	**Lag0**	**Lag1**	**Lag2**
Average Precipitation	0.05	0.015	-0.073
Average minimal temperature	-0.18	-0.007	0.156
Average maximal temperature	-0.483	-0.456	-0.073
Average mean relative humidity	0.423	0.554	0.526
Average maximal relative humidity	0.431	0.576	0.554
Average Wind Speed	-0.195	-0.119	0.038

The findings imply that suitable climatic conditions would exist at delays of one and two months for mosquito reproduction and the successful completion of their incubation periods (EIPs). These elements are necessary for mosquitoes to successfully spread malaria vectors to humans. Notably, there is a two-month lag effect between wind speed and malaria prevalence in this research location, which suggests that malaria transmission would be very high. This suggests that areas close by that are asymptomatic right now might be vulnerable to catching the illness.

The impacts of precipitation and relative humidity, which lag by one month, seem to be more than adequate for the establishment of mosquito breeding sites and the development of human infection potential. Moreover, it has been discovered that average wind speed, average maximum and mean relative humidity, and average min temperatures are all very good for mosquito growth and disease transmission on a broad scale. All of these results point to the importance of climatic variables with lag times between one and two months in establishing favourable environments for mosquito proliferation, incubation, and disease transmission.

4.2.1.3. Confirmatory factor analysis (CFA)

To determine the right number of components to be derived from the meteorological data, Confirmatory Factor Analysis (CFA) was used. Seven observable indicators were included in the analysis. In the end, two latent components supported the final model that included four observable indicators. Fit indices were much better than the original models once the first model was corrected, as Figure 23 illustrates. In addition, the standardised residual distribution was less than it was in the first models. The suggested cut-off values were used in order to validate the CFA model. For the Tucker-Lewis Index (TLI) and Comparative Fit Index (CFI), the recommended threshold is 0.90. For the Root Mean Square Error of Approximation (RMSEA), the recommended range is 0.06 or below.

The results indicated that the CFI exceeded 0.90, and the RMSEA was within the 0.06 threshold, denoting a well-fitting model (Browne, 1993, p.142).

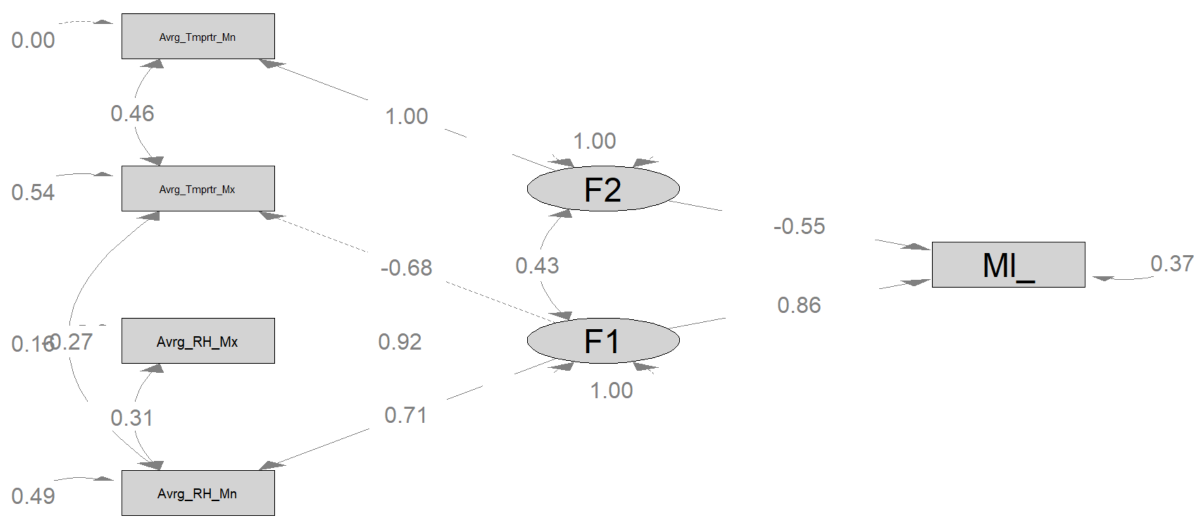


Figure 23: Depicts the initial model, which illustrates the relationship between climate factors and malaria incidence. The black/grey rectangles represent the measurement variables, while the black/grey ellipses denote the latent variables.

It was discovered that the robust fitting indices, such as the Root Mean Square Error of Approximation (RMSEA), the Comparative Fit Index (CFI), and the Tucker-Lewis Index (TLI), were all within an acceptable range. This suggests that, with TLI=1, CFI=1, Standardised Root Mean Square Residual (SRMR)=0.008, and RMSEA=0, the model fits the data extremely well (Gbaguidi *et al.*, 2024b, p.4). Furthermore, each latent variable was found to be statistically significant and had a factor loading exceeding 50%.

4.2.1. 4. Structural equation model (SEM)

The data set did not meet the requirements of the Henze-Zirkler test (p-value = 0), which indicated that the data was not normal. Correlation matrix table XIII (see the annexes) shows the means, standard deviations, and bivariate correlations for every variable in the analysis.

The correlation matrix table was examined to see whether multicollinearity existed between the variables. Specifically, numerous predictors, particularly among the meteorological factors, were found to be highly correlated, as evidenced by the magnitude of the relationships (Gbaguidi *et al.*, 2024b, p.4).

Given the SEM analytical technique's superior handling of intercorrelated independent variables through the development of latent constructs and direct and indirect pathways, which avoid the propensity to distort coefficient estimates, this is one of the requirements for using it (Bollen, 1989, p.146).

Figure 24 provides a visual depiction of the model that is being studied. First, it is important to confirm that the suggested cut-off values for the fit indices are within the allowed range before looking at the connections in the model.

When the model in Figure 24 was examined more closely, the following fit indices were found: Tucker-Lewis Index (TLI = 1), Comparative Fit Index (CFI = 1), Standardised Root Mean Square Residual (SRMR = 0.008), chi-square (348.113, df = 10, not significant), and Root Mean Square Error of Approximation (RMSEA = 0.000) (Gbaguidi *et al.*, 2024b, p.4).

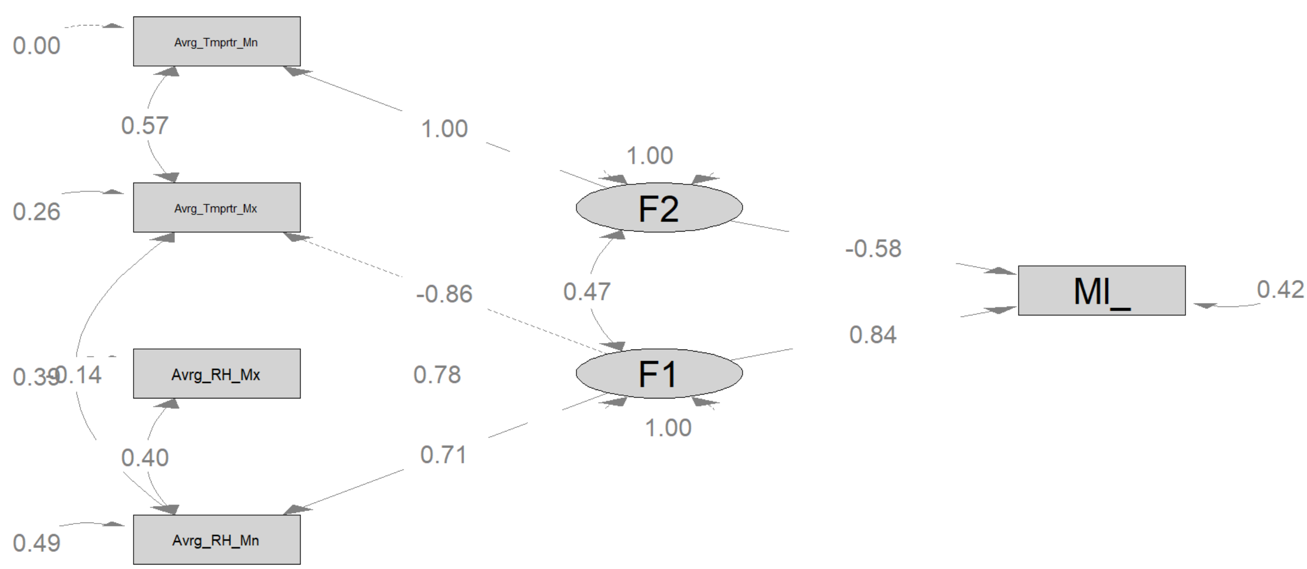


Figure 24: The link between malaria incidence and climate conditions depicted in the final model route diagram; the latent variable is represented by the grey ellipse, and measurement variables are shown by the black grey rectangle

These figures demonstrate how well the model fits the data and suggest ways to determine how ecological factors affect the prevalence of malaria.

4.2.1.5. Impacts of climatic variables on malaria incidence

The analysis of the model depicted in Figure 24 reveals the following direct effects: factor 1 had a direct effect of 0.84, while factor 2 had a direct effect of -0.58. The direct effects of the individual climatic variables on the incidence of malaria were as follows: average maximum temperature (-0.86), average maximum relative humidity (0.78), average mean relative humidity (0.71), and average minimum temperature (1.00). Additionally, the model shows the indirect impacts of factor 2 (0.39), average maximum temperature (1.00), and average mean relative humidity (1.59). The total effects of the variables on malaria incidence were as follows: average maximum relative humidity (0.78), average mean relative humidity (2.30), average maximum temperature (0.14), average minimum temperature (1.00), factor 1 (0.84), and factor 2 (-0.19). Factor 1 had the largest direct influence and the highest overall effect on the incidence of malaria in the study region out of the two variables found using exploratory factor analysis (Gbaguidi *et al.*, 2024b, p.4). This implies that the most important hidden meteorological element influencing malaria prevalence is factor 1. Thus, it is possible to calculate and forecast the prevalence of malaria in the northern Benin region by using the average value of component 1.

4.2.1.6. Intelligent malaria outbreak warning model

The algorithm that would best predict the prevalence of malaria in the research regions must be chosen in the next step. The average maximum relative humidity, average mean relative humidity, and average maximum temperature indicated by factor 1 were shown to be the most significant hidden meteorological factors influencing the prevalence of malaria in the section above.

Three distinct machine learning algorithms including support vector machine (SVM), linear regression (LiR), and negative binomial regression (BiR) models were used to create the malaria outbreak warning model (Gbaguidi *et al.*, 2024b, p.4). Following the training and testing of the different algorithms (as seen in Figure 25), the effectiveness of each model was evaluated in order to determine which algorithm performed the best in terms of accuracy when forecasting the occurrence of malaria in the northern area of Benin (Table XI).

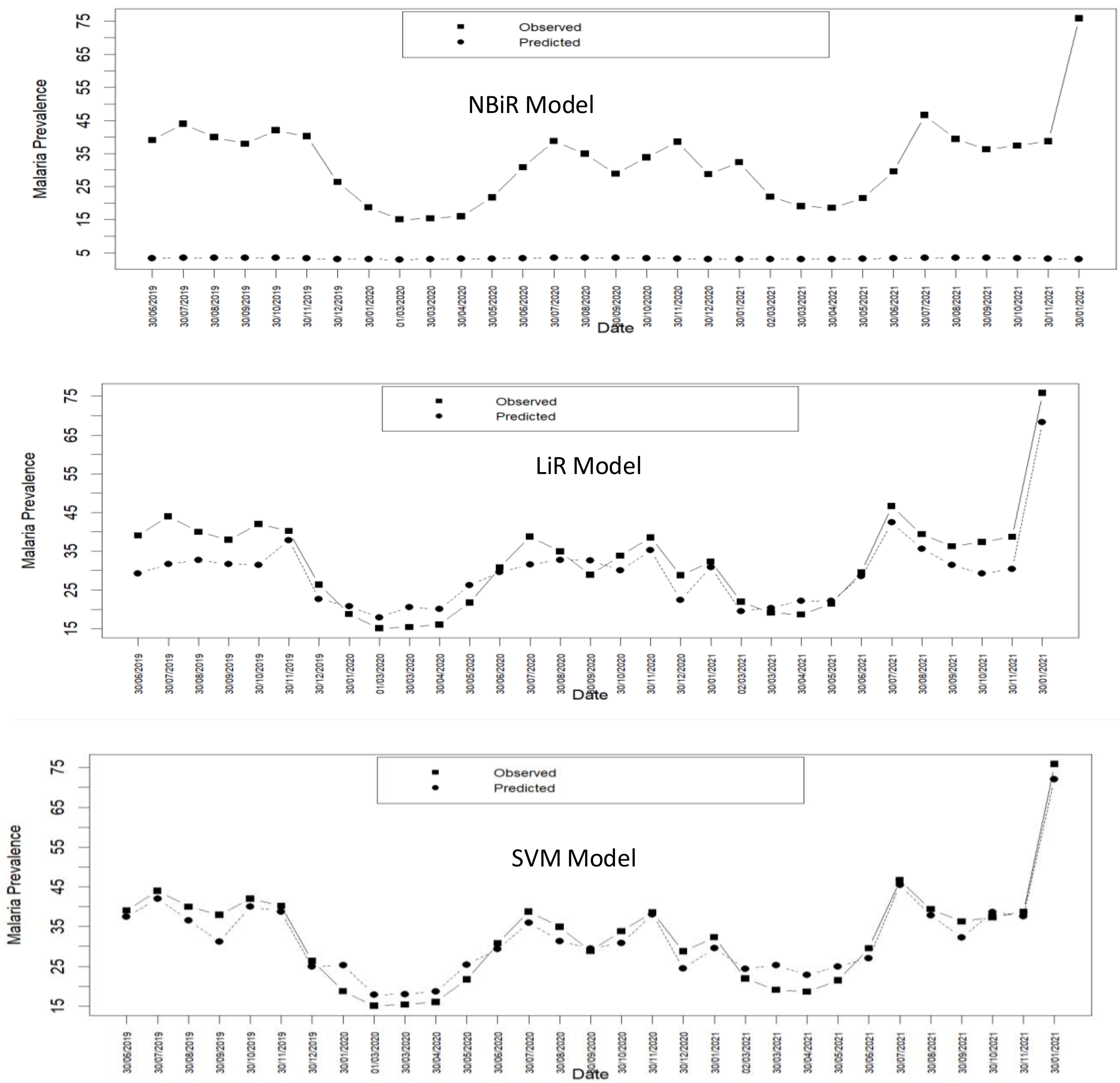


Figure 25: Malaria incidence test with SVM, NBiR, and LiR

Table XI displays the performance metrics for the three machine learning models:Linear Regression (LiRM), Negative Binomial Regression (BiRM), and Support Vector Machine (SVM) including Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). We can determine from the analysis of these error metrics that the SVM model outperforms the other two models (LiRM and BiRM) in providing the most optimal solution for predicting the occurrence of malaria.

Table X: Model performance assessment

Item	MAE	MSE	RMSE	Predicted R2
LiR	2.50	11.07	3.33	66%
SVM	1.66	5.89	2.43	82%
NBiR	22.11	504.84	47.22	66%

In summary, the best model for forecasting the prevalence of malaria in Northern Benin is the support vector machine (SVM) (Gbaguidi *et al.*, 2024b, p.4).

4.2.2. Malaria outbreak early warning

4.2.2.1. Prediction of malaria incidence under scenarios RCP4.5 and RCP8.5

The RCA4 regional climate model used in this study was developed at the Swedish Meteorological and Hydrological Institute and has provided nearly 120 simulations in the CORDEX project (Coordinated Regional Climate Downscaling Experiment). The model considers all of the geographical and temporal dimensions at which ecosystems affect climate through physical, chemical, and biological processes. The temperature, relative humidity, and rainfall projections were derived from the Rossby Centre Regional Atmospheric Climate Model (RCA4) simulations conducted as part of the Coordinated Regional Downscaling Experiment (CORDEX). The Earth System Grid Federation server, which is powered by the RCA4 model, provided the CORDEXAfrica data used in this study.

We used the downloaded CORDEX data under two typical concentration pathway (RCP) scenarios, RCP4.5 and RCP8.5, in the northern area of Benin to estimate the incidence of malaria using the Intelligent Malaria Outbreak Model (the SVM model) that they built. The data were downscaled for the periods 2021-2030, 2031-2041, and 2041-2050 using the regional climate models RCA4/HadGEM, RCA4/CSIRO, and RCA4/MIROC. Under the RCP4.5 scenario, the regional climate models RCA4/HadGEM2, RCA4/CSIRO, and RCA4/MIROC are associated with an increase in malaria incidence over the 2021-2030, 2031-2040, and 2041-2050 periods. However, the RCA4/HadGEM2 model is linked to a decrease in malaria incidence during the 2041-2050 period under the same scenario (Gbaguidi *et al.,* 2024b, p.4). Conversely, under the RCP8.5 scenario, the incidence of malaria is projected to decrease over the 2021-2030 period when driven by the RCA4/CSIRO and RCA4/MIROC models. Conversely, the RCA4/HadGEM2 model is associated with an increase in malaria incidence over the same period under the RCP8.5 scenario (Figure 26).

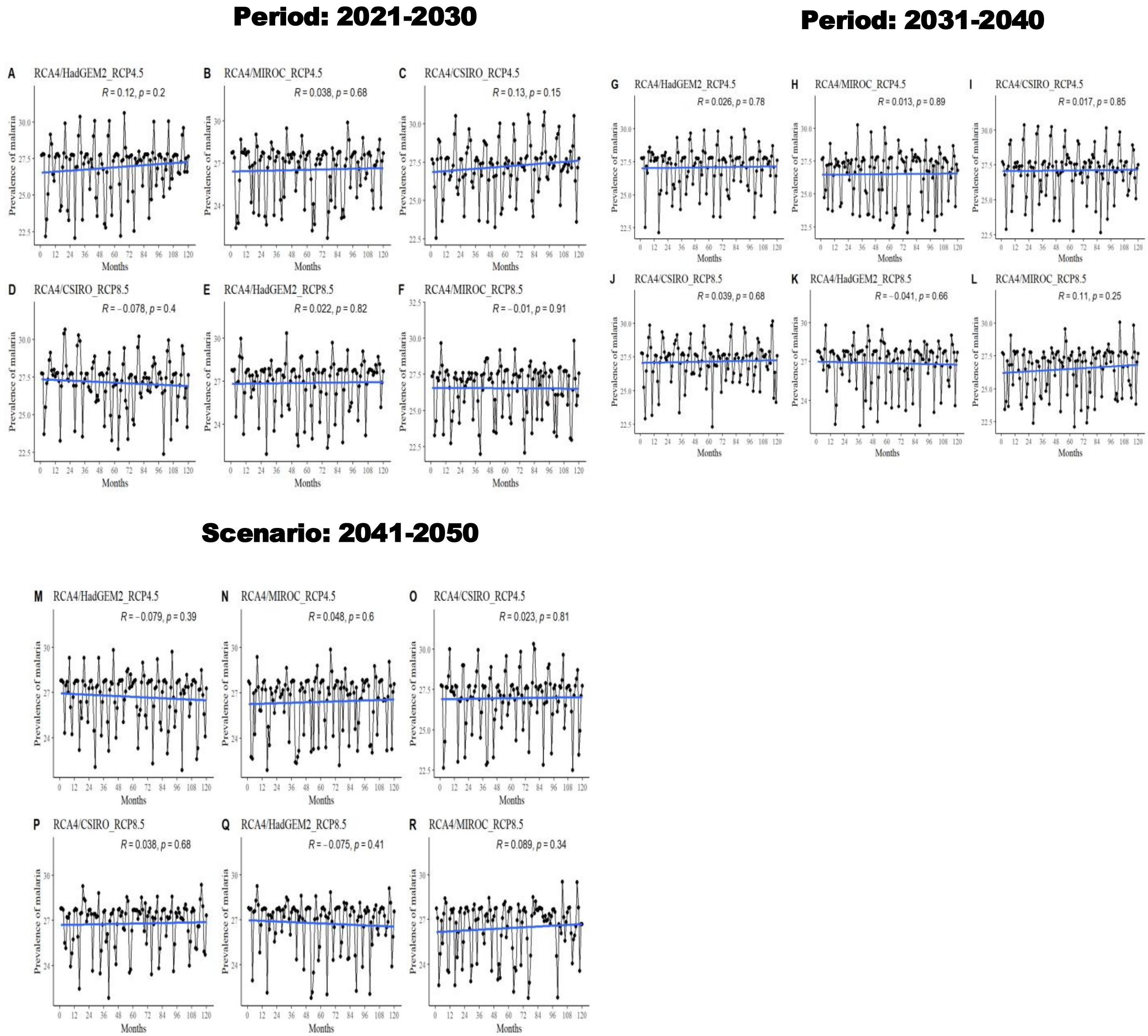


Figure 26: Malaria incidence prediction for 2021–2030, 2031–2040, and 2041–2050 under RCP4.5 and RCP8.5 by RCA4/HadGEM2, RCA4/CSIRO, and RCA4/MIROC

Overall, the projection suggests that, with the exception of the 2021–2030 timeframe, the incidence of malaria would rise under both the RCP4.5 and RCP8.5 scenarios during the 2021–2050 period. The RCP8.5 scenario predicts that the expected consequences of climate change will cause the incidence of malaria to decline throughout this initial era.

4.2.2.2. An intelligent malaria outbreak warning system in the northern region of Benin

Our goal is to decrease the spread of malaria in Benin by working together with stakeholders and malaria programs. To that end, we have created a web application that is particularly meant to handle malaria outbreak notifications. The monthly and hourly incidence of malaria in Benin is predicted by this application using a support vector machine (SVM) model. The application may be accessed at https://malaria-outbreak-benin.streamlit.app/.

Both manual and automatic data entry are supported by the app. This application estimates the probability of a malaria epidemic by choosing a particular city or area and using data from the preceding month up to the present hour. The app shows the current state of the outbreak forecasts along with their accompanying predictions. Users also have the ability to manually enter a set of meteorological measurements, in which case a prediction and the accompanying status will be produced. Figure 27 shows that it is compatible with both English and French.

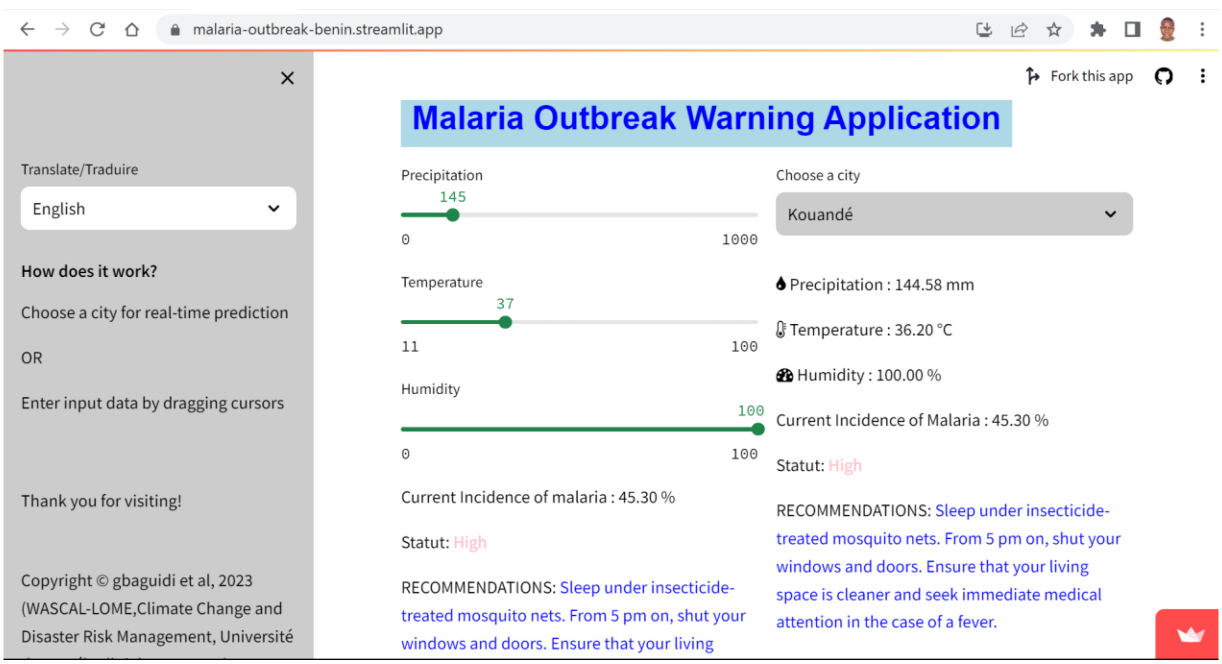


Figure 27: Early warning application web for malaria outbreak in Benin

The app is readily available to users at no cost due to its internet accessibility. Both local people and policymakers in Benin find this application to be a useful resource. It is a useful tool for remaining up to date on the likelihood of malaria in any district in Benin. The program enhances users' ability to make educated decisions and take proactive steps to reduce the effect of malaria by offering precise forecasts and epidemic alerts. Its accessibility and ease of use add to its value as a tool for improving Benin's efforts to prevent and control malaria.

Discussion

One useful method for preventing the spread of malaria is the malaria early warning model. The average mean relative humidity, average maximum relative humidity, and average maximum temperature are the climatic elements that have the greatest influence on malaria infection in the northern area of Benin. The incidence of malaria is positively impacted by these factors. This outcome is in line with the research of (Modu *et al.*, 2017, p.6), which found a positive correlation between the incidence of malaria and the lowest temperature and relative humidity.

With the exception of the 2021-2030 period, the predictions show that the incidence of malaria is expected to increase under both the RCP4.5 and RCP8.5 scenarios during the 2021-2050 period. Under the RCP8.5 scenario, the impacts of climate change are expected to cause the incidence of malaria to decline throughout this early era. Under the RCP4.5 scenario, a rise in malaria incidence is anticipated in the northern area of Benin throughout the 2021-2030, 2031-2040, and 2041-2050 years. It is clear that in the research locations, the risk of contracting malaria is rising due to climate change. Anopheles density is really impacted by climate change, which also undermines existing and future vector control methods, according to research done in Northern Benin (Spray *et al.*, 2018, p.3).

Climate changes or different weather conditions may impact infectious diseases, specifically, those transmitted by insect vectors and contaminated water (Lowe *et al.*, 2013, p.1; Sominahouin *et al.*, 2018, p.9, Cella *et al.*, 2019, p.4). (Afrane et al, 2012, p.12) confirmed that temperature increases promote the rapid digestion of blood supply, which in turn promotes a significant increase in fecundity, with the development of better reproductive fitness and a greater ability to produce more offspring.

A study conducted by Salako in the Alibori province of northern Benin confirmed that the biting rates of Anopheles gambiae are higher in the rainy season than in the dry season (Salako et al., 2018, p.8). (Subtil *et al.*, 2014, p.237) study in South Benin certified that rainfall ensures the persistence of peri-domestic larval sites in villages with continuous vector biting rates. The risk of malaria infection is markedly elevated during the rainy season in the northern region of Benin. These findings have corroborated the effect of climate change on the transmission of malaria in the northern part of the country.

The study carried out by (Diouf *et al.*, 2021, p.1) in West Africa found that the prevalence of malaria is expected to increase in the southern part of the region in the future. This result was consistent with our study, which revealed an increase in the prevalence of malaria under RCP4.5 and RCP8.5.

According to research by (Parham *et al*, 2010, p.620), who created a basic model of climate-related malaria transmission that sheds light on how sensitively the disease spreads to variations in temperature and precipitation, using climatic factors to predict the risk of infection is also consistent with this approach. It is crucial to incorporate future climate forecasts into epidemiological models and take climate factors into account when designing monitoring systems in order to enhance the accuracy of predicting malaria prevalence and outbreaks in the setting of climate change (Olson JAP and SH, 2006, p.5635; Djohy & Gwimbi, 2015, p.17).

The increase in malaria incidence over the 2021-2050 period is supported by the projection of the IPCC that predicted that malaria may threaten some previously unexposed regions of South America and Sub-Saharan Africa (SSA) in 2050 under the current climate change associated with the increase in CO_2 concentrations and increase in atmospheric temperature(IPCC, 2014, p.69).

The effectiveness of the continuing intervention measures aimed at controlling malaria in the region depends critically on the continued monitoring and assessment of the existing and future state of malaria transmission in northern Benin.

IV.3. Using vegetation health indices based on Advanced Very High-Resolution Radiometers (AVHRR) to model and predict malaria in northern Benin, West Africa

4.3.1. Dynamics of malaria

Figure 28 depicts the yearly time series of the incidence of malaria in northern Benin from 2009 to 2021. We analyse the relationship between the incidence of malaria cases and time, which is denoted by the variable 'Year'. The two variables have a statistically significant positive connection, according to the regression model (Ysp = 24.37 + 6.05 * Year, P-value < 0.001) (Gbaguidi *et al.*, 2024a, p. 7). This means that, based on regression analysis and a mean of 66.74 malaria cases, the annual percentage rise in malaria cases is anticipated to be around 9.07%. There was a substantial correlation (p-value=1.59e-08) between the year and the number of malaria cases.

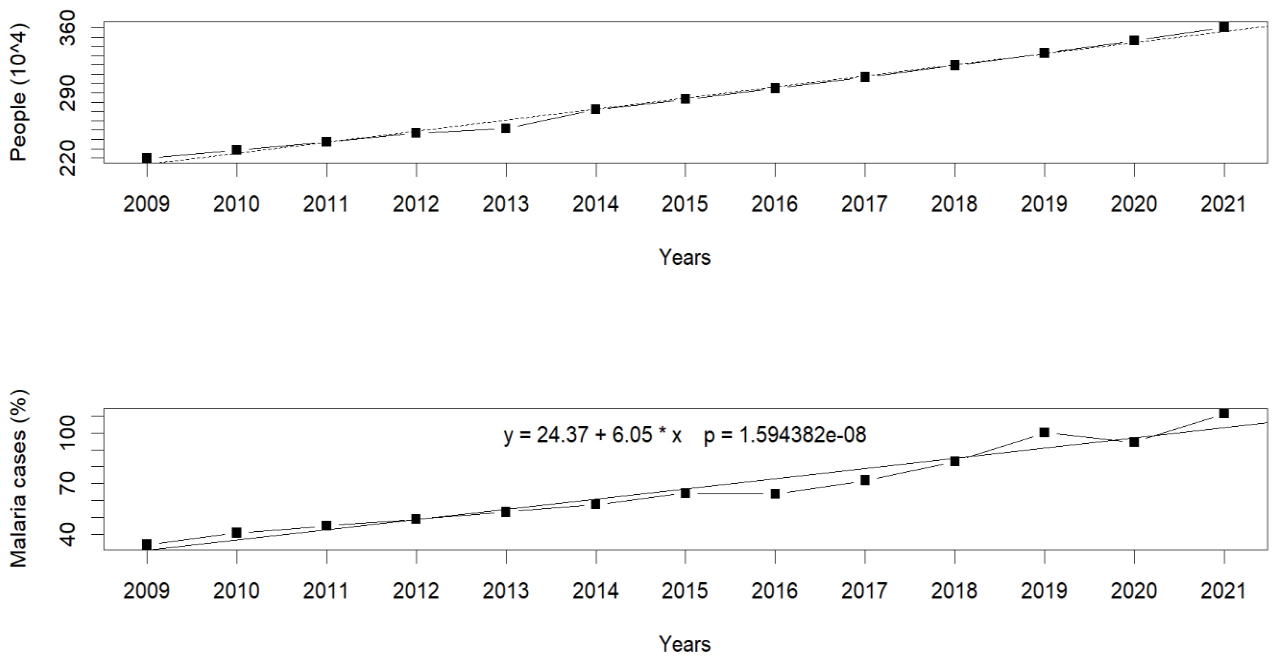


Figure 28: Time series for the population and the malaria cases.

The results indicate a noteworthy yearly increase in the prevalence of malaria, underscoring the urgent necessity of putting into practice efficient control and prevention strategies to deal with the growing public health emergency that malaria poses in the area.

4.3.2. Dynamics of vegetation health in the lowest and highest malaria years

The year with the fewest (2009) and most (2021) malaria cases was chosen for inquiry to get a basic understanding of whether climatic circumstances indicated by vegetation health (VH) indices provide any significant indications of the potential of malaria development. Figure 29 exhibits the dynamics of the Temperature Condition Index (TCI), Vegetation Condition Index (VCI), and overall Vegetation Health Index (VHI) for the two severe malaria case years, 2009 and 2021, across the 2009-2021 timeframe. In the selected malaria-prone sites, the patterns of the VH indices across these years were compared (Gbaguidi *et al*., 2024a, p. 7).These factors, as represented by VH indices, offer some helpful indicators regarding the likelihood that malaria may develop. For both years of malaria cases, there are more instances during the rainy season (May to November) and fewer cases during the dry season (December to April). As illustrated in Figure 29 (A), the year with the fewest malaria cases (2009) had a high TCI (warmer weather) from weeks 1–22 and weeks 38–47, and a low TCI (cooler conditions) from weeks 23–37 and weeks 48–52. The year with the highest malaria cases (2021) had the opposite pattern. Warmer temperature slows down mosquito activity, whereas cooler weather increases it.

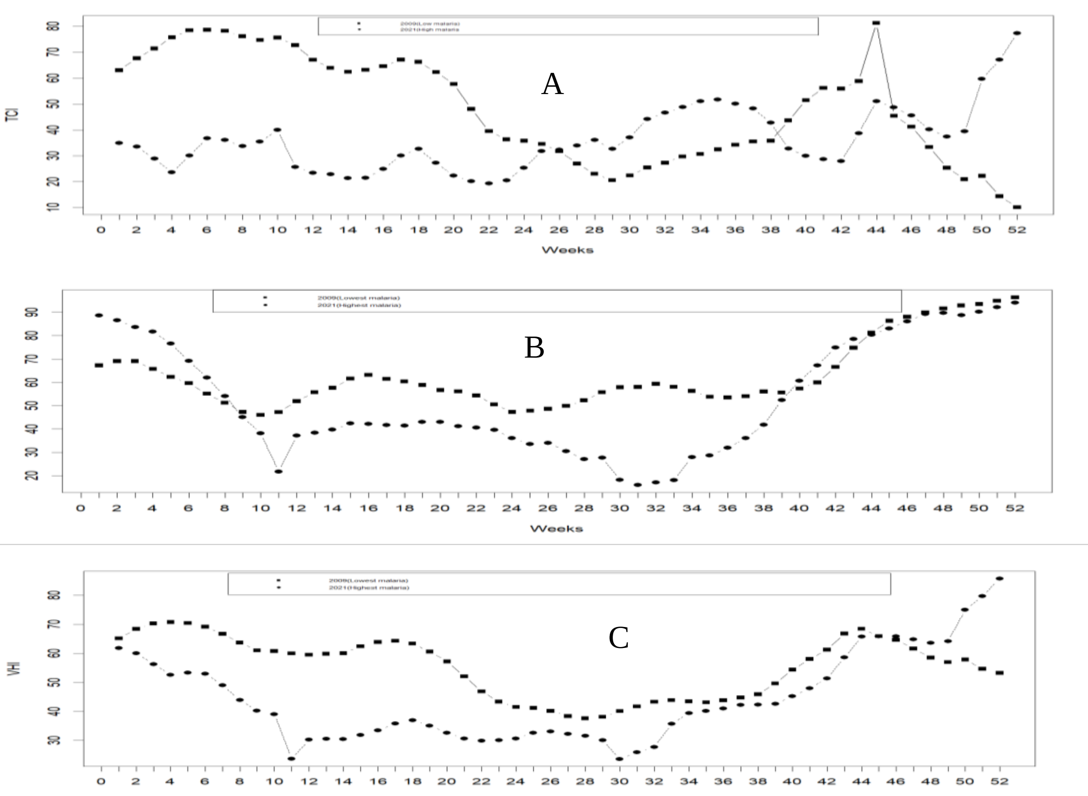


Figure 29: Dynamics of the Temperature Condition Index (TCI), Vegetation Health Index (VHI), and Vegetation Condition Index (VCI) for the two years between 2009 and 2021 exhibiting the fewest occurrences of malaria and the most instances (2021).

Throughout the rainy season (weeks 23–47), both the Vegetation Condition Index (VCI) and the Vegetation Health Index (VHI) show elevated mosquito activity and malaria transmission during the years with fewer cases and with more cases. The scenario is exactly the reverse during the dry season (weeks 48–22), as Figure 31(B and C) illustrates (Gbaguidi *et al*., 2024a, p. 7).

4.3.3. Correlation analysis

We are motivated to examine the relationship between malaria incidence and vegetation health indices (TCI, VCI and VHI) because of the dynamics of vegetative health during the lowest and greatest malaria incidences. The monthly malaria incidence and the weekly Vegetation Health Index data were linked since monthly data on malaria incidence is available. The dynamics of the Pearson association between the monthly malaria incidence (Yw) and the weekly vegetation health indices for the years 2009–2021 are shown in Figure 30. According to the results, there is a range of -0.64 to 0.86 association between malaria incidence and the Temperature Condition Index (TCI). At the start of the rainy and dry seasons, from May to the end of November (weeks 14–48) and January to mid-March (weeks 1–10), respectively, there is little association (below 0.55). The association between the TCI and the incidence of malaria rises from -0.62 to -0.59 in weeks 11-13, or from mid-March to April 30 (Gbaguidi *et al*., 2024a, p. 7). During this time, the incidence of malaria and TCI are inversely correlated. The correlation rises from 0.74 to 0.86 in December (weeks 49-52), marking the beginning of the dry season. This suggests a strong positive relationship between TCI and the incidence of malaria, beginning in week 49. A strong association was found between the start and finish of the dry season, indicating that hot weather lowers mosquito populations and, in turn, lowers the risk of malaria infection. A TCI higher than 42 is harmful to mosquito growth and activity (Gbaguidi *et al*., 2024a, p. 7).

Beginning in May (weeks 19–21), the link between wetness (Vegetation Condition Index, or VCI) and malaria incidence increased from 0.72 to 0.74, coinciding with the emergence of mosquito breeding places and their activity. The latter two weeks of December, or weeks 51–52, were linked to increased mosquito activity. Moisture encourages mosquito growth and the transmission of malaria. The May and December cycles exhibit a strong association, which aligns with the findings displayed in Figure 30. A VCI greater than 55 inhibits mosquito activity (Gbaguidi *et al*., 2024a, p. 7) .

The association between the Vegetation Health Index (VHI) and the incidence of malaria increases from weeks 19 to 52, which corresponds to May through December. High malaria incidence and mosquito activity are linked to this time of year. It is significant to observe that the connection is negative for weeks 29 through 32 in June. This may be the result of things like more vegetation cover, which would provide shade and cut down on mosquito breeding grounds, or better vegetation, which would boost biodiversity and include mosquito-eating natural predators (Gbaguidi *et al.*, 2024a, p. 7). The VHI shows a varied connection in the earliest weeks and a significant positive association in the latter weeks, following a pattern resembling that of the TCI and VCI.

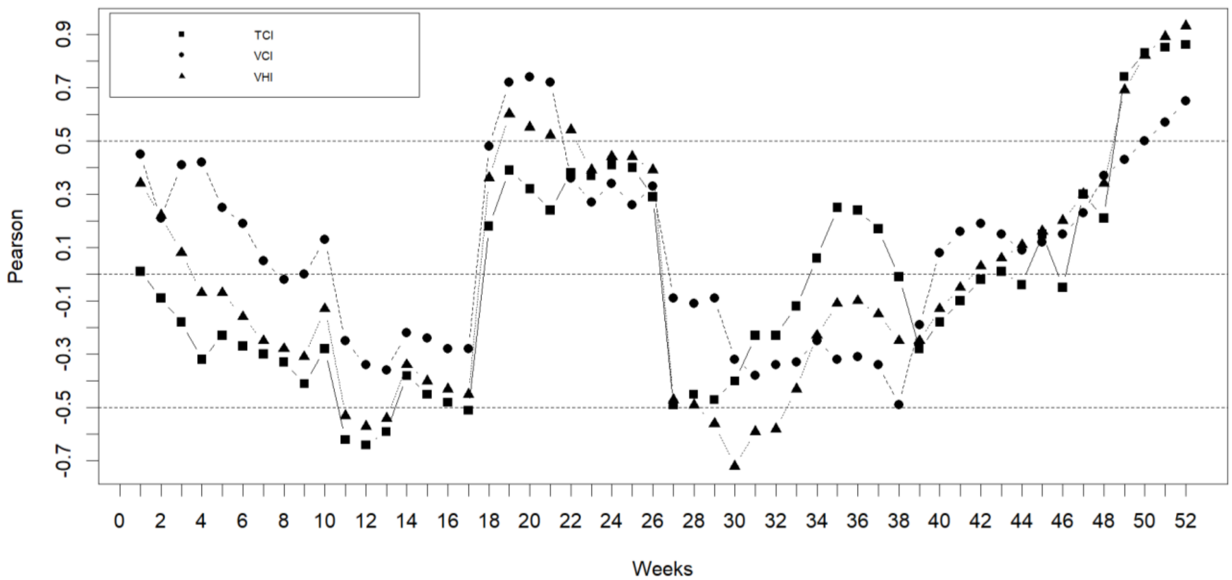


Figure 30: Pearson correlation coefficient with the monthly incidence of malaria index (Yw) and the weekly Temperature Condition Index (TCI), Vegetation Health Index (VHI) and Vegetation Condition Index (VCI).

The correlations observed suggest that more suitable weather conditions, as highlighted by maximal Temperature Condition Index (TCI), Vegetation Condition Index (VCI), and Vegetation Health Index (VHI) values, may contribute to increased malaria infection. This research emphasises the necessity of taking into account weather patterns and vegetation health when assessing and managing malaria outbreaks. It also suggests that monitoring vegetation health indicators might be useful as an early warning system for predicting and mitigating malaria spread in impacted regions.

4.3.4. Malaria outbreak early warning using Advanced Very High-Resolution Radiometer (AVHRR)-based vegetation health

To determine whether vegetation health (VH) and malaria incidence are strongly correlated during favourable weather conditions that encourage mosquito activity intensification and multiplication, models were built with the assumption that variables pertaining to the Temperature Condition Index (TCI), Vegetation Health Index (VHI) and Vegetation Condition Index (VCI) would only be included if their correlation coefficient with the monthly malaria incidence index (Yw) was greater than 0.55 (P-value <0.05). Four models were chosen using a particular set of independent variables based on these ideas: (A) mean VCI for weeks 19-21 (VCI19-21), (B) mean VHI for weeks 49-52 (VHI49-52), (C) the same variable in A and mean VHI for weeks 29-32 (VHI29-32), and (D) the same variable in (B) and TCI for weeks 11-13.

The support vector machine (SVM), principal component regression (PCR) and ordinary least squares (OLS) were used to regress the weather-dependent malaria incidence (Yw). A description of the numerous models that were built and the various metrics that were used to evaluate each model's performance and validation is shown in Tables XII, XIII, and XIV. According to Table XII, which illustrates the OLS regression models, Model A appears to have the best performance and the lowest error in prediction based on the provided criteria (Gbaguidi et al., 2024a, p. 7). The fact that the projected values have the lowest Root Mean Square Error (RMSE) of 2.43 suggests that they are relatively close to the observed values. Additionally, the model's high R-squared value of 0.75 indicates that there is good match between the actual and projected values. Moreover, the normality of the residuals was verified by the Shapiro-Wilk test (P-value = 0.77). The variance of errors in the linear regression model is consistent across all levels of the independent variables. This is a desirable attribute of a tailored linear regression model, according to the studentized Breusch-Pagan test, which yielded a P-value of 0.27.

Table XI: Ordinary Least Squared Regression (OLS)

Models	Shapiro–Wilk	RMSE	MSE	MAE	R-squared Predicted
(A)=4.85+ 0.28*VCI19-21	0.77	2.43	5.89	1.53	0.75
(B)=-8.23+0.44*VHI49-52	0.88	4.70	22.05	3.82	0.35
(C)=33.66+0.09VCI19-21-0.35*VHI29-32	0.17/0.02	7.47	55.82	5.70	0.29
(D)=6.67--0.05*TCI11-13+0.21*VHI49-52	3.17E-04	3.460	11.980	2.790	0.27

In contrast, Models B, C, and D display high prediction errors with RMSE values of 4.70, 7.47, and 3.46, respectively. The residuals are not distributed normally, as seen by Model D's lowest Shapiro-Wilk score (3.17E-05). Model C exhibits the largest average discrepancy between the anticipated and actual values, which is also reflected in its highest MSE and MAE values.

Model D appears to be the model with the lowest error for forecasting the prevalence of malaria among the SVM regression models shown in Table XIII. Its lowest RMSE (1.91) suggests that, in this instance, the anticipated and observed values are the closest (Gbaguidi et al., 2024a, p. 7). The model's strong ability to predict both actual and anticipated values is further demonstrated by its high R-squared score of 0.78. Models B and C had larger prediction errors, with RMSE values of 4.47 and 6.93, respectively. Despite having significant prediction errors (3.04), Model A has a good R-squared value of 0.60. As a result, Model D fits the data better than Model A and makes accurate predictions about the occurrence of malaria (Gbaguidi et al., 2024a, p. 7).

Table XII: Support Vector Machine Regression (SVM)

Models	RMSE	MSE	MAE	R-squared Predicted
(A)Yw= f(VCI19-21)	3.04	9.25	1.88	0.60
(B)Yw = f(VHI49-52)	4.47	20.00	3.33	0.41
(C)=Yw = f(VCI19-21,VHI29-32)	6.93	48.02	4.50	0.41
(D)Yw = f(VHI49-52,TCI11-13)	1.91	3.65	1.61	0.78

Model B appears to be the most accurate model in the dataset for forecasting the prevalence of malaria, according to the criteria given in Table XIV, which shows the PCR regression models. Included in this model are the variables VHI49-52 and TCI11-13, with an RMSE of 3.46 and an R-squared value of 0.27 (Gbaguidi *et al.*, 2024a, p. 7).

Table XIII: Principal Component Regression (PCR)

Models	RMSE	MSE	MAE	R-squared Predicted
(C) PCR(VCI19-21,VHI29-32)	6.23	38.79	4.29	0.53
(D) PCR (VHI49-52, TCI11-13)	3.46	11.98	2.79	0.27

In general, the models that provide the lowest level of error for predicting the monthly incidence of malaria are the Support Vector Machine (Model D) and Model A from Ordinary Least Squares regression. On the other hand, the malaria prediction will remain unchanged in Model D, which was constructed using Principal Component Regression, despite having a relatively low R-squared value.

We may assess how well Models A and D perform in forecasting the occurrence of malaria by examining Table XV and Figure 31 using various criteria. Model A has a bias of 0.83 because the mean value of the actual malaria incidence is 19.64 and the mean value of the projected malaria incidence is 18.81 (Gbaguidi et al., 2024a, p. 7). In Model D, the bias is 0.196 because the mean value of the projected malaria incidence is 14.65, whereas the mean value of the observed malaria incidence is 14.85. This shows that Model D's projected values are more in line with the actual values, suggesting that Model D would be a better predictor of the occurrence of malaria (Figure 31).

Table XIV: OLS and SVM regression models A and D's corresponding observed and independently simulated percentages

Models	Metrics	Observed	Simulated	Bias
A	Mean	19.64429	18.81024	0.834045
	Standard_Deviation	5.20000	3.55	2.461077
D	Mean	14.848	14.65172	0.196282
	Standard_Deviation	4.265327	3.613902	2.002904

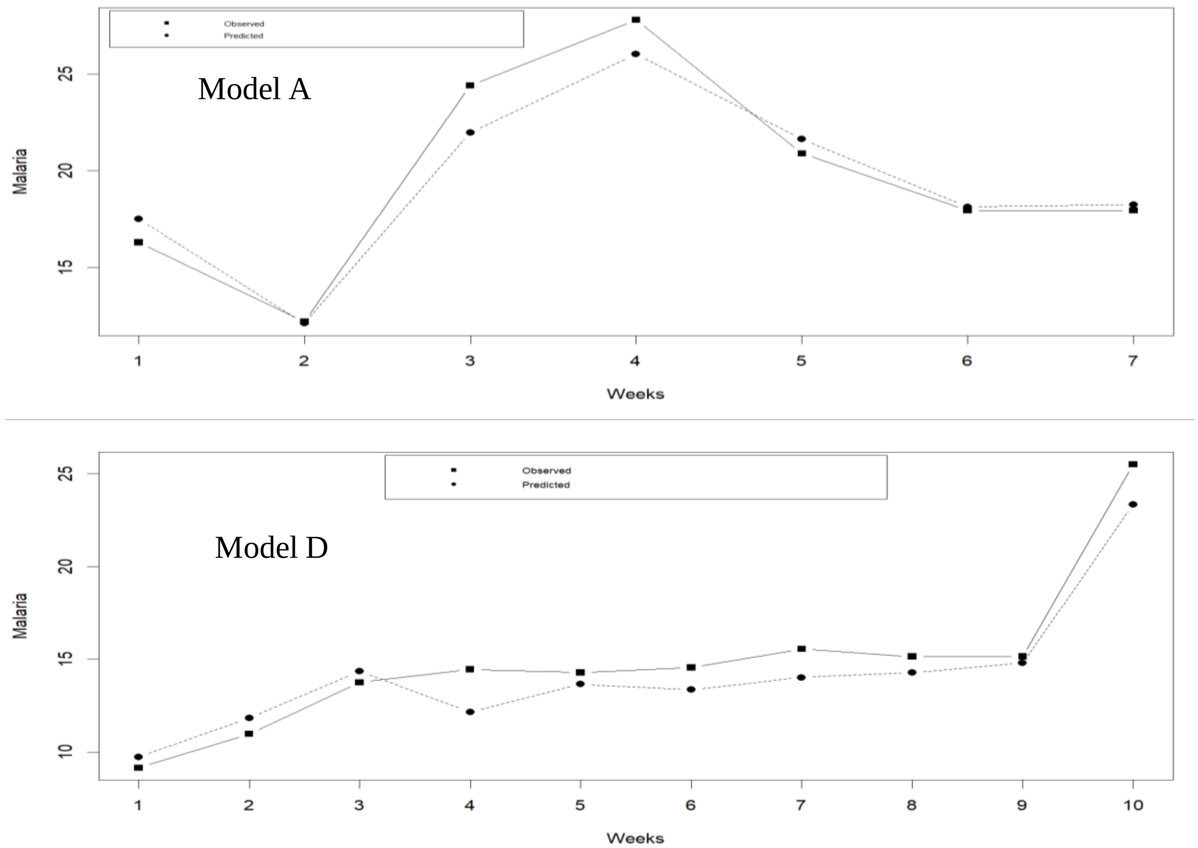
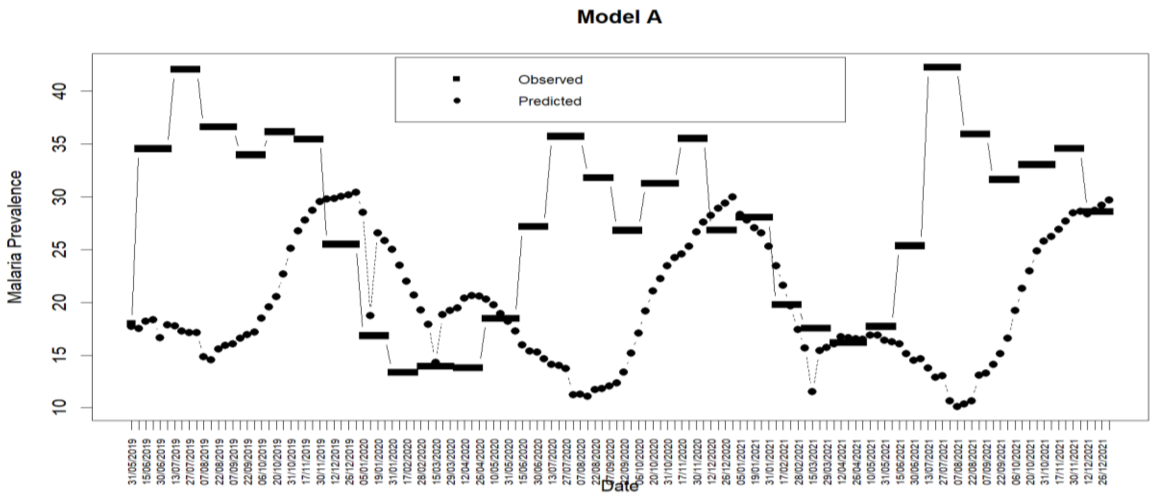


Figure 31: Simulated and observed percent of malaria incidence from model D and model A of the random sampled test data

Furthermore, one crucial statistic to take into account is the standard deviation of the observed and anticipated incidence of malaria. In Model A, there is a 2.46 discrepancy between the standard deviation of the expected malaria incidence of 3.55 and the observed malaria incidence of 5.20. In Model D, there is a 2.00 discrepancy between the standard deviation of the projected malaria incidence, which is 3.61, and the standard deviation of the observed malaria incidence, which is 4.265 (Figure 32). Given that Model D has a smaller bias and a smaller gap between the standard deviation of the observed and projected malaria incidence, it may be more accurate at forecasting values that are closer to the genuine values.



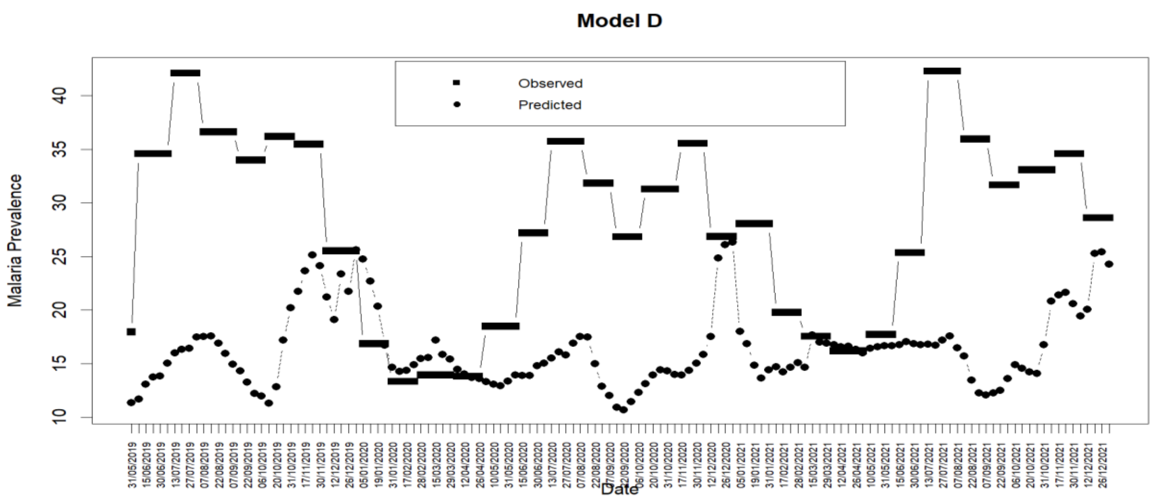


Figure 32: Time series of model D and model A's observed and simulated percent incidences of malaria for model validation using historical sampling test data

Discussion

Mosquitoes are the main carriers of the illness, and their ability to reproduce and survive is greatly influenced by the health of the vegetation. The amount of mosquito breeding sites is influenced by a variety of climatic conditions, such as temperature, humidity, and rainfall, which are frequently strongly associated with the condition of the vegetation.

The relationship between malaria incidence and vegetation health in the northern region of Benin is seasonally dependent. A noteworthy association was discovered between the temperature of the soil and the prevalence of malaria between the latter two weeks of December and the second half of March through April 15. The high intensity of the air temperature during January and March causes the soil to have a high temperature throughout these months. A high Temperature Condition Index (TCI) score lowers mosquito activity, which in turn lowers the spread of malaria. It is not beneficial for mosquito reproduction or multiplication when the mean TCI value exceeds 42 (Gbaguidi *et al.,* 2024a, p. 7). The main reason why there is less malaria during the dry season is because of this.

In contrast, mosquitoes prefer a TCI value in the range of 0 to 30. These TCI values might account for the TCI within this range during the wet season and the poor correlation seen during the rainy season, which runs from May to November. The prevalence of malaria and TCI in Tripura, India, were shown to be significantly correlated by (Nizamuddin *et al*. 2013, p.110). The authors concurred that fewer persons get infected when the TCI score is low. There is strong evidence that vegetation promotes mosquito activity and multiplication during the rainy season, as seen by the strong link found between malaria incidence and soil wetness (Vegetation Condition Index, or VCI). VCI, which is a measure of soil moisture, is what causes the high intensity of malaria that was seen in December. Malaria incidence and the plants Health Index (VHI), which gauges the growth and health of plants, are highly connected during the rainy season. This result is in line with (Kogan et.,2019, p.1) study's findings, which revealed that vegetation health affects malaria occurrence.

Model D predicts the occurrence of malaria better than Model A. Model D forecasts 78% of cases of malaria. Additionally, Model D predicts one month ahead of the start of the high malaria transmission season (during the rainy season and at the start of the dry season) by using both the TCI11-13, which corresponds to the period from March 15 to April 15, and the VHI49-52, which corresponds to the month of December (Figure 7). This model's projection is given for the second halves of March through April 15 and December (Figure 7). On the other hand, Model A predicts 75% of malaria cases, and its malaria prediction for May coincides with mosquito activity, or the start of the rainy season (Gbaguidi *et al*., 2024a, p. 7). This result is in line with the research done in the Indian region of Tripura by (Nizamuddin *et al.*, 2013, p.110). In the northern Benin research region, both models are applicable. When it comes to accounting for seasonal fluctuation, the two models work well together. The health of the vegetation is expected during both the rainy and warm seasons.

The Support Vector Machine (SVM) model (Model D) is the most accurate model for estimating the incidence of malaria in northern Benin. This model is less prone to outliers because of its focus on improving the margin between different classes and its role in preventing overfitting. SVM can predict malaria activity by one month, both during the wet season and at the beginning of the dry season. Alternatively, each predictor variable has a coefficient in the Ordinary Least Squares (OLS) (Model A) model, which makes evaluating its influence on the outcome variable easier. Still, Model A does a good job of predicting the frequency of malaria cases in the northern region of Benin based solely on the weekly Vegetation Condition Index (VCI) during the weeks 19–20 of May. Before mosquito activity starts in May, Model A can assist in implementing early measures. When it comes to giving precautionary advice during the dry season, Model D excels. The status of the vegetation in northern Benin must be closely monitored in order to comprehend the spread of malaria. It is shown that machine learning models, including SVM and OLS, can predict the onset of malaria and direct preventive actions.

IV.4. Assessing the environmental and socioeconomic susceptibility to malaria in the context of changing climate in northern Benin.

4.4.1. Vulnerability indicators

4.4.1.1. Exposure (exp) and susceptibility (Sus) indicators

Figure 33 shows the exposure and susceptibility variables used to determine malaria vulnerability. A total of five (5) exposure indicators and three (3) susceptibility indicators were carefully chosen to determine their impact on malaria vulnerability. These indicators give crucial insights into the precise factors that increase malaria susceptibility.

Analysing the maps given in Figure 33 reveals that particular areas, especially Tanguieta, Materi, Toucoutouna, Cobli, Perere, Sinende, and Natitingou, have a larger incidence of household members. Furthermore, more children under the age of five were found in the districts of Parakou, Tchaourou, Kouande, Kerou, Kalale, N'Dali, Djougou, Sinende, and Natitingou. Furthermore, a higher frequency of household visits was observed. Furthermore, some districts such as Nikki, Parakou, Kouande, Sinende, and Kalale have optimal temperature conditions for malaria transmission. Copargo, Djougou, Bassila, Cobli, Tchaourou, Parakou, and Boukoumbe districts all have an abundance of greenery.

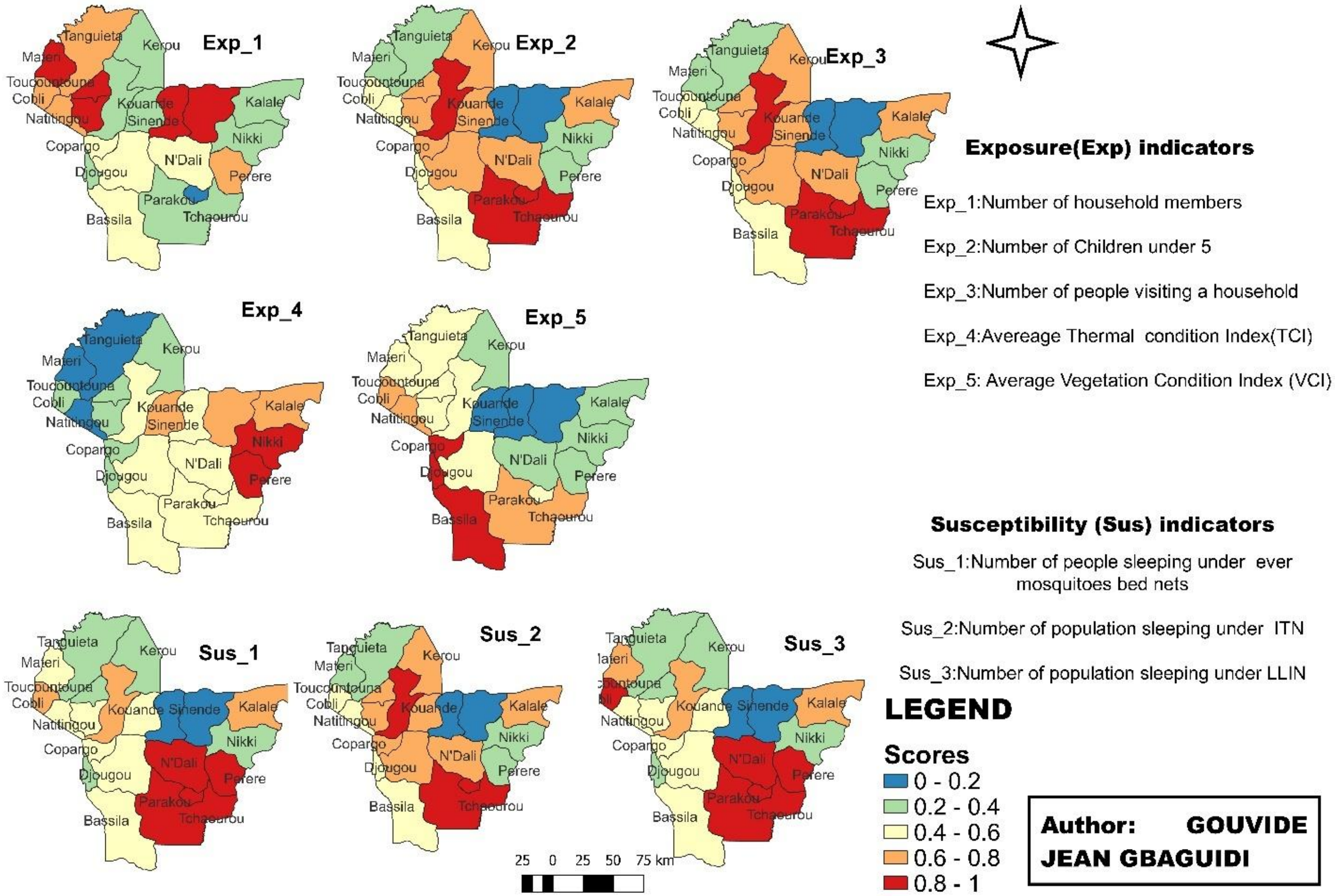


Figure 33: Exposure and susceptibility indicators maps used in the vulnerability

Concerning vulnerability, it was discovered that the districts of Parakou, Tchaourou, Perere, N'dali, Cobli, Kouande, and Kalale had low rates of mosquito net usage for sleeping. Furthermore, the usage of insecticide-treated nets (ITNs) was much lower in Parakou, Tachaourou, Copargo, Djougou, N'Dali, Kouande, Natitingou, Kerou, and Kalale. Similarly, just a few household members slept under long-lasting insecticide nets (LLINs) at Parakou, Tchaourou, N'dali, Perere, Kalale, Cobli, Materi, and Kouande.

4.4.1.2. Lack of resilience (LoR) indicators

Figure 34 indicates the lack of resilience indicators used to assess vulnerability to malaria. A total of 15 indicators were used for this purpose. Materi, Cobli, Ouake, Copargo, Djougou, and Parakou districts have a deficit lack of educated people (LoR_1). Exception Parakou and Kerou, as well as all other districts in the research region, lack access to safe and sanitary sewage disposal (LoR_2). The majority of districts have a tiny fraction of their population without health insurance, although certain districts, such as Parakou, Tchaourou, Kerou, Kouande, Pehonco, and Kalale, have a small number of homes with health insurance (LoR_3). In terms of credit accessibility (LoR_4), the districts of Parakou, Tchaourou, Pehonco, Kouande, and Kalale rank high, whereas Toucountouna, Djougou, and Perere rank medium. Tanguieta, Materi, Toucountouna, Boukoumbe, Sinende, and Bembereke have an abundance of agriculturally productive land (LoR_5). The districts of Parakou, Tchaourou, Bokoumbe, Cobli, Materi, Kerou, Kouande, Pehonco, Kalale, Perere, and Ouake have the highest level of access to information, especially to radio (LoR_6). In addition to these areas, N'Dali has a large number of television-connected homes (LoR_7). Parakou, Tchaourou, Nikki, and Kalale have the largest proportion of mobile phone-owning families. Bassila, N'Dali, Nikki, Sinende, and Bembereke have fewer households that own motorbikes (LoR_9).

In contrast, just a few homes in the districts of Ouake, Djougou, Copargo, Kerou, and Toucountouna had been sprayed with mosquito repellent in the last year (LoR_10). Tanguieta, Sinende, Bembereke, Boukoume, Materi, Pere, Bassila, and Toucountouna all have poor literacy rates (LoR_11). Livestock ownership (birds or farm animals) is widespread in the districts of Cobli, Ouake, Djougou, Bassila, N'Dali, Parakou, and Tchaourou (LOR_12). In Materi, Cobli, Tanguieta, Bembererke, Sinende, Bassila, Djougou, Perere, Natitingou, Tanguieta, and Toucountouna areas, only a limited percentage of people have bank accounts to protect their finances (LoR_13). Except for Bembereke, which has a noticeably poor status in this respect (LoR_14), all districts in the research region have adequate internet access.

Natitingou, Boukoumbe, Djougou, Sinendé, Bembèrèkè, Toucountouna, and Bassila have inadequate access to safe drinking water (LoR_15). Natural gas is not widely used as a cooking fuel in any district (LoR_16).

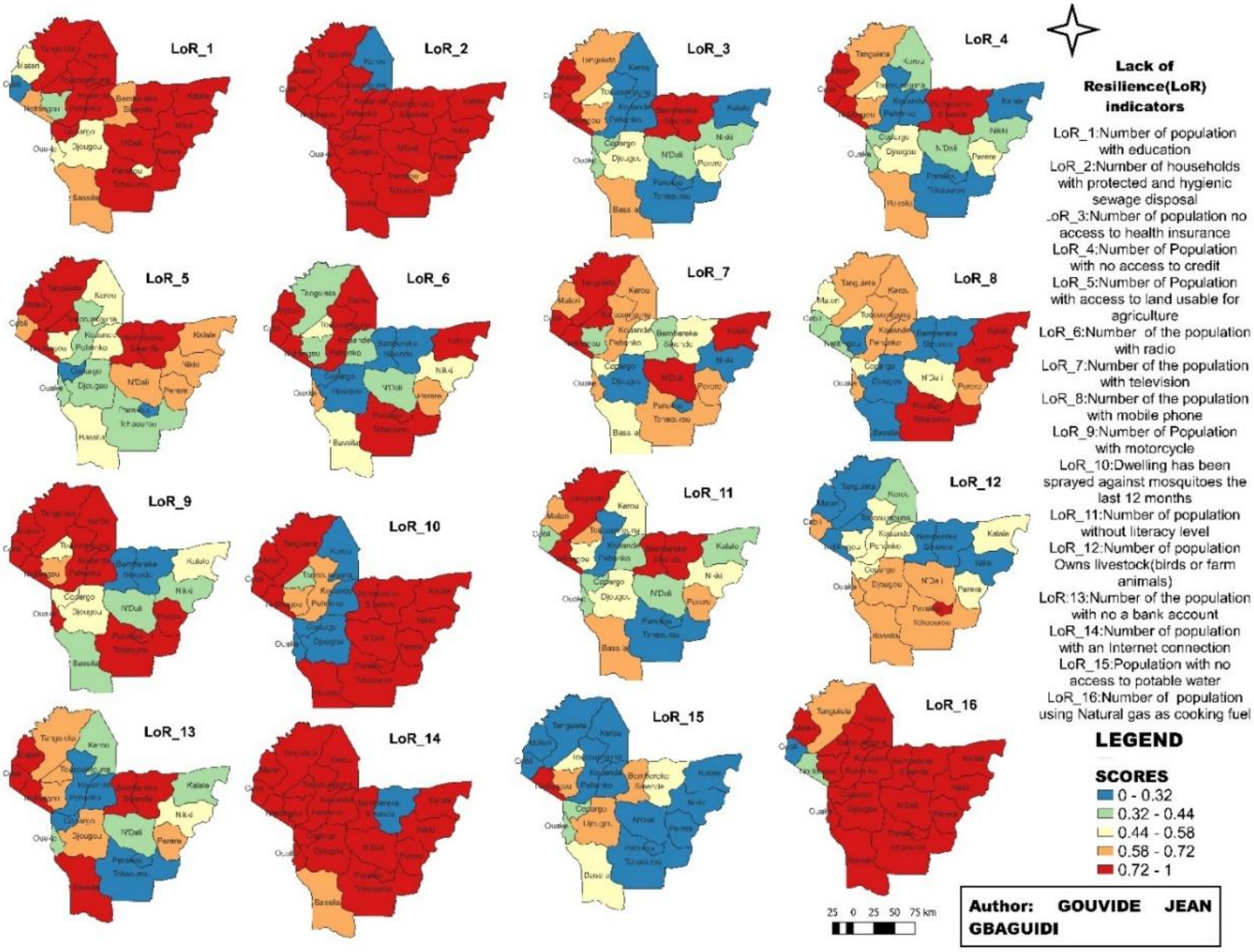


Figure 34: Lack of resilience indicators maps used in the vulnerability.

4.4.2. Vulnerability Index(VI)

To conduct a quantitative assessment of malaria vulnerability in Benin's northern region and present it within a Geographic Information System (GIS) framework, the vulnerability index was computed using principal component analysis (PCA), with the first principal component (PCA1) explaining approximately 45.24% of the total variance. This work effectively constructed the Malaria Vulnerability Index (VI) and generated a complete malaria vulnerability map for the provinces of Atacora, Borgou, and Donga using GIS spatial analytic techniques (Figure 35).

The eigenvalues returned from the PCA reveal the amount of variation explained by each PCA. Table XVI, which displays the PCA findings, shows that the first principal component (PCA1) accounts for roughly 45.24% of the total variance, implying that PCA1 captures a significant amount of the characteristics leading to malaria risk. The precise number of components contributing to malaria susceptibility equals the number of eigenvalues larger than one (Guttman, 1954). So, the first five principal components (PCA1, PCA2, PCA3, PCA4, and PCA5) account for 83.50% of the variation (Table XVI).

Table XV: Factor scores from PCA and associated statistics

Indicators	Eigenvalues	Proportion	Cumulative	Mean	SD	Scoring factor: PCA1
Exp_5	10.86	0.45	0.45	0.48	0.26	0.08
LoR_1	3.73	0.16	0.61	0.70	0.23	0.02
LoR_2	2.34	0.10	0.71	0.91	0.22	0.08
LoR_6	1.99	0.08	0.79	0.59	0.31	0.17
LoR_7	1.12	0.05	0.83	0.61	0.26	0.02
LoR_8	0.77	0.03	0.87	0.55	0.25	0.23
LoR_9	0.63	0.03	0.89	0.66	0.27	0.18
LoR_10	0.61	0.03	0.92	0.70	0.37	0.06
LoR_12	0.49	0.02	0.94	0.45	0.24	0.23
LoR_14	0.39	0.02	0.96	0.87	0.22	0.15
LoR_16	0.29	0.01	0.97	0.90	0.26	0.06
Sus_1	0.27	0.01	0.98	0.52	0.27	0.23
Sus_2	0.20	0.01	0.99	0.56	0.24	0.26
Sus_3	0.11	0.00	0.99	0.54	0.27	0.21
Exp_1	0.09	0.00	1.00	0.55	0.27	0.27
Exp_2	0.05	0.00	1.00	0.49	0.25	0.25
Exp_3	0.03	0.00	1.00	0.40	0.27	0.27
Exp_4	0.01	0.00	1.00	0.45	0.25	0.03
LoR_3	0.00	0.00	1.00	0.51	0.28	0.28
LoR_4	0.00	0.00	1.00	0.52	0.27	0.28
LoR_5	0.00	0.00	1.00	0.60	0.25	0.25
LoR_11	0.00	0.00	1.00	0.54	0.24	0.29
LoR_13	0.00	0.00	1.00	0.55	0.26	0.27
LoR_15	0.00	0.00	1.00	0.35	0.24	0.17

Figure 35 exhibits the vulnerability index for each district in the provinces of Atacora, Borgou, and Donga. The examination of this map shows that the districts of Materi, Cobli, Boukoumbe, and Perere are the most vulnerable in the study region. Tanguieta, Toucountouna, Natitingou, and Sinende follow soon behind.

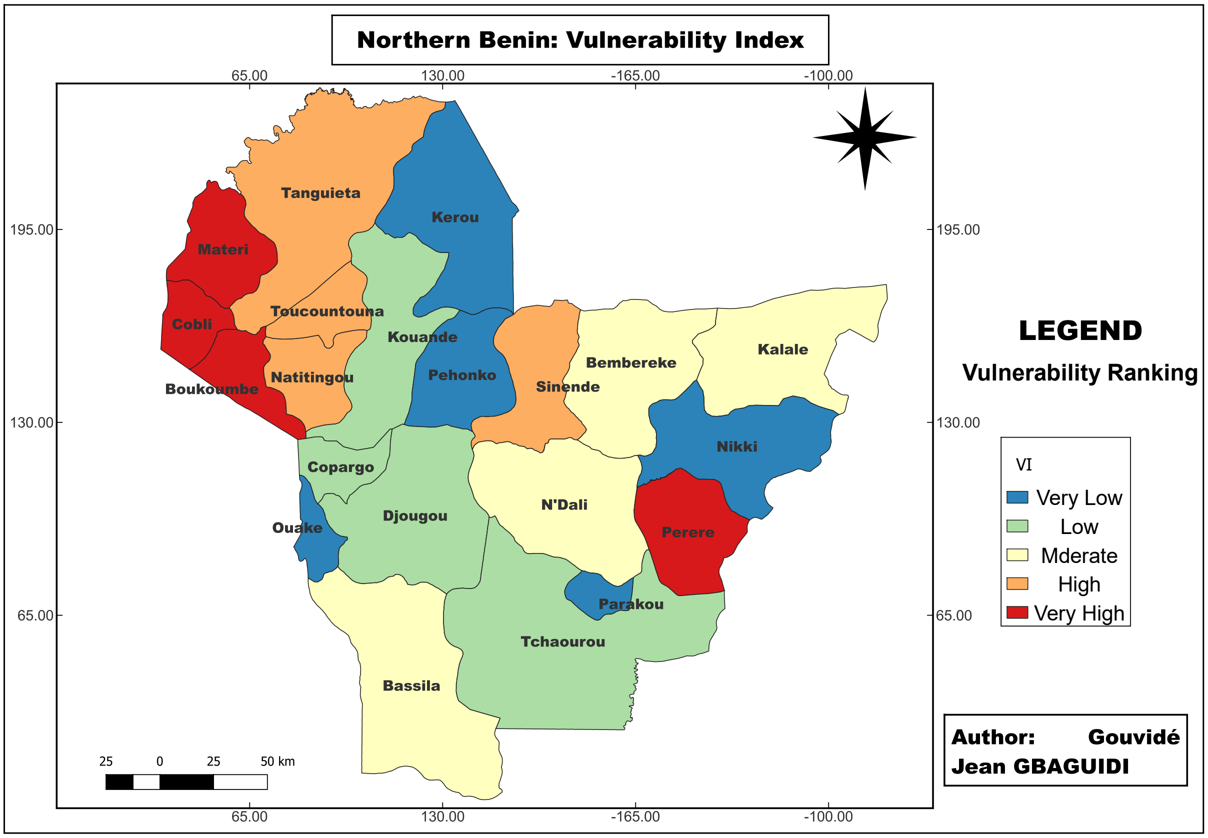


Figure 35: Map of the vulnerability index of the province of Atacora, Borgou and Donga

4.4.3. Pearson correlation between the vulnerability index (VI) and indicators

Table XVII shows the association between the vulnerability index (VI) and numerous variables, allowing us to identify elements that significantly contribute to malaria vulnerability reduction in the research region. Several of the variables examined had statistically significant associations with the VI, showing their relevance in malaria risk reduction.

LoR_7 (number of people with television) and LoR_10 (dwellings sprayed with mosquito repellent) had p-values of 0.08 and 0.04, respectively, indicating a moderate correlation with reduced vulnerability to malaria. Furthermore, LoR_14 (the number of persons in the population with an Internet connection) had a non-significant p-value of 0.95, indicating that it had no effect on malaria resistance.

In particular, LoR_8 (the number of people with a mobile phone), LoR_12 (the number of people who own livestock), and LoR_16 (the number of people who use natural gas as a cooking fuel) all had significant p-values (0.04, 0.05, and 0.01, respectively), indicating a strong negative correlation with the VI. This implies that utilising natural gas as a cooking fuel, owning cattle, and possessing a cell phone are all connected with a lower risk of malaria.

In addition, indications of malaria exposure Exp_1 (number of household members), Exp_2 (number of children under 5), and Exp_3 (number of persons visiting a family), as well as indicators related to community knowledge and awareness. LoR_3 (population without health insurance), LoR_4 (population without access to credit), LoR_5 (number of populations with access to agricultural land), LoR_11 (number of populations without literacy), and LoR_13 (number of people without a bank account) all had highly significant p-values (all 0.00). These markers had high positive relationships with the VI, underlining their significance in increasing sensitivity to malaria in northern Benin.

In conclusion, sleeping beneath ITNs, owning mobile phones, having livestock, and cooking with natural gas are all important variables in reducing malaria sensitivity in the research region.

Table XVI: Pearson correlation between the vulnerability index (VI) and indicators

Evaluation Items	**Indicators**	**P- value***	**t**	**Correlation**
Exp_1	Number of household members	**0.00**	**4.45**	**0.71**
Exp_2	Number of Children under 5	**0.00**	**3.70**	**0.65**
Exp_3	Number of people visiting a household	**0.00**	**3.94**	**0.67**
Exp_4	Thermal condition (TCI_Mean)	0.05	-2.05	-0.43
Exp_5	Vegetation Condition (VCI_Mean)	0.74	0.33	0.08
Sus_1	Number of people sleeping under ever mosquito bed nets	0.76	-0.31	-0.07
Sus_2	Number of populations sleeping under ITN	**0.04**	**-2.20**	**-0.45**
Sus_3	Number of populations sleeping under LLIN	0.88	0.15	0.03

Evaluation Items	Indicators	P- value*	t	Correlation
LoR_1	Number of populations with education	0.10	-1.73	-0.37
LoR_2	Number of households with protected and hygienic sewage disposal	0.13	1.60	0.34
LoR_3	Number of populations with no access to health insurance (Mutual; community organisation, Insurance)	**0.00**	**5.84**	**0.80**
LoR_4	Number of Population with no access to credit	**0.00**	**6.34**	**0.82**
LoR_5	Number of Population with access to land usable for agriculture	**0.00**	**4.69**	**0.73**
LoR_6	Number of populations with radio	0.75	0.32	0.07
LoR_7	Number of the population with television	0.08	1.84	0.39
LoR_8	Number of the population with mobile phone	**0.04**	**-2.22**	**-0.45**
LoR_9	Number of Population with motorcycle	0.94	-0.07	-0.02
LoR_10	Dwelling has been sprayed against mosquitoes the last 12 months	**0.04**	**2.15**	**0.44**
LoR_11	Number of populations without literacy level	**0.00**	**3.68**	**0.64**
LoR_12	Number of populations Owns livestock (birds or farm animals)	**0.05**	**-2.09**	**-0.43**
LoR_13	Number of the population with no a bank account	**0.00**	**6.20**	**0.82**
LoR_14	Number of populations with an Internet connection	0.95	-0.06	-0.01

Evaluation Items	Indicators	P- value*	t	Correlation
LoR_15	Population with no access to potable water	0.14	1.56	0.34
LoR_16	Number of populations using Natural gas as cooking fuel	**0.01**	**-3.00**	**-0.57**

***P-value<=0.05 significant**

These findings emphasise the need of committing resources to preventative programs, conducting community education campaigns, and promoting cleaner cooking fuel alternatives in order to improve malaria control measures and create resilience in the research region.

Discussion

Malaria vulnerability evaluation used a variety of markers to measure exposure, susceptibility, and lack of resistance. Materi, Cobli, Boukoumbe, and Perere are the most vulnerable, with values ranging from 0.81 to 1. The districts of Kerou, Pehonco, Nikki, Ouake, Parakou, Kouande, Copargo, Djougou, and Tchaourou were the least vulnerable to malaria in the study area. These districts have particular qualities that make them less vulnerable. Factors such as reduced incidence of household members and children under the age of five, rising air temperatures, and increased usage of mosquito nets (ITNs) indicate a higher level of protection against malaria transmission. Furthermore, some districts shown some signs of resiliency. owning cell phones, owning animals, and utilising natural gas as cooking fuel may all contribute to their reduced vulnerability to malaria. Our findings are consistent with the study done by (Danhoundo & Wiktorowicz, 2018, p.286) in Benin, who agreed that the use of insecticide-treated nets (ITNs) is an effective preventive tool against malaria transmission.

The lack of efficiency in reducing malaria susceptibility through the use of Long-Lasting Insecticidal Nets (LLINs) might be attributable to Anopheles mosquitoes developing resistance to specific insecticides, notably pyrethroids, as a result of continuous LLIN usage. This result is similar with a research done in southern Benin, which identified the widespread use of LLINs as a key driver of mosquito resistance to the pesticide included in the nets (Sovi *et al.,* 2013, p.1). Moiroux strengthens our findings by demonstrating a favourable association between LLIN usage, mosquito bite rates, and LLIN coverage in Benin (Moiroux, *et al.*, 2012a. p.1).

The growth of agricultural areas increases the number of mosquito breeding sites, making it the principal driver of malaria transmission in populations surrounding farms. (Sominahouin *et al.*, 2019, p.1) 's study in northern Benin, which coincided with our study areas, concluded that the high risk of malaria transmission in agricultural areas is attributed to the destruction of natural vegetation cover due to agriculture and alterations in meteorological parameters.

The spread of malaria is directly related to the population's economic condition, as indicated by our results that a lack of access to credit increases the vulnerability of communities to malaria in northern Benin. Socioeconomic variables influence people's capacity to use antimalarial medications. Health-seeking behaviour differs according on community affluence, with lower socioeconomic groups preferring to cheaper malaria preventive approaches, which might make them more vulnerable than wealthier socioeconomic groups (Pierrat, 2022, p.1; Onwujekwe *et al.*, 2011, p.1087).

There is a strong association between increased malaria risk and agricultural area expansion, which leads to the proliferation of mosquito breeding and development sites. The growth of agricultural land increases the danger of malaria for those who live near farms. Land cover and land use play important roles in malaria control (Sissoko *et al.,* 2017a, p.2). The increasing sensitivity to malaria in specific regions of the research area may be related to increased agricultural operations, which create optimal circumstances for mosquito growth and multiplication (Nwaneli *et al.*, 2020, p.179). In the northern area of Benin, a rise in the number of children under the age of five is associated with a higher risk of malaria. Children under the age of five are more vulnerable to malaria due to their weakened immune systems and inability to defend themselves from mosquito bites. Malaria is more likely to affect households with a higher number of children. The findings of (Velema L *et al.,* 1991, p.434)'s study done on the coast of Benin confirm our results, emphasising that children under the age of five are more sensitive to malaria, making them very vulnerable to the disease. Furthermore, our research shows that communities with a large inflow of individuals from outside or neighbouring areas are more prone to malaria. This vulnerability is caused by the possible entry of malaria-carrying mosquitoes from severely afflicted regions into the host area. Mosquitoes may travel over 10 km to infect neighbouring locations, assisted by wind speed.

Finally, access to information is critical in malaria control. Having access to a phone to collect information from the malaria early warning system greatly reduces vulnerability to malaria in northern Benin.

These findings might be useful to politicians, healthcare practitioners, and organisations focussing on malaria control and prevention. The districts with reduced vulnerability can serve as models for successful interventions and practices that can be used in other regions to reduce malaria occurrence. Furthermore, resources and efforts may be directed towards areas that are more vulnerable to malaria, addressing their unique issues and improving their resilience.

Conclusion

In light of the aforementioned results, this study in northern Benin found a substantial link between climate variables and malaria incidence. According to the study, maximum temperature and relative humidity play an important role in malaria multiplication. This might lead to the creation of an early warning system for malaria, allowing politicians and public health specialists to build successful policies. An intelligent malaria outbreak warning model with an 82% accuracy rate was created to help with proactive malaria prevention and control activities. The study also emphasised the need of using real-time vegetation health indices from satellite pictures to predict and respond to malaria outbreaks. The vulnerability assessment determined which areas were most vulnerable to malaria, allowing authorities to prioritise resources and solutions. The findings help to understand malaria transmission and susceptibility in Benin, emphasising the relevance of environmental variables, early warning systems, real-time data, and focussing on sensitive regions in malaria preventive and control initiatives.

CHAPTER V: GENERAL CONCLUSION AND RECOMMENDATIONS

Chapter five: General conclusion, limitations and recommendations

5.1. General conclusion

In conclusion, this research conducted in northern Benin has yielded significant insights into the role of environmental factors in malaria transmission and vulnerability. The findings highlight a strong correlation between environmental variables, including precipitation, temperature, and relative humidity, with the incidence of malaria. Notably, maximum temperature and relative humidity emerged as crucial factors influencing the spread of malaria in the region. These findings hold great potential in the development of a malaria early warning system, enabling policymakers and public health specialists to implement targeted strategies for mitigating malaria and addressing the impact of climate change on its transmission.

The study has demonstrated the reliability and effectiveness of an intelligent malaria epidemic outbreak model based on a support vector machine in predicting malaria incidence in the study area. With an impressive accuracy rate of 82%, this model proves to be a valuable tool for proactive malaria prevention and control initiatives. By accurately predicting malaria prevalence, policymakers and public health authorities can take timely and targeted actions to mitigate the impact of the disease and protect vulnerable populations. Additionally, the research has projected an increase in malaria incidence over the 2021-2050 period under different climate scenarios, with a decrease expected under the RCP8.5 scenario during the 2021-2030 period. These projections highlight the critical need to address climate change and its implications for malaria transmission to protect public health. As a result of this research, a web-based application specifically built for malaria epidemic warnings was created. This web application provides a simple framework for evaluating malaria risk in Benin. Its accessibility and ease of use contribute to its usability as a tool for improving malaria prevention and control efforts in Benin.

Additionally, the study emphasised the relevance of employing real-time vegetation health (VH) indicators derived from satellite images to predict and respond to malaria outbreaks. VH indices, such as those derived from the AVHRR sensor on NOAA polar orbiting satellites, can monitor environmental conditions influencing mosquito reproduction and survival, which are the principal vectors of malaria. Access to such data enables public health experts and stakeholders to better plan for and respond to possible malaria outbreaks, especially in high-risk areas such as Northern Benin. Online services, such as the NOAA/NESDIS website, make this information more accessible, considerably improving malaria preventive and management efforts, as well as overall health outcomes.

Furthermore, the vulnerability assessment conducted as part of this research offered significant information on the districts most vulnerable to malaria in Benin's northern region. Districts such as Materi, Cobli, Boukoumbe, and Perere were the most vulnerable, owing to factors such as a higher incidence of household members, children under the age of five, and thermal conditions conducive to malaria transmission. This understanding enables policymakers to prioritise resources and measures in these high-risk locations, lowering the malaria load and improving health outcomes.

Finally, this study has improved our understanding of malaria transmission and vulnerability in Benin's northern region. The findings emphasise the importance of environmental factors, the potential of early warning systems, the utility of real-time data, and the importance of focusing malaria preventive and control efforts on susceptible locations. We can assist in lowering the burden of malaria and improve health outcomes in Benin and other malaria-endemic countries by considering climate change, implementing effective measures, and strengthening health systems.

5.2. Limitations

One of the main limitations of this study is the lack of long-term availability of malaria data (number of cases). The available data spans only from 2009 to 2021 and is provided at a monthly resolution. This limitation can significantly impact the developed malaria model and introduce bias, impairing its accuracy in predicting malaria incidence in the study areas.

Another constraint in this doctoral research is the limited number of meteorological stations. The province of Donga lacks its own meteorological station, necessitating the use of data from neighboring stations to obtain temperature, relative humidity, and wind speed information. Additionally, certain districts within the study areas lack rainfall gauge stations. This deficiency can compromise the model's performance in predicting malaria incidence at the district level, potentially introducing bias in those districts where data were not included in the calculation of average values incorporated in the model. Consequently, the prediction accuracy may be compromised in these districts, leading to observable errors.

Furthermore, the available vegetation health indices are provided at a weekly resolution, while the malaria data is available at a monthly resolution. This mismatch between the number of malaria cases and vegetation health indices used to assess the impact of land use change on malaria transmission can result in weak correlations between these variables. Obtaining high-resolution malaria data would greatly enhance the development of accurate malaria models, reducing errors in the predictions. Notably, the malaria models derived from vegetation health indices perform well in predicting malaria incidence one month prior to the onset of the high malaria transmission season (during the rainy season and at the beginning of the dry season). However, their performance could be further improved with reliable malaria data.

On the other hand, the assessment of the vulnerability of the local community to malaria is limited by the availability of respondents willing to participate in the survey. Since respondents' participation in the survey is voluntary, this contributes to a lack of socio-economic information during the vulnerability assessment.

5.3. Recommendations

Our findings showed that climate has a significant impact on the transmission of malaria in northern Benin. Taking strategic actions to mitigate the influence of changes in the climate on the transmission of malaria in Benin is crucial and urgent. The following recommendations can help foster the elimination of malaria transmission and reduce the climate impact on human health.

- ❖ **Targeted malaria interventions**: Prioritise districts with higher vulnerability, such as Materi, Cobli, Boukoumbe, and Pèrere, for targeted malaria control interventions. These could include increased distribution of insecticide-treated nets (ITNs), indoor residual spraying, and educational campaigns.
- ❖ **Education and awareness**: Implement community education campaigns in vulnerable districts to raise awareness about malaria prevention and treatment. Emphasise the proper use of ITNs, the importance of seeking timely medical care, and the risks associated with mosquito breeding sites.
- ❖ **Clean cooking fuel**: Promote the use of clean cooking fuels, such as natural gas, to reduce indoor air pollution and the attractiveness of households to malaria-transmitting mosquitoes. Incentivise the adoption of cleaner cooking technologies.
- ❖ **Agricultural practices**: Encourage sustainable agricultural practices that minimise mosquito breeding sites. Guide land use and land cover to reduce the expansion of areas conducive to mosquito breeding.

- **Access to healthcare**: Improve access to healthcare services, especially in vulnerable districts. Ensure that healthcare facilities are equipped to diagnose and treat malaria promptly.
- **Children's health**: Focus on interventions to protect children under the age of five, who are particularly vulnerable to malaria. This may include targeted distribution of bed nets and vaccinations against malaria.
- **Socioeconomic support**: Explore strategies to improve the socioeconomic status of vulnerable communities. This could involve microfinance programs, access to credit, and income-generating opportunities.
- **Mobile technology**: Leverage mobile phone penetration for health communication. Use mobile phones to disseminate malaria-related information, early warning alerts, and reminders for preventive measures.
- **Community-based surveillance**: Establish community-based surveillance systems to detect and respond to malaria outbreaks promptly. Engage community health workers and volunteers in these efforts.
- **Cross-border cooperation**: Given the potential for mosquito transmission across borders, collaborate with neighbouring regions or countries such as Togo, Niger, Burkina Faso, and Nigeria on malaria control strategies. This could include information sharing and coordinated interventions.
- **Research and monitoring**: Continuously monitor and evaluate the impact of interventions. Invest in research to understand evolving factors contributing to malaria vulnerability and adapt strategies accordingly.
- **Resource allocation**: Allocate resources efficiently, directing more funding and support to districts with higher vulnerability while maintaining essential services in lower-risk areas.

  By implementing these recommendations, stakeholders can work towards mitigating the impact of climate change on human health, reducing the vulnerability to malaria in the northern region of Benin and improving overall public health outcomes.

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Appendixes

Appendixe1*:* Published Articles

Paper1: Potential impact of climate change on the transmission of malaria in northern Benin, West Africa

Theoretical and Applied Climatology
https://doi.org/10.1007/s00704-023-04818-1

RESEARCH

Potential impact of climate change on the transmission of malaria in Northern Benin, West Africa

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Abstract
Malaria is one of the greatest public health challenges in sub-Saharan Africa. Benin records malaria as the leading cause of mortality and morbidity. This study aims to analyze the climate and examine the relationship between the incidence of malaria and climatic variables in Northern Benin. The precipitation concentration index (PCI), Pettit test, Mann Kendall (MK) test, and Sen's slope method estimates were used to analyze the trends of temperature, rainfall, and rainfall intensity using monthly data from 1991 to 2021 at two meteorological stations and nine rain gauge stations in northern Benin. Pearson correlation tests, principal component analysis, and plots were computed to determine the relationship between malaria incidence and climatic variables over 2009–2021. Total precipitation and rainfall intensity are decreasing. The temperature showed a positive trend with an increase in the monthly and annual temperature. Monthly rainfall; minimal, maximal, and mean; relative humidity; and mean and maximal temperature have a significant positive correlation with malaria incidence. A range of 80–220 mm of precipitation, 25–35°C of temperature, 55–85% of relative humidity, and 1.6–2.7 m/s of wind speed is suitable for the transmission of malaria. Maximal temperature and relative humidity may have a large influence on how much malaria spreads in Northern Benin. These factors could help to develop a malaria early warning system in the study area.

1 Introduction

Malaria is widely recognized as the most dangerous infectious disease in Sub-Saharan Africa (SSA) and presents a significant public health challenge in West Africa. The environment plays a crucial role in shaping the health outcomes of societies. Unfortunately, in many developing countries, the environment has a particularly adverse impact on health (Adefemi et al., 2015).

The Special Reports on Regional Impacts of Climate Change by the Intergovernmental Panel on Climate Change (IPCC, 2022) have established that climate change has a significant influence on vector-borne diseases. The dynamics and distribution of malaria are strongly influenced by climatic factors. Several studies have demonstrated a strong correlation between malaria prevalence and climatic variables (Ayanlade et al., 2020; Diouf et al., 2021; Donnees et al., 2010; M'Bra et al., 2018). Temperature, humidity, rainfall, and wind speed all contribute to malaria incidence by affecting the duration of mosquito and parasite life cycles or by influencing the behavior of humans, vectors, or parasites (Kogan et al., 2008; Parham et al., 2010).

Malaria has emerged as the most serious vector-borne illness in West Africa. The Anopheles mosquito, particularly the Plasmodium falciparum species, is the primary driver of malaria in Africa, responsible for the majority of severe cases and deaths, while also displaying resistance to treatment (Ayanlade et al. 2013).

The prevalence case of malaria in the World Health Organization (WHO) African Region in 2020 is estimated at 228 million cases, accounting for about 95% of global

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Paper2: Towards an intelligent malaria outbreak warning model based intelligent malaria outbreak warning in the northern part of Benin, West Africa

Gbaguidi *et al. BMC Public Health* (2024) 24:450
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BMC Public Health

RESEARCH Open Access

Towards an intelligent malaria outbreak warning model based intelligent malaria outbreak warning in the northern part of Benin, West Africa

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Abstract

Background Malaria is one of the major vector-borne diseases most sensitive to climatic change in West Africa. The prevention and reduction of malaria are very difficult in Benin due to poverty, economic insatiability and the non control of environmental determinants. This study aims to develop an intelligent outbreak malaria early warning model driven by monthly time series climatic variables in the northern part of Benin.

Methods Climate data from nine rain gauge stations and malaria incidence data from 2009 to 2021 were extracted from the National Meteorological Agency (METEO) and the Ministry of Health of Benin, respectively. Projected relative humidity and temperature were obtained from the coordinated regional downscaling experiment (CORDEX) simulations of the Rossby Centre Regional Atmospheric regional climate model (RCA4).

A structural equation model was employed to determine the effects of climatic variables on malaria incidence. We developed an intelligent malaria early warning model to predict the prevalence of malaria using machine learning by applying three machine learning algorithms, including linear regression (LiR), support vector machine (SVM), and negative binomial regression (NBiR).

Results Two ecological factors such as factor 1 (related to average mean relative humidity, average maximum relative humidity, and average maximal temperature) and factor 2 (related to average minimal temperature) affect the incidence of malaria. Support vector machine regression is the best-performing algorithm, predicting 82% of malaria incidence in the northern part of Benin.

The projection reveals an increase in malaria incidence under RCP4.5 and RCP8.5 over the studied period.

Conclusion These results reveal that the northern part of Benin is at high risk of malaria, and specific malaria control programs are urged to reduce the risk of malaria.

Keywords Climate change, Malaria, Prediction, Northern Benin

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Paper3: Application of Advanced Very High-Resolution Radiometer (AVHRR)-based vegetation health indices for modelling and predicting malaria in Northern Benin, West Africa

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Malaria Journal

RESEARCH Open Access

Application of advanced very high-resolution radiometer (AVHRR)-based vegetation health indices for modelling and predicting malaria in Northern Benin, West Africa

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Abstract

Background Vegetation health (VH) is a powerful characteristic for forecasting malaria incidence in regions where the disease is prevalent. This study aims to determine how vegetation health affects the prevalence of malaria and create seasonal weather forecasts using NOAA/AVHRR environmental satellite data that can be substituted for malaria epidemic forecasts.

Methods Weekly advanced very high-resolution radiometer (AVHRR) data were retrieved from the NOAA satellite website from 2009 to 2021. The monthly number of malaria cases was collected from the Ministry of Health of Benin from 2009 to 2021 and matched with AVHRR data. Pearson correlation was calculated to investigate the impact of vegetation health on malaria transmission. Ordinary least squares (OLS), support vector machine (SVM) and principal component regression (PCR) were applied to forecast the monthly number of cases of malaria in Northern Benin. A random sample of proposed models was used to assess accuracy and bias.

Results Estimates place the annual percentage rise in malaria cases at 9.07% over 2009–2021 period. Moisture (VCI) for weeks 19–21 predicts 75% of the number of malaria cases in the month of the start of high mosquito activities. Soil temperature (TCI) and vegetation health index (VHI) predicted one month earlier than the start of mosquito activities through transmission, 78% of monthly malaria incidence.

Conclusions SVM model D is more effective than OLS model A in the prediction of malaria incidence in Northern Benin. These models are a very useful tool for stakeholders looking to lessen the impact of malaria in Benin.

Keywords AVHRR, Vegetation health, Malaria, Forecasting, Benin

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Parameters Climatic variables	t	P-Value	Cor	t	P-Value	Cor	t	P-Value	Cor
	Parakou			Nikki			Bembereke		
Max-Relative Humidity	5.72	**00**	0.42	7.0373	**00**	0.5	6.17	**00**	0.45
Min-Relative Humidity	6.9	**00**	0.49	8.43	**00**	0.57	7.89	**00**	0.54
Mean-Relative Humidity	6.6	**00**	0.47	8.14	**00**	0.56	7.37	**00**	0.52
Rainfall	5.8	**00**	0.42	4.88	**00**	0.37	5.95	**00**	0.44
Mean-Temperature	-6.52	**00**	-0.47	-8.95	**00**	-0.59	-7.8	**00**	-0.54
Max-Temperature	-7.15	**00**	-0.5	-10.04	**00**	-0.64	-8.64	**00**	-0.58
Min-Temperature	-1.92	0.06	-0.1536	-2.32	**0.02**	-0.1877	-2.23	0.027	-0.18
Wind speed	-5.2	**00**	-0.39	-6.35	**00**	-0.46	-4.56	00	-0.35
	Natitingou			Boukoumbe			Tanguieta		
Max-Relative Humidity	5.63	**00**	0.43	6.7258	**00**	0.53	4.44	**00**	0.44
Min-Relative Humidity	3.77	**00**	0.31	4.93	**00**	0.42	3.6	**0.001**	0.37

Parameters Climatic variables	t	P-Value	Cor	t	P-Value	Cor	t	P-Value	Cor
Mean-Relative Humidity	4.7	**00**	0.37	5.9	**00**	0.48	4.13	**00**	0.42
Rainfall	3.14	**0.002**	0.26	3.84	**00**	0.34	4.31	**00**	0.43
Mean-Temperature	-3.33	**0.001**	-0.27	-4.2	**00**	-0.37	-4.95	**00**	-0.48
Max-Temperature	-5.24	**00**	-0.41	-6.8	**00**	-0.54	-6.09	**00**	-0.56
Min-Temperature	0.47	0.64	0.04027	0.45	0.65	0.04214	-0.94	0.352	-0.1
Wind speed	1.11	0.27	0.09	-0.51	0.613	-0.05	-1.55	0.126	-0.17
		Bassila			Djougou			Copargo	
Max-Relative Humidity	6.03	**00**	0.46	2.21	**0.029**	0.19	4.51	**00**	0.36
Min-Relative Humidity	4.36	**00**	0.35	0.81	0.419	0.07	3.03	**0.003**	0.25
Mean-Relative Humidity	5.24	**00**	0.42	1.45	0.149	0.13	3.77	**00**	0.31
Rainfall	2.87	**0.005**	0.24	1.04	0.3	0.09	3.51	**0.001**	0.29
Mean-Temperature	4.69	**00**	-0.38	-3.5	**0.001**	-0.3	-2.5	**0.014**	-0.21

Paramters Climatic variables	t	P-Value	Cor	t	P-Value	Cor	t	P-Value	Cor
Max-Temperature	-6.5	**00**	-0.49	-2.93	**0.004**	-0.25	-4.18	**00**	-0.34
Min-Temperature	-0.08	0.935	-0.01	-1.74	0.085	-0.15	0.65	0.517	0.06
Wind speed	0.65	0.518	0.06	1.35	0.18	0.12	2.04	**0.043**	0.17

Appendixe3: Table XVII: Loading of the first three dimensions

Climatic factors	Dim.1	Dim.2	Dim.3
Precipitation	0.158	-0.096	**0.888**
Minimal_temperature	0.068	**0.952**	0.13
Maximal_temperature	**-0.916**	0.224	0.093
Mean_relative humidity	**0.938**	0.284	0.056
Maximal_relative humidity	**0.889**	0.353	0.021
Wind Speed	-0.024	0.55	-0.457
Minimal_relative Humidity	**0.955**	0.231	0.071
Mean_temperature	-0.692	**0.647**	0.138
Malaria incidence	0.588	-0.312	-0.201

Appendixe4: Table XVIII: Correlation matrix of climatic variables and malaria incidence.

Item	Mean	Std.Dev	Average Precipitation	Average minimal temperature	Average maximal temperature	Average mean relative humidity	Average maximal relative humidity	Average Wind Speed	Average Malaria incidence
Average Precipitation	113.96	71.58	1.00						
Average minimal temperature	21.76	1.40	-0.01	1.00					
Average maximal temperature	33.53	2.25	-0.14	0.16	1				
Average mean relative humidity	65.43	13.03	0.12	0.32	-0.76	1			
Average maximal relative humidity	83.38	11.72	0.06	0.39	-0.67	0.96	1		
Average Wind Speed	2.03	0.37	-0.18	0.36	-0.01	0.04	0.05	1	
Average malaria incidence	28.22	6.10	-0.04	-0.18	-0.48	0.42	0.43	-0.2	1

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