SPATIAL MODELLING OF MALARIA PREVALENCE IN KENYA

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DECLARATION

I hereby declare that this thesis is my original work and to the best of my knowledge has not been presented for a degree award in this or in any other university.

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APPROVAL

The undersigned certify that they have read and hereby recommend for acceptance of Murang'a University of Technology, a thesis entitled **"Spatial Modelling of Malaria Prevalence in Kenya."**

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DEDICATION

I dedicate my thesis work to lovely wife Eunice, my daughter Talia and my sisters Rose, Doris and Nancy and many friends and Family. A special feeling of gratitude to my loving mother Hellen, whose words of encouragement and push for tenacity ring in my ears. My God bless you all.

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ABSTRACT

Malaria is a leading cause of deaths in Kenya. A vector-borne disease caused by parasite of genus plasmodium; the disease is introduced into the human circulatory system from bites caused by infected female anopheles' mosquitoes. A lot of effort and resources has been put in the fight against malaria, with large amount of national budget being used in the fight against malaria in developing countries which has led to underdevelopment, impoverished livelihoods and low human development index. Malaria burden affects the world's poorest countries. About 90% of the malaria burden is reported in sub-Saharan Africa. Malaria cases are significantly high in countries of south-East Asia, Western Pacific region, Mediterranean and the Americas. As of 2017, five countries India, Uganda, DR Congo and Mozambique accounted for half of malaria cases reported around the world. In Kenya, the disease has led to impoverished livelihoods with the poorest communities of the country being the most affected. The disease has led to high mortality cases in children under five years and pregnant women. Loss of man hours and work days among adults in the country, leading to low productivity. Studies have shown that there has been a general lack of knowledge on how select demographic and social economic conditions risk factors affect the prevalence of malaria in Kenya. The method of the study involved performing the spatial models for malaria prevalence in Kenya while relaxing the assumptions of stationarity. The assumptions of linearity allowed some covariates like age to have a non-linear effect on prevalence of malaria. Using random walk model of 2^{nd} order and the assumption of stationarity, it allowed covariates to vary spatially. Conditional autoregressive model was used. Data from malaria indicator survey of 2015 (KMIS-2015) was used for the study. Both the social-economic and demographic variables were used as predictor variables. These included education level, wealth index, age, access to mosquito nets and place of residence. From the study, demographic and social-economic factors were found to have significant impact on Prevalence of malaria in Kenya. Most cases of malaria were reported in lake, western and coastal regions. The most prone areas were Kisumu, Homabay, Kakamega and Mombasa. There were less cases in central Kenya counties like Nyeri, Tharaka-Nithi with a significant number reported in arid and semi-arid regions of Northern-Kenya counties of Garissa, Mandera, Baringo. Rural population was more susceptible to malaria compared to those in urban areas. The odds of getting (verse not getting malaria) in urban places of residence increases by 0.84, which is estimated to .096, CIs 95% (0.70, 1.01), and a p-value .069. Malaria prevalence varied significantly from one region to another. The study established that Spatial autocorrelation exists among regions mostly due to weather patterns, geography, cultural practices and socio-economic factors.

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ACRONYMS AND ABREVIATIONS

An.	Anopheles
BSVCP	Bayesian spatially varying coefficient process
CAR	Conditional Auto-regressive
DIC	Deviance Information Criteria
GoK	Government of Kenya
GWR	Geographically weighted regression
HDSS	Health and demographic surveillance system
INLA	Integrated Nested Laplace Approximations
WHO	World Health Organisation
DFID	Department for international Development.
MOH	Ministry of Health
NMIS	National Malaria Indicator Survey
KNBS	Kenya National Bureau of Statistics
KMIS	Kenya Malaria Indicator Survey
IRS	Indoor Residual Spraying.
LLINs	Long Lasting Mosquito Nets
KHS	Kenya Health Service
KMIS	Kenya Malaria Indicator Survey
OR	Odds Ratio
MARA/ARMA	Mapping Malaria Risk in Africa
KeMRI	Kenya Medical Research Institute
PMI	Project management Institute.
UNICEF	United Nations Children's Fund

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

Malaria is a disease caused by single cell parasites of genus Plasmodium. There are four identified species of the genus plasmodium namely: *plasmodium vivax*, *plasmodium malaria*, *plasmodium ovale* and *plasmodium falciparum*, of these, *plasmodium falciparum* poses the biggest threat to humans who are not immune. The disease is introduced into the human circulatory system from bites caused by infected female anopheles' mosquitoes. Up to 80% of the reported cases over 90% of deaths resulting from the disease have been identified to be caused by parasites of genus *plasmodium falciparum* (Carrera et al., 2019).

As one of the greatest problems facing our society in terms of mortality and morbidity, the occurrence of malaria in many parts of the world has been correlated with poverty, lack of social necessities and ignorance in some communities, with the countries recording high malaria cases recording low economic growth as compared to those certified as being malaria free. According to economics, malaria is greatly responsible for stalled growth in many countries with records of up to 1.3% annual growth penalty in many countries where the case of malaria is endemic, and especially in most of African countries, a term referred to as "growth penalty"(Robinson et al., 2015).

In Kenya, malaria is a major cause of mortality and morbidity, statistics have shown that, over half of Kenya's population is at risk of malaria, accounting for more than 40% of outpatients in hospitals attendance with over 20% being admissions to health facilities according to KeMRI statistics reported by (Desai et al., 2014). It has been estimated that a lot of man hours are lost annually to the disease with an estimated 170 million working days reported to being lost. According to (Mogeni et al., 2016), reports from the government shows that pregnant women and the children under the age of 5 years are most vulnerable group to malaria, with an estimated 20% of deaths reported in children below 5 years of age being caused by malaria.

Several environmental factors greatly influence transmission of malaria in various regions in the country, specific factors are at interplay thus their effects may differ from one region to the other. Some topographic variables like elevation, slope and several other factors influence the development of *anopheles* mosquitoes. Population density, proximity to wetlands as well as lowlands has been identified as one of local spatial variations with a significant association with the spread of malaria. In some other regions like Senegal and Ethiopia, there has been a demonstration of a spatial relationship between climatic variabilities like rainfall and the occurrence of malaria(Homan et al., 2016).

When there is rainfall, relative humidity is increased, thus indirectly benefiting the development of *anopheles* mosquitoes, since an increase in humid condition prolongs the adult life of the mosquitoes and increases the number of breeding sites thus promoting reproduction. Other factors that contribute to the growth and development of larvae are temperature and availability of water. Larvae are highly sensitive to temperature changes. For instance, temperatures above 28 degrees Celsius have been seen to greatly reduce the spread of malaria in Africa (Snow et al., 2015).

There is a knowledge gap in our community, and rampant misconceptions on Malaria. However, the risk and transmission intensity of malaria shows a reasonable temporal and spatial variations directly related to variations in temperature, rainfall, altitude, human settlement and topography(Sultana et al., 2017). The biology of mosquitoes is greatly influenced by climatic conditions. Therefore, climate conditions influence its transmission in malaria endemic countries

Major effort has been put in the fight against malaria. For instance, in late 1800, in the United States of America, wire gauzes were introduced in most of housing facilities to act as physical barriers to the fight against the parasite. Although crude, by then the method seemed to work. In other areas around the world, for instance in Algeria, oil was spilled on water bodies thought to harbor the parasites as control mechanism for the mosquito larvae development. However, the continued use of this method rendered large swathes of water bodies not safe for other uses like animal consumption. A factor that made the method less attractive to the locals (Mogeni et al., 2016).

Although associated with some degrees of success, the method was not ideal thus was shunned. Thus, within the course of early 20th century to its mid years, several methods to combat the problem of larvae that grew to adult anopheles' mosquitos were adopted. Some of these were reported to be toxic, ranging from the use of Arsenic and its derivatives in bid to win the war over the parasites. Known as the wonder drug, Paris green was extensively used in and around Europe to fight against malaria in spite of the availability of other pesticides like quinine. Following the introduction of the Paris green, most countries in 1940s had registered elimination of *Anopheles gambiae*. These includes countries like Brazil and Egypt. However, it is important to note that there has not been a single effective method to combat malaria world over. This has prompted the used of different approaches around the world to fight malaria (Were et al., 2019).

Indoor residual spraying (IRS) has over the years come up as a strong contender method for protecting persons from malaria especially in malaria endemic regions. For instance, there has been a mega leap in the number of persons protected, from slightly above 10 million mark to over 50 million individuals as a result of using this, method (Rue et al., 2009). This represents over 8% percent of persons at risk of malaria in Africa.

However, use of treated mosquito nets, mosquito repellants and some other off-the-shelve sprays has been hailed as major method of combating the disease in most households especially in Kenya. Indoor spraying with insecticides in most of the areas where most of the Anopheles species have been identified to habit has also seen major success (Zhou et al., 2016). The use of long-lasting mosquito nets (LLINs), that have been treated with insecticides in beds has been hailed as one of most effective methods.

1.2 Statement of the Problem

Malaria still remains an economic burden as well as posing a substantial threat globally, with time proving almost impossible to eradicate for almost a century now. In Sub-Sahara Africa, malaria has been greatly attributed to poor human development index. The disease has been associated with poverty, underdevelopment and lack of basic social necessities. In Kenya, Malaria has been one of the leading causes of death, especially in children aged below age five attributing to over 20% of all deaths reported in children in this age bracket and also causing high number of deaths in pregnant women too (Carrera et al., 2019). The control of mosquitoes and malaria has posed a major challenge, operating at a wide spatial scale. By incorporating the right approaches, studying the geographical distribution of any given disease forms a solid basis in establishing the right approaches, interventions and right control mechanisms for the disease and at the same time having the ability to gauge their effectiveness. Such study may also show possibility of identifying underlying ecological factors with which the disease is associated with. Therefore, understanding the risk factors of malaria, spatial distribution and spatial effects of risk factors help in policy formulation and coming up with tailor made policies and approaches on control of malaria in Kenya.

1.3 Objectives of the Study

1.3.1 General objective

The general objective of the study was to determine the spatial distribution of malaria prevalence in Kenya.

1.3.2 Specific objectives.

1. To investigate the relaxation the stationarity assumption on the effects of risk factors on the prevalence of malaria in Kenya.
2. To determine the malaria risk factors in Kenya.
3. To determine the spatial variation of malaria prevalence in Kenya.

1.4 Hypothesis

H_0: There is no significance relationship between malaria risk factors and the spatial prevalence of malaria

1.5 Justification of the Study

As one of the greatest medical dilemmas of the 21st century, Malaria has over the years delayed and negatively impacted the economies of developing countries most of which are in Africa. There has been a general knowledge gap especially among professionals in health in identifying of undocumented risk factors especially in area they operate to come up with tailor made solutions to malaria problem. Various studies as discussed have shown that there has been a general lack of knowledge on how select demographic, geographical, social and climatic conditions risk factors affect the prevalence of malaria in Kenya. Thus, incorporating the right approaches, studying the geographical distribution of any given disease forms a solid basis in establishing the right approaches, interventions and control mechanisms for the disease, and at the same time having the ability to gauge their effectiveness. Such study may also show possibility of identifying underlying ecological factors with which the disease is associated.

Generally, there has been a broken link between climate and medical data on malaria prevalence in Kenya. More so, information systems on health have been weak due to irregular reporting, poor coordination and lack of case detection of malaria(Carrera et al., 2019). Based on such knowledge there arises a need to have a risk-based maps so as to focus more efforts on high-risk areas in order to tailor make intervention strategies for improving monitoring, distribution and control of malaria.

1.6 Significance of the study

Malaria is a major health burden in Kenya and most of Sub-Sahara Africa. The findings of this study will help in coming up with tailor made solutions to combat malaria. Incorporating the right approaches, studying the geographical distribution of any given disease forms a solid basis in establishing the right approaches, interventions and control mechanisms for the disease, and at the same time having the ability to gauge their effectiveness. This study may also show possibility of identifying underlying ecological factors with which the disease is associated. Using Bayesian Spatially varying coefficient process (BSVCP), the study relaxed the stationarity assumption to allow covariates to vary spatially, that way it was possible to show how malaria is spatially distributed in the country based on select risk factors. The study enabled risk maps be generated so that the distribution and prevalence of malaria can be marked regionally.

1.7 Scope and Limitation.

The study used data at a national scale. Thus, there is the possibility of some risk factors going unnoticed and large sets of missing data since a small sample was used as a representative of the total population. On the other hand, the assumption of stationarity in the study was one of the limiting factors, some risk factors have been assumed to be stationary, and this implies that these factors do not change over time.

1.8 Contribution of the Thesis

This thesis has made the following contributions;

1. It has showed the effect of malaria in Kenya at a more up-close and specific levels.
2. It has also showed how malaria is spatially distributed in the country
3. The study has also made a contribution on the ways that the government can effectively use to combat malaria
4. The study has also contributed to the body of knowledge with the publication of these findings in science journals

1.9 Organization of the Thesis.

The thesis is organized categorically from chapters one up to chapters five. These chapters cover a variety of areas all that make up the entire thesis. Chapter one introduces us to the situation of malaria, the causes as well as the factors that contribute to the development of malaria causing pathogens

Chapter two takes us through the situation of malaria from a world perspective, scaling it down at continental level (Africa), and down to the country level (Kenya). This chapter discusses the different risk factors and how they contribute or have contributed to the spread of malaria in the Country. The situation of malaria is discussed extensively in this Chapter.

Chapter three takes into account the methodology and the data used to come up with the deduction on malaria situation. This chapter discusses the key methods that are essential incoming up with the conclusions based on the data.

Chapter four discusses the results of the study. This chapter gives a visual representation of malaria situation based on the discussions of the former chapters 1, 2 &, 3. This chapter informs the conclusions and recommendations of the study, it brings into reality the situation of malaria from an analytical point of view.

Chapter five, is the conclusion and recommendations chapter. This chapter inform and explains the results obtained from the study. It gives the view of the researcher in regard to answers obtained from the analysis. Similarly, this chapter gives the researchers view on the measures that can be put in place to improve the situation as it is.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

Malaria is vector-borne disease caused and spread by bites from female anopheles' mosquito, a parasite of genus plasmodium. In human beings, four parasites are responsible for causing malaria, namely: *Plasmodium vivax*, *plasmodium malaria*, *plasmodium ovale* and *plasmodium vivax*(Were et al., 2019).

In the study(Gosoniu et al., 2006),carried research on modelling of the geostatistical malaria risk data in Mali. Bayesian geostatistical models was used to the malaria risk data in quantifying the environmental-disease relations, identification of significant malaria predictors and transmission in the environment and provided a model-based malaria risk predictors together with their precision. The models used in the study were based on the assumption of stationarity. In the study, they implied that the spatial correlation is a function of the distance between location and independence of location. The model fit for the study as well as its predictions was based on the markov chain Monte Carlo methods (MCMC). From the study, the results indicated that the stationarity assumption was a very important factor, since it had a major influence on the significance of environmental factors and the corresponding malaria risk maps.

Between the year 2007 and 2015, parasite prevalence was used as measure, to determine the prevalence of malaria in areas with high endemic cases. These studies established that more conclusive investigations were not carried out in order to establish the malaria mortality cases in different age group. According to (Khagayi et al., 2019), the study used parasitological data from the annual cross-sectional surveys taken from Kisumu (HDSS) in determining the prevalence of malaria parasites. The study used household surveys and verbal autopsy's (VA) in obtaining the data on the causes of malaria specific mortality. The study used Bayesian negative binomial geo-statistical regression models in the investigation of parasite prevalence of clinical malaria and mortality in the various age groups. The estimates were obtained based on yearly data from the aggregated data collected for over a period of one year. The results from the study were that malaria parasitaemia from cross-sectional surveys was associated with mortality in the various age groups. The study showed that clinical malaria was associated with cases of malaria mortality than the parasite prevalence. The study noted that the effects was much higher in children between the ages of 5 to 14 years in comparison with other groups.

(Homan et al., 2016)carried out a study that explored the role that local demographics, social and environmental factors played on malaria across various regions in western Kenya. The study explored the spatially varying risk factors for malaria in Kenya in order to obtain insights on how the human and environmental factors play in sustaining the transmission and prevalence of malaria. The study used a standard linear regression model where multiple variables were fitted to help explain how much of spatial variation on malaria prevalence could be explained by the demographic and environmental data. Making the assumption of non-stationarity of the risk factors, the geographically weighted regression walk (GWR) was performed. The effects of local multicollinearity and spatial autocorrelation was given a much more attention to detail. The results from the study were that, combining the data from these surveys, multivariate linear model showed that outdoor occupation, population density as well as higher social economic status, and population density increased the risk of malaria, the model included environmental and household factors. The local geographically weighted regression (GWR) model made substantial improvements and the model fitted considerably, the results of the study was that the relationship of malaria and the risk factors varied spatially in these regions. Depending on the area of the island, outdoor occupation, population density, as well as socio-economic status had a positive or negative association with the prevalence of malaria.

(Tuyishimire, 2016), carried out a study in south eastern region of Rwanda to model the malaria risk factors. The study aimed at assessing the relationship between the malaria risk factors and its prevalence in this region, the study spatially model's malaria risk factors. In the study, spatial statistics was used to obtain the spatial clusters of malaria prevalence in the study regions. The analysis on these clusters showed that zones with high malaria risk, also known as malaria hotspots as well as those zones with low and moderate distribution of malaria risk characterized the distribution of malaria. The study showed that the prevalence of malaria varied from one household to another, the same case for one administrative unit to the other. The study used a logistic regression model to assess the relationship between the malaria risk factors and the prevalence of malaria. The results from the study clearly showed that the rate of infection with malaria increased with proximity to the irrigated farmlands. More so, the size of the household was also seen to increase the rate of malaria infection considerably. Similarly, poor housing quality was associated with a high risk of malaria infection. These factors (size of household, low housing quality and irrigated farmlands) were seen as the main malaria underlying factors.

A survey carried out in Uganda to establish the prevalence of malaria among the children below five years, the study explored the progress of the control interventions and then establish the how malaria is geographically distributed across the country. A Bayesian geostatistical model with statistically varying coefficient was used with used in determining the effects of interventions at both national and regional level.to identify the most important forms and predictors, spike and slab was used in selecting the variables. The results from the study showed indoor residual spraying (IRS) and insecticide treated nets (ITN) was seen to have a very significant effect overall but varied in terms of protective effect on the prevalence of malaria. Environmental factors like rainfall, land cover, temperatures of day and night, as well as the type of area were significantly associated with prevalence of malaria the study found out that malaria was significantly high in rural areas compared to urban areas, on the other hand , malaria prevalence was seen to increase with age of the child while higher education levels and high household socio economic-status was seen to drastically decrease the cases of malaria prevalence (Ssempiira et al., 2017).

In the study to investigate the spatial relationship between the occurrence of malaria and environmental risk factors in South Sumatra province in Indonesia, the study investigated six potential ecological factors associated with malaria. Ordinary least squares method (OLS) and geographically weighted regression (GWR). The spatial variability and the global patterns of associations between the cases of malaria and a set of selected ecological factors were explored. The results from the study were that different geographical and environmental parameters were important at different global and village level(Hasyim et al., 2018). Distance from the forest, altitude and rainfall were used as independent variables. In global OLS, these variables were seen to have a significant effect on cases of malaria. However, the relationship between malaria and environmental factors had a strong spatial variation in different regions.

Having the right knowledge on the how the primary vectors are distributed is crucial since it plays a great role in providing with key information in the designing of transmission models so as to target control measures(Were et al., 2019). On the other hand, they are crucial to understand how the existing interventions have an impact on the relative abundance of these vectors, where an alternative control is needed. In this study, predictive species distribution models generated suitability probability, a multinomial generalized additive model was used in producing the relative abundance estimates for *anopheles funestus, Anopheles arabiensis and anopheles gambiae.* The models estimated effects of indoor insecticide interventions on these abundances were made using the post-Intervention maps. The results of the study were that the abundance of several of different risk factors differed depending on habitat preference. It also showed that each intervention strategy varied depending on the risk factors. For instance, residual spraying had a great impact on the relative abundance of *anopheles fenustus* and lesser effects on *anopheles gambiae.* However, the results noted that insecticide treated nets reduced the relative abundance of these species drastically and in equal measures(Sinka et al., 2016).

2.2 The Situation of Malaria in the World

Malaria, being a vector borne disease is more predominant in tropical and in subtropical world regions. In most developing countries of the world, malaria has become a major challenge as so much efforts and resources are focused in fighting the disease at the expense of some other important national development agenda with an estimated 300 to 500 million individuals being infected with the disease annually in the countries of Africa, South East Asia, the Mediterranean as well as west pacific region. In Kenya, the country is at initial stage of fight against malaria. Being at the control stage, the country still has a long way to go in order to be certified, malaria free with the attainment of elimination and eradication stages, which are the three stages for a malaria free society(Robinson et al., 2015).

Malaria threatens around 40% of the world population who live in the poorest countries (Zhou, et al., 2016). World health organization (WHO) approximates that

435,000 people died as a result of disease in 2015 . The majority of the victims are children. Approximately 60% of children below five years. Studies also show that most people who know about prevention measures of malaria rarely practiced the steps. From the world malaria records that were availed in 2018, the report has shown that there was a surge in the cases of malaria, from a record of 217 million cases registered in 2016 to 219 million cases in 2017(Khagayi et al., 2019).

2.3 Malaria situation in Africa

In 2015, 80% of deaths related to malaria occurred in Africa. In Africa, Kenya is among the significant regions that are malaria-endemic. This makes it a leading concern in public health. Malaria epidemics usually occur when conditions favor their transmission. It is, therefore, vital to understand the present situation of malaria in the world so that people can plan on its elimination. The disease can be diagnosed, treated, and prevented(Robinson et al., 2015).

Climatic factors have contributed to the increased number of mosquitos and made the transmission of malaria favorable in countries where the disease is endemic. A recent world malaria report released in 2018, showed that 219 million cases in 2017 were reported around the globe. This was an increase from 217 million cases recorded in 2016 from 91 countries across the world. The disease is widespread in Asia and Africa. Recent World Health Organization report declared this disease endemic in seventy-six countries. It has, therefore, created an economic burden in these countries around the globe and thus contributing to poverty and limited commercial development as a large chunk of GDP is invested in fighting the diseases(Carrera et al., 2019).

The number of deaths caused by malaria decrease as age increases. The most vulnerable group are children below five years. On the other hand, malaria prevalence usually increases as the children age increases. Children aged 10-14 years tend to suffer more in terms of prevalence, which is 10.22%. Malaria prevalence is considerably higher among male children (approximately 8.23%) than female children (around 8.04%) (Robinson et al., 2015) .UNICEF/WHO indicates that malaria is a substantial public health dilemma in Africa. This is, in particular, the highland and semi-arid regions of Africa, whereby deaths are annual. The climatic factors that contribute to and influence the biology of the mosquitos are relative humidity, temperature, and rainfall. A case for many African countries especially in sub-Saharan Africa that have favorable conditions to harbor malaria pathogens. Once the adult mosquitos emerge, their survival is determined by rains, moisture, and altitude (Zhou et al., 2016). The Plasmodium falciparum causes most of the malarial infections.

In the year 2017, data from the World Health Organization showed that there were about 219 million incidences of malaria cases in 87 countries. Rates of malaria are highest in southern parts of the equator, south Sahara, and central regions of Africa(Carrera et al., 2019). The *plasmodium falciparum* type of malaria is common in most African countries, it accounts for the largest share of all malaria cases. World health organization statistics, show that Africa has made a lot of progress when it comes to reducing malaria prevalence in the world. Since 2000, the rate of deaths caused by malaria in Africa has diminished. However, some regions have had this progress stalled and reversed. In the year 2017, *Plasmodium falciparum* had accounted for over 90% of all malaria cases. In the same year, five countries from Africa accounted for almost half of all the malaria cases in the world. Nigeria accounted for 25%, DRC had 11%, and Mozambique had 5%, and Uganda, which had 4 % (Ntirampeba et al., 2017) .

2.4 Malaria in Kenya

The population of Kenya in 2018 was projected to be 47.9 million people as per the Kenya National Bureau of Statistics. Of this population, 16% are children below 5 years, 42% are children below 15 years. According to(Snow et al., 2015). Malaria is a significant public health problem in Kenya affecting this age group. Malaria is impoverishing poor communities in the country. It is one of the leading causes of mortality and morbidity in Kenya. The risk of Malaria is low in Nairobi and its immediate surroundings, other areas include Eastern, highland regions above 2500m, western, and rift valley regions.

To achieve the various goals set to make Kenya Malaria free. Effective planning and allocation of resources is essential. This will require high-quality evidence on malaria distribution under different settings of transmission, their access to the various interventions, and the epidemiology of the disease. The evidence should be at multiple geographic units. Under the new 2010 Kenyan constitution, matters relating to health have been devolved to the county governments. To achieve the goals of reducing malaria prevalence in the country, allocation of resources, and effective planning are paramount. Therefore, this will require high-quality evidence about the epidemiology of this disease, and the population distribution in the different transmission settings. The other factors that are responsible for the spatial heterogeneity of the malaria vectors and intensity of transmission are land cover changes and land use, house buildings, levels of household protection measures against the spread of mosquitos, and topography(Macharia et al., 2018). According to the 2015 UN's development index, Kenya was ranked 146th out of a total of 188 countries. This index measures adult literacy, per capita income, and life expectancy(Were et al., 2019).

From the routine health system data, malaria accounts for about 20% of all outpatient consultations. Transmission of the disease and the risk of being infected is determined by rainfall patterns, temperature, and altitude in Kenya. The terrain and altitude variations have contributed to climate change in the country. The coastal regions have tropical while the interiors that are northeast and the north experience temperate climatic conditions (Ntirampeba et al., 2017). October to December, Kenya experiences short rains, while from March to May, long rains occur. The temperatures are highest between February and March. The temperatures are then lowest in between July and August. Malaria prevalence in Kenya, therefore, varies considerably across season and geographic regions. Kenyan highlands, represent fringe areas between unstable and stable transmission.

According to (Sultana et al., 2017), data analysis of the Kenya malaria indicator survey (KMIS) of 2015 showed that out of 34 million people, 25 million are at risk of getting malaria. From the above assessment, we can estimate that 70% of the Kenyan population is at the risk of being infected by the disease. The most vulnerable people to the infection are pregnant women and children below 5 years. However, prevalence among women decreased among pregnant women as wealth and education increased(Idris et al., 2016). Malaria prevalence among children below five years has also experienced a downward trend.

To address these risks, the country is stratified into epidemiological zones. Endemic areas are regions of stable malaria and have altitudes that range from the sea levels in the coastal areas up to 1300m around western Kenya in the Lake Victoria basin. In these regions, the transmission is intense throughout the whole year(Were et al., 2019). The five coastal counties have malaria prevalence that ranges from 5 to 20%. From the 2018 population projections, 29% of the population lives in malaria-endemic zones. Some sub-counties in two of the lake endemics counties have been classified as highland-epidemic.

The second zone is the highland and epidemic-prone regions. The transmission of malaria in western highlands is seasonal and has considerable year-to-year variations. The whole population in this region is vulnerable, and the case-fatality rates are higher than endemic areas in the event of an epidemic. 20% of the Kenyan population lives in this region. Highland-epidemic prone areas in this region are two sub-counties in Kakamega and Bungoma (both are endemic counties in the lake region) and two sub-counties in Baringo (seasonal risk county). The malaria prevalence ranges from 5-20%, basing on statistics from the WHO, (2015), (Robinson et al., 2015).

The third epidemiological zone is seasonal malaria transmission regions. It consists of semi-arid and arid areas of northern parts of Kenya. During rainy seasons, these regions usually experience small periods of intense transmission of malaria. This region is the largest in terms of geographical size (has 15 counties) and has 17% of the total population. Malaria prevalence in these regions ranges from 1-5%. The fourth zone is low malaria-risk regions. It covers ten counties located in the central Kenyan highlands and Nairobi. It has approximately 34% of the total population(Sultana et al., 2017).

Significant efforts have been taken to eliminate and reduce malaria in Kenya and other parts of the world. The national malaria control program, as well as the ministry of health, have implemented sound policies and strategies in this fight. (Idris et al., 2016) recommends that control and prevention strategies be intensified in endemic ad epidemic zones (coastal and lake zones). There are several organizations and initiatives set up, such as the national malaria control plan, Rollback Malaria, President's Malaria Initiative, and many other international campaigns to fight malaria. They are involved in mass education, funding, prevention, and control of malaria. Community-based surveys, the national ministry of health, peer-reviewed journals, published sources, and personal correspondence are some of the sources of data for mapping malaria prevalence and transmission in the country. For continuous spatial modeling, surveys in Lamu in coast region, and Homabay in Lake. Victoria. The majority of the infections were *Plasmodium. Falciparum* (92%), *Plasmodium. malariae* (6%) and *Plasmodium ovale* (2%)(Jenkins et al., 2015).

Malaria being a vector-borne disease, poses severe health risks to the world population, particularly Kenya. The disease has killed thousands of people yearly. We can attribute this to insufficient research regarding what causes it and inefficient control measures. In Kenya, particularly, the country has received technical support and significant funding from WHO, DFID, PMI, and other international donors and partners to help reduce the burden created by Malaria in Kenya. A statistical analysis of malaria prevalence could be used to investigate the association of the distribution of different species of vectors and the climatic variables. Besides, an in-depth understanding of the local environmental factors that influence malaria can be useful in eliminating the disease(Mogeni et al., 2016).

Malaria has for decades been a killer disease globally and has shown crucial health issues in Sub-Saharan Africa. Kenya saw a declining malaria declination to 8% in 2015 from 11% in 2010, with signs it can decline further. The commendable progress shuttered through current reports of a severe malaria epidemic in 2017 between September to October that began in five nations and has rapidly spread to 10 countries within the semi-arid Kenya region. The nations involve Marsabit, Samburu, Baringo, West Pokot, and Turkana in the Northwestern part, while Isiolo, Wajir, and Mandera in the Northern region and Tana River and Lamu in the coastal area of the nation. The rising epidemic has led to crippling health disasters never seen before. Already, beyond 50 deaths got reported, beyond 2000 adults and kids have been diagnosed with the disease and 400 have been hospitalized (Mulambalah, 2018).

Research shows three counties have worst been hit: Marsabit, Baringo, and Turkana. The situation is believed to worsen due to reasons like impacted regions supposed to encounter short trains that can develop more breeding areas for malaria vectors and spread. Moreover, the disease attacks sites traditionally unrelated to the disease naturally; people impacted have no immunity to Malaria (Mulambalah, 2018). Thus, each age group is relatively vulnerable to Malaria. Thirdly, the scene gets more complex by the claimed resistance of domestic malaria parasites to present drugs.

Fourth, the disease occurs at the scene of a vital disaster in the health area due to constant industrial actions that began early in 2017. Further, the senior pastoral communities in the influenced nations and the shift of refugees promote the cross-border distribution of the epidemic to the following countries like Somalia, Ethiopia, and Uganda. In summary, the recent malaria epidemic needs to be addressed instantly. Malaria refers to a treatable alongside preventable disease that needs not kill persons in the current world. The country states need to realize the altering sequences of Malaria spread fostered by man factors and climate changes. There is also a need for a successful malaria policy and strategies to fight the epidemic, (Mulambalah, 2018)

2.4.1 Malaria in Kenyan Highlands

Abiotic, Biotic and socioeconomic aspects impact malaria epidemiology. The spread in western Kenya is deemed heterogeneous and varies significantly between households and villages. It is claimed that abiotic, socioeconomic elements like structure and housing designs alongside the utilization of mosquito-prevention methods alongside prophylaxis impact malaria infection and clinical malaria incidence. The kinds of houses influenced the incidence of clinical Malaria. In the current study, significant persons with clinical Malaria lived in homes built from mud, houses with exposed eaves alongside grass-hatched. Such sort of house design probably enables mosquitoes to fly in alongside bite(Essendi et al., 2019). Thus, it provides less safety contrasted to houses made with blocks and iron-roofing sheets having closed eyes.

Multiple studies have proved that the lack of mosquito defense techniques like bed nets, doors, screen windows, and burning coils alongside sprays are crucial risk factors for malaria incidence. Besides, a family's socioeconomic status is linked directly to the affordability of mosquito defense approaches at the individual level. Apart from insecticide-treated bed nets given for free, each other mosquito safety approaches have to be bought. Thus, whether the spouse is self-employed or employed can define the mosquito safety approach every family utilizes. Moreover, the academic rank of household spouses would reflect if they had clarity on malaria risk and used needed knowledge-founded precautions to prevent mosquito bites,(Essendi et al., 2019).

High altitude has brought significant impacts on malaria spread due to lower temperature rising the time needed for sporogony within mosquitoes, which downsizes the chances of transmission cycle finished as mosquitoes fail to live long to allow parasite development. Most studies in the highlands of Kenya have sensed a difference in malaria prevalence over reasonably small changes in sea level. Studies have shown that, there is a 16% reduction prevalence for every 50 m height of elevation. Several studies show no difference in parasite estimates within the reasonably small altitude ranges in the areas under investigation (Cook et al., 2019). The opposite is true;

altitude can impact longer-term malaria vulnerability, with less seroprevalence sensed in the greatest altitude bands.

The overnight movement away from home has also been identified as a risk factor for greater Plasmodium falciparum incidence. Despite highland sectors having a likelihood of lower receptivity to infections due to cool temperatures, exposure to imported diseases is a crucial risk due to structured population shifts to regions with lower altitudes for commercial aims. Travel is noted as a risk factor in the highland sectors of Kenya. However, studies claim travel is not linked with greater infection prevalence due to the majority of travel likely being non-endemic Nairobi. The revealing of risk factors is quite precise when using incident measures to reveal new infections and more prolonged periods of diseases (Cook et al., 2019).

2.4.1.1 Individual measures against Malaria

Many cases have shown the stagnation of progress in fighting against Malaria. For such reasons, there is a need to employ new mosquito control strategies and tools to reinforce recent utilized approaches to gather the benefits established in fighting Malaria. Despite the current malaria control approaches emphasizing indoor residual spying and long-lasting insecticide-treated nets, multiple measures can be employed at household rank to minimize bites in men. Such processes involve mix and deployment of house screening on windows, doors and eaves to prevent access of adult mosquitoes. Hose screening serves like environmental management serving to abolish mosquito breeding places near homes (Ng’ang’a et al., 2021). Deployment of such an approach is needed regarding there are than 80% of malaria spreading takes place indoors, mostly at night.

The night is most likely time for persons to get bitten alongside those infected with Malaria. Thus, closing the windows or window screening and opening eaves can downsize the probability of mosquito bites. Such measure reduces the chances of the disease prevailing indoors. Currently, clinical trials have proven full house screening alongside ceilings gives valuable safety from anemia alongside exposure to malaria spread. Moreover, various studies have claimed that Western Kenya can have house modifications, including insect screen ceilings established from present domestic materials alongside insecticide-treated eaves tubes, which lead to a vital reduction in man exposure to malaria vectors. Enhancement in housing design has contributed to reducing Malaria in various parts of the globe. Safeguarding mosquitoes from entering houses has more benefits like defending household members reasonably and at each period whilst indoors (Ng'ang'a et al., 2021)

Malaria control projects in Sub Saharan Africa include the utilization of Pyrethroid insecticides both in indoor residual spraying and long-lasting insecticide nets. Currently, the disease relies on pyrethroids, the remaining class of insecticide accepted to get impregnated on nets and is also widely applied in indoor residual spraying projects in Africa. Correct application of malaria management tools can lead to remarkable downsizing of morbidity alongside mortality related to Malaria. There is the great hope of removing Malaria in Africa through insecticides and residual sprays as they prove effective. However, the current rise of mosquitoes to pyrethroids has turned into a crucial issue and a risk to malaria vector control interventions, (Wanjala & Kweka., 2018).

Long-lasting insecticidal nets have widely been used for malaria prevention alongside control intervention in Africa. However, achieving universal coverage and precise use of such nets is complex in sub-Saharan Africa. In 2015, about 52% of targeted Kenyan households had reached a net, but only 42% utilized the tool regularly. Whether LLNs are efficiently used to avoid Malaria relies on a complicated mix of factors. According to a study on Kenyan highlands, seasonal precipitation sequences alongside vector density are linked with the net use (Ng'ang'a et al., 2021)

Sleeping structures, like sleeping on the ground and the presence of sectors amenable to hanging nets, proved to be linked with the use of such nets. Other aspects related to the use of the nets in developing nations involve bed net owner, net shape, alongside gender. The primary factor is inconvenience resulting from hanging the net alongside heat discomfort in the bed net due to ranged airflow (Ng'ang'a et al., 2021). User's marital status, distance to close health services where nets get obtained and even bed net density can impact the use of the long-lasting insecticidal nets.

2.4.1.2 Government intervention in Malaria outbreak

The state needs to give adequate diagnostic facilities alongside the equipment. Adhering to general elections in 2013, the health service industry got moved to counties in the same year's August. The counties are accountable for three ranks of care: primary care services, community health services and county referral services. In times of recent outbreaks, the absence of accessible, well-staffed alongside, the well-equipped hospital was cited as the crucial factor boosting the situation. Patients were supposed to travel long distances to get treated. Regarding residents, along with local leaders, those who died had failed to get treatment in time (Owino, 2018).

Unfortunately, residents within remote villages cannot get to nearby health cantered found kilometers away. Poor roads in such regions have worsened the case more as patients should walk long distances for treatment. Enough supply of antimalarial to health centers can aid reduces the issue. Moreover, the county states need to consider employing mobile clinics in emergency cases. The country state needs to invest in ambulances for ferrying patients from far-flung sectors of counties. The country states on the parts need to give enough safety to such industries for reassurance of medical staff alongside development partners (Owino, 2018). This makes sure that health centers are efficiently operated, particularly in times of outbreaks.

There is also a need for targeted larval management. The considerably localized alongside focal nature of breeding sites in such areas can give good chances to control targeted larval. The habitats are few, easily traceable and well-defined. They usually involve pan dams, trenches, ditches and irrigation canals that makeup almost 60% of breeding sites for malaria vectors. Better surrounding control that consists in filling up the unneeded ditches alongside trenches, draining stagnant water alongside applying larvicides into irrigational canals can minimize vector population immensely (Owino, 2018).

Moreover, since *Anopheles arabiensis* feeds on livestock alongside man is a crucial malaria vector, zoo prophylaxis, elevating herd sizes, can be a plausible vector control approach. However, this can be counterproductive in areas where significant livestock densities result in the converging of multiple herders in grazing lands of communities. This has the chance of raising vector densities alongside great man biting rates within such grazing lands and malaria spread rates. The move to concrete houses having sealable windows can minimize exposure to bites (Owino, 2018). House kinds have usually turned more crucial micro-epidemiological aspects in malaria spreading.

General health education and awareness aimed mainly at the less educated are needed. Victims can find treatment faster and avoid exposing themselves to bites by sleeping under insecticide-treated bed nets. This can ensure that they never become reservoirs for mosquitoes to be inoculated into the following individual. Pregnant women also need to get sensitized to the gains of using antimalarial drugs during pregnancy. A crucial preventive tool not yet adopted in Kenya is the four-dose malaria vaccine known as Mosquirix. The vaccine is recently under examination, and Kenya is on top in the trials. Such vaccines can give solutions to residents in seasonal spread zones (Owino, 2018).

Malaria affects about 3 billion individuals within the globe leading to over 438,000 dead people, with Africa responsible for 88% of such deaths. Within Sub-Saharan Africa, 90% of deaths are caused by Malaria. However, it has led to 3.5 million clinical events within Kenya, leading to 10,700 deaths every year, with those staying in Western Kenya being more vulnerable. Poor use of malaria safety interventions is the critical driver causing counts to surge. Abolition of vector via larval source control, indoor residual spraying alongside the use of biological means has never yielded 100% leads (Mukabane et al., 2022).

The offering of the bed net alongside its accurate utilization to limit vector-man interaction yielded a vital reduction in the number of harms but has not yet entirely prevented transmission. Status in eliminating Malaria in Kenya alongside Sub-Saharan Africa is encountered with several issues involving downsized funding and reduced prioritization of malaria management activities. To entirely experience the impact, malaria management tools need to be installed in populations exposed to infection. The attempt towards this but malaria resurgence in Western Kenya highlands points to a focal point (Mukabane et al., 2022). The research aimed to discuss risk factors for the malaria scourge.

2.4.2 Malaria Situation in Lake region

The frequency of malaria within dwellers of said Lake Victoria area has been severe for some time. The habitat linked well with the lake could be conducive to the survival of a large population of malaria transmission. Some researchers believe that lake ecosystems, notably aquatic hyacinths, are the reservoir of carriers for the disease. A large proportion of larval habitats in the lake were confined to places that had been bordered by towering apical vegetation, such as bushes, and which were indeed not vulnerable to the tides. Lagoons that were isolated from either the reservoir by gravel barriers accounted for almost 50% of the nearby ecosystem types (Omondi & Kamau, 2018)**.** The lagoons were home to a diverse range of environments. It was the purpose of this investigation to determine if malaria larvae reproduce in the lakeside ecosystems and surrounding lagoon basins. It was discovered that there was an anopheles larval stage in the surface water of the said lake and surrounding pools situated along with a roughly wide range of kilometers of the shoreline in the Nyanza region. This paper aims to discuss the scenario of malaria in the Kenyan lake region of Nyanza.

Habitats on the Lake

Anopheles arabiensis and Anopheles gambiae, the two most important in the region of Africa malaria carriers, typically congregate in tiny, well-lit intermittent puddles of groundwater. It's already been established that malaria larvae may be found in stationary lagoons along the lakefront when dense trees have been removed there are many tiny ponds in the marshes surrounding the lakeside that may develop appropriate vector homes. However, despite subsequent findings suggesting hatching happens in continuous and moderately lagoons, the features of their environments indicate indicating larvae could rarely spawn inside the waterbodies directly.

According to the findings of this research, an arabiensis appeared by far the highest prevalent viral organism at the lakefront sample locations, in contrast to earlier research that found this viral to mostly nest in tiny, well-lighted impermanent ponds. Inside the lake sections with grassy fields, including in the exposed parts, this variety was often seen (Minakawa et al., 2012). When it came to locations that were vulnerable to tides, an. arabiensis is a little prevalent. For the ecosystems to be secluded and protected, giant adaptive vegetation should be planted around them, the system that automatically which hatching locations on the ground are created. Given a large number of affirmative spots as well as the wide distribution of favorable areas, it appears that this organism was widespread across the reservoir. The probability of ovulation inside the lakeside environments ought not to be discounted, even if eggs might accidentally reach the water from neighboring puddles on the ground after high rains. For their part, lake environments could function as repositories, and movement from lakefront ecosystems would help the establishment of mating populations in freshly developed nearby basins.

2.4.2.1 Water Hyacinth habitats

Also proven by the findings of this research is that plasmodium mosquitoes may thrive within the basin hydrangea strands in Headwaters. It had previously been noted that an. funestus complicated eggs were found in an aquatic plant bed in this research region, but now is this same initial subject to conclusively demonstrate that malaria vectors may be found in many aquifers' hydrangea beds around the lakeside (Omondi & Kamau, 2018). A number of all other quaternion and prospective vector organisms were discovered in the aquifer hydrilla beds of a lagoon; nevertheless, findings from the unadjusted and adjusted tests indicated that, when likened to other ecological niches inside the lagoon, the aquifer hydrilla vegetation is far more appropriate for

Just an. rivulorum. When it came to aquatic hydrangea fields mostly in the reservoir, Anopheles funestus s.s. constituted the second-highest common viral strain found.

It is reputed that both forms may be found in populated ecosystems, with aquatic species seeming to be a better fit for these environments than other forms of foliage. The results of the survey indicate that such a basin is somewhat satisfactory for something like an funestus s.s. than previously assumed, but these organisms were found in several aquifer hydrangea beds that had been entangled by a sequence of tree trunks during the research study (Omondi & Kamau, 2018). This is similarly higher probable for Anopheles rivulorum to be found in certain environments, however, the inclination was stronger for even a funestus s.s. compared to an. rivulorum. Anopheles funestus s.s. seemed to be likewise higher probable to happen in these settings. The eggs of the aquatic weeds caught by non-woody floating vegetation including those uncovered towards the waters, on the other hand, could be detected in far lower numbers. The trees, it would seem, help to reduce the impact of tides on the environment and hence help to maintain them. The aquatic plants' ecosystem coupled with evergreens would create an ecosystem that is comparable to what that found in big landscaped ponds just on terrain where its organism is often found in its natural setting.

Throughout this research location, which is situated inside the Lake Victoria areas in Kenyan Gulf, extensive aquatic species occupied a higher percentage of the eastern shoreline. This is because aquifer mobility is restricted in this location, and the aquifer species are frequently stranded. Additionally, plants border the shores of the said bay, allowing the aquatic species to grow in abundance. This was shown in this research when it was discovered that plants were related to a percentage of the aquatic weed locations studied. According to the findings of this research, an. rivulorum may live on aquifer hydrangea fields covered in thick non-woody aquatic vegetation. This kind of ecosystem is more widespread compared to the tree-dominated ecosystems there in the bay, despite the reduced abundance under certain circumstances(Omondi & Kamau, 2018).

2.4.2.2 Habitats close to the lake

Lakes and reservoirs accounted for about 50% of all stationary aquifer basins, with the majority of lakes and waterways concentrated across the region's western bays and towards its north end. Bodies of water and aquatic perennials seem to be primarily determined by the geography and geological aspects of the area whence they originate. The majority of wetlands remained big and sufficient to support a diverse range of plant life, and this in response supported a diverse range of ecological niches.

On the flip side, hardly large sprouting vegetation nor buoyant species could be found in the remaining kinds of environmental and artificial lakes. As a consequence, the funestus s.s. and An. rivulorum populations in wetlands increased significantly (Stuckey et al., 2012). The marshes had various pockets of exposed grassland, where An. arabiensis and An. gambiae s.s. were the most common species. In actuality, the life forms an arabiensis is perhaps the highest prevalent organism identified in marshes. Because An. arabiensis embryos need a fast turnaround duration over An. funestus s.s. larval, it is conceivable that large concentrations of An. arabiensis hatchlings will be found if circumstances are favorable. Nevertheless, to evaluate if wetlands generate more of an. arabiensis when contrasted to other carriers, it is necessary to measure the site is surrounded by every ecological niche inside wetlands (Stuckey et al., 2012). For example, if the distance occupied by forested environments is greater than the region surrounded by exposed fields, the overall output of An.

funestus is likely to be greater over those of An. arabiensis in bodies of water, but for An. arabiensis, the average productivity could be lower. In the same way, the generation of anopheles mosquitoes within every pond category could be calculated only based on concentration. Despite this, because of the increased performance of An. arabiensis, it was found that viral concentrations in constructed waters were significantly higher than in marshes or other naturally occurring bodies of water.

Furthermore, regarding the magnitude of the bodies of water, it is expected that wetlands will remain active across the year, increasing their overall vector output. As a result, wetlands are anticipated to serve a greater essential influence on regional malaria infection than that the other kinds of pools across the shores of Lake Victoria's eastern border (Stuckey et al., 2012). In addition, the discovery that wetlands are a primary home for An. funestus sp. provides more credence for this concept. This variety is somewhat more setbacks and oriented than An. arabiensis, and as a result, the earlier variety is regarded to be a better successful carrier than the latter. Even though this research does not evaluate waterways reservoirs, past studies have shown that reservoirs by the beach seem to be more prolific in the research region. Inner ponds are typically transient, and typically generate the majority of their viral throughout the rainy period. As a result, although the reservoir groundwater table varies much, steady surface runoff waters of the reservoir settle down the basins across the beach; as a result, basins near the beachfront are sufficient to elicit disease carriers year-round. Streams and huge ponds are two more potential parasite sites to consider. Perennial streams with vegetative ecosystems and ponds, on the other hand, are lacking in this research region. Tiny ponds might occur on the dry banks of ephemeral flows, although the majority of them are only there for a short time.

2.4.2.3 Malaria prevention in the lakeside

This strategy document, produced in 2000, discussed numerous ways to increase ITN service to achieve a goal of 60 percent by 2005 for communities at hazard. As a result, numerous methods of distributing ITNs to dangerous groups had become developed. Voluntary public circulation initiatives, as well as corporate release, were among the options available. Just several ITNs were provided by experimental facilities or non-governmental groups during this timeframe, but most came from for retailing industry (NGOs) (Omondi & Kamau, 2018)**.** As a result of here, the authorities tried a variety of methods to serve the countryside poor and ensure maximum inclusion of at-threat communities via publicly marketed market industry nets or government-subsidized nets. Although in 2006, a widespread to provide 3.4 million nets paid for by the state to kids younger aged five was initiated utilizing US$ 17 million by either the GFATM phase II financing to deliver 3.4 million netting to kids between July and September 2006. Almost immediately, research was released that evaluated the effectiveness of various distribution strategies in respect of expanded inclusion and equality in populations across four distinct malaria ecosystems.

Free public campaigns were shown to be the most efficient and fair method in this investigation. Nets were shown to have a considerable influence on preventing malaria deaths in similar areas. As a result of this research, the WHO amended its ITN recommendations and now recommends that mosquito nets be given out free of charge to those who are most in need (Omondi & Kamau, 2018)**.** With the help of financing from DFID, to WHO-Kenya, and USAID, plus partial assistance from GFATM Cycle II, a countrywide program to re-treat contaminated nets using K O-TAB 1-2-3 and restore ripped or broken nets was launched in 2008. There seem to be several 1.93

million nettings that were disinfected, and 207,290 that had been ripped were rectified, respectively.

Seasonally adjusted outbreak preventive activities have been implemented from 2007 instead of a reaction strategy by addressing indoor residual spraying. Mostly in three regions of Homa-Bay, Migori, and a portion of Kisumu wherein malaria infection has been ongoing since 2010, a new initiative using IRS and LLIN was launched in Kisumu exclusively addressed the Nyando area (Omondi & Kamau, 2018).

Based on the information above, even though the spread of malaria in the Lake Victoria area of Kenya has slowed, the disease must be completely eradicated from the region. A nation evaluation of patterns in malaria adverse events reveals that not all patterns are created comparable; significant distinctions subsist in the sequence of malaria enrollment among spots, and these deviations necessitate further effort to determine what is obligated to advertise a diagnostic transformation throughout the Nyanza region. Although interference reportage and financial backing for malaria prevention and influence in Kenya have risen in the decades noted in this essay, there are several depictions of the shifting burden of diseases obtainable, and the handful of findings accessible are either from secluded, centralized findings or are of reviews at the national scale, so too is the case in this article.

2.4.3 Malaria situation In Kenyan Coast

Billions of shillings have been channeled into the fight against malaria through delivery of drugs and control measures. These measures together have helped to reduce mortality rate as a result of malaria. The fight has however been made difficult by changes in climate and the changes in the methods of land use. It is difficult to predict the future risk of malaria if the increasing and declining trends cannot be properly understood (Le et al., 2019). This in turn affects plans for eradication of malaria. The research in this paper covers the long-term changes in malaria prevalence along the Kenyan coast providing insights to long term and short-term malaria cycles. The Kenyan coast is made up of Kilifi, Kwale and Mombasa counties and occupies a 21,000-kilometer square of land. The land if populated by tropical forest, Savanna and dry thorn bush as well seasonal swamps and plantations. The highest altitude on the plain land is 845 meters above sea level. Three major rivers feed into the Indian ocean and are filled by a number of seasonal streams.

Most habitats of the region are Mijikenda with Mombasa, Kilifi, Malindi, Mtwapa, Ukunda and Msambweni as the major urban centers. The rural communities are subsistence farmers growing maize, millet, cassava and beans. The weather is inter-tropic with short rains witnessed between November and March/April. The heaviest rains between April and May and originates from the monsoon winds that blow from the southeast. The Anopheles gambiae and Anopheles funestus are the major malaria vector species (Mulambalah, 2018). The Anopheles gambiae predominates the region with its sibling Anopheles merus occupying the Indian Ocean coastline and the Anopheles arabiensis occupying the northern parts of Kilifi County. Anopheles gambiae s.s is more common to the south near Tanzanian border. The information for the research was collected from National ministry of health archives and research centers along the Kenya coast. The nets used before 2005 required retreatment every six months and could only be effective in one 12-month cycle. Since 2005 long lasting treated nets we used and were effective for up to three years. The data that was used is both published and unpublished.

2.4.3 Characteristics Contributing to Malaria cases

Along the Kenyan coast, prevalence of the Plasmodium falciparum parasite has been on the rise from 1974 to 1987. The spread reduced between 1991 and 1992 but then started rising until 2014 when it declined. This was mainly as a result of variations in rainfall and the resistance to chloroquine and the introduction of sulfadoxine (Le et al., 2019) **.** The period between 1974 and 1981 had lower than average long-term annual and long rains. Malaria prevalence increased between 1974 and 1978. Between 1982 and 1987 the coastal region experienced rainfall higher than average increasing malaria prevalence. High malaria prevalence was witnessed during the 1993 drought. In 1994 there were heavy rains and el-nino rains were witnessed in 1997 increasing the prevalence of the malaria parasites.

Between this time the parasite prevalence went low even though rainfall above normal was witnessed. However, the prevalence declined between 2002 and 2006 when there was drought witnessed in the region. There were heavy rainfalls between 2006 and 2007 but these had no effect on the increase or decline of the parasite prevalence. The drought between 2008 and 2010 reduced the prevalence. In 2011 the continued drought led to a rise in the prevalence and this was further witnessed during the rainfall of 2014 which was above average. Malaria parasite prevalence in the coastal region has been greatly affected by rainfall, vector control and use of anti-malaria drugs (Nderu et al., 2019) **.** Malaria control was mostly done using CQ and pyrimethamine drugs since the 1970s.

Resistance to these drugs increased malaria prevalence during periods when there was rainfall that fall way below average measures. There was only 43% use of insecticide treated nets in 2006 among all age groups up until 2010. This led to a decline in the malaria parasite prevalence and a reduction of the effects of the parasite transmission until 2012. The effectiveness of the nets went down between 2011 and 2014 and participated in the increase of the prevalence in addition to be higher than average rainfall reported during this time. The use of long-lasting insecticide nets was not as effective when tested using a small number of people as compared to the powerful secular trends. The large-scale accessibility of the malaria drugs such as CQ and the low price they were sold for increased the use of these drugs resulted in the resistance to these drugs as a result of continued use (Mulambalah, 2018) **.**

2.4.3.1 Measures to combat malaria

Chloroquine and pyrimethamine were used as mass-drug administration at settlement schemes at Sabakai-Malindi in Kilifi County, Shimba hills in Kwale county in the 1970s. the first case of resistance to chloroquine was reported in 1978. Resistance to in vitro CQ was reported in 1982 while resistance to in vivo was reported in 1983. More than 40% of infected children failed to clear the infection within seven days of CQ treatment. In 1999 CQ was replaced with pyrimethamine and full sensitivity of the parasites was evidenced in 1987 with infections being cleared with seven days and patients remaining uninfected up to the fourteenth day (Forsyth et al., 2022) **.** Resistance to SP was reported in for in vitro and in vivo in 1993. National treatment policy was changed in 2004 and Artemether-Lumefantrine was recommended but due to implementation and training, SP was still being used for treatment until 2007.

Resistance to CQ in the 1980s resulted into increase in malaria parasite prevalence until the 1990s. The prophylactic effect of CQ resulted in reduced malaria prevalence in the 2000 era. The replacement of SP with AL was done before it was rendered totally ineffective the Malindi community formed PUMMA (punguza mbu sahau malaria) in 2002 which means eradicate mosquitoes forget malaria. The group is responsible for hiring scouts who look for mosquito breeding sites inside Malindi and report the mosquitos as well as delivering samples for testing. The Mosquito scouts are financed by Swiss organization Biovision. The scouts are also responsible for reduction of mosquito reproduction such as the use of small fish to eat the larvae in ponds and pools. This has greatly reduced mosquito population in the area.

2.4.3.2 Regional spatial distribution of Malaria

The three counties of Kilifi, Kwale and Mombasa contains 279 sub-locations that have a median area of 26km^2. The distribution of the parasite prevalence is uneven in time and space. During a recent test 43% of the people tested positive. Between march and May of 2018, the test recorded the lowest number of positive cases but the period between June and August of the same year recorded 45% of positive cases and a similar recording was made between December 2018 and February 2019. For an analysis of temporal changes Bayesian conditional autoregressive generalized linear mixed model with spatial temporal effects is used (Nderu et al., 2019). This model assumes that children between two years and ten years represent the binomial random variable which is a function of the probability of infection per location at a particular time. In Malindi, malaria is a threat to the lives of both adults and children as well as the livelihood of the community.

A lot of people die including women and children under five years as well as pregnant women. Immunity in malaria is developed quickly. The spatial effects were both structured an unstructured. In Kilifi prevalence of malaria parasites reduced between 1998 to 2010 and this also reduced the number of pediatric malaria admissions in Kilifi as well as declining admissions in Malindi and Msambweni (Forsyth et al., 2022) . This also reduced the infection prevalence among pregnant mothers in the southern part of the coast. The prevalence however rises between 2011 and 2014. Between 1974 and 1981 there were log rains which were lower than average but malaria prevalence increased between 1974 and 1978. Between 1982 and 1987 there were heavy rains higher than normal increasing malaria prevalence. The long-term cycles make it possible for temporal effects of rainfall to be examined (Kamau et al., 2020) **.** Poor coverage by ITNs increased malaria prevalence reducing the prevalence.

Due to their ineffective period, the LINs distributed to the masses in 2012 did not reduce the prevalence in 2014 because their effective period had already passed. The replacement of CQ with the combination of amodiaquine and SP played a great role in reducing the prevalence during a period that was characterized by strong rains. Development of resistance to half-life drugs such as CQ and SP led to the changing of policies introducing AL to the circulation. Developing of resistance is the greatest source of large-scale use of malaria drugs (Le et al., 2019). The analysis for malaria prevalence is done on the hotspots and secondary hotspots of the coastal region. The homestead uses of ITNs and LLINs has been applied in the research based on overnight use of the nets per homestead. Ponds and pools are common habitats for the anopheles' species with Anopheles fenestus and anopheles coustani being mainly found in Kilifi and Kwale.

2.4.3.3 Government measures to fight malaria

Use of insecticide treated nets were used along the Kenyan coast between 1993 and 1995 as randomized clinical trials in the north Kilifi creek and the southern parts of kwale county. There were few coverages of insecticide treated nets between 1995 and 2003. From October 2004 ITNs were offered free of charge at clinics for maternal and child welfare. Since May 2005 there have been long lasting treated nets in circulation. Before then nets needed to be retreated every six months and were only effective for a single twelve-month cycle. The long-lasting treated nets were found to be effective for three years with reducing effectiveness every year (Mulambalah, 2018) .They were rendered in-effective on the fourth year. In October 2006 Long, lasting treated nets were delivered freely during the first mass door-to-door campaign. These nets did not have a wide coverage between 2006 and 2012. Due to the declining prevalence Insecticide treated nets were still given out during routines until 2012 when a mass campaign was done delivering over 1.5 million nets.

This was followed by delivery routines until December 2014. This did not prevent malaria prevalence from rising between 2011 and 2014. The distribution of insecticide treated nets reduced the prevalence between 1997 and 2005. The President Uhuru Kenyatta launched Kenya Malaria Youth Army on 22nd July 2021 in Kilifi to bring youth from all over the country to help with the fight against malaria and to improve maternal and child health. This was in support of the Africa Leaders Malaria Alliance movement to eliminate malaria in Africa. Its aim of to eliminate malaria by 2030. The Youth Army is mandated with the responsibility of raising awareness, sensitization of community activities and disseminating malaria messages (Okoyo et al., 2021)**.** The army will implement policies and support malaria prevention measures for communities. The army will distribute insecticide treated nets, spray larvicides at malaria breeding sites and indoor residual spraying of homes in the lake and coastal regions of the country.

The army is also responsible for the delivery of the tools for prevention diagnosis and treatment of malaria in the different parts of the country. The team is also responsible for improved malaria surveillance and strengthening of health systems and to help in data sharing for the inclusivity in decision making. The team is responsible for initiation dialogues that involves social and economic processes in the contribution to malaria and overall health agenda. The Youth Army will leverage on NYS to facilitate indoor residual spraying of homes in counties that are malaria prone. The government has rolled out RTS, S/AS01 vaccine for children who are six months old and above. The vaccine will be prioritized in the coastal region which is greatly affected. The government is also rolling out insecticide-treated bed nets and indoor pesticide spraying (Okoyo et al., 2021) **.** This is also done in conjunction with accessing malaria diagnosis and treatment.

2.4.4 Malaria in Arid and Semi- Arid areas

Malaria situations in Kenya are most prevalent in arid and semi-arid lands in the country. These areas are often related to endemicity such as Embu, Kitui, and Machakos. More than four million are reported annually in Kenya. This statistic also supports a five percent mortality rate among patients who are suffering from severe malaria. Additionally, transmission patterns in the country are influenced by rainfall, altitude, and vector species which is an underrated yet important contributing factor. Stable malaria cites an occurrence in areas of Nyanza and Coast province (Mwaura et al., 2022) **.** The transmission rates for these counties are high with an average of one mosquito bite per person and week, annually.

Areas such as Nairobi and Central Kenya are at an advantage due to the altitude level of sixteen hundred meters and therefore are seen as malaria-free. The first focus area of spread as per this paper is the unstable areas such as Embu, Kitui, Machakos, Marigat, and Ngurumani. These areas are classified into the Eastern and Rift valley provinces respectively. The definition of unstable malaria points out it is the type of transmission that is seen in areas of low endemicity. Another definition cites unstable malaria as a type seen in areas without malaria or among non-immune persons. The epidemics alter according to human behavior and climate factors.

The three areas of Eastern province and two areas of the Rift valley are under the unstable classification. Spatial distribution in these areas is a tool that monitors the impact of control. The three areas carry the same type of malaria, which is Plasmodium falciparum. This parasite is the most prevalent in these three regions (Mwaura et al., 2022)**.** One of the uniform effects of the spread of malaria among the three areas in the Eastern province is economic loss. Malaria and poverty are ultimately connected in various ways. The spread of the disease results in major trade losses as the disease is geographically specific. This means that the disease does not necessarily occur because of poverty.

This paper highlights the geographical advantage that areas such as Nairobi and Central province hold since they carry a medium altitude. Apart from geography being the main contributing factor in Embu, Kitui, and Machakos, ecological conditions are a contributing factor too. This supports the mosquito vectors to determine the distribution and intensity of the disease. Statistics for the three regions considered the intensity of malaria with one percentage less per person, annually (Malinga et al., 2019) **.** Additionally, this factored in a ten percent reduction in malaria with an associated pattern of less than one percent growth.

As it is known, a malarious community is an impoverished community. This is true, especially for the Arid and Semi-Arid lands. One of the challenges that follow the study of malaria is the lack of high-quality data, especially for the affected regions in ASAL. For both the stable and unstable regions, the occurrence of low income and the spread of malaria are affected by the tropics due to poor soils, low agricultural productivity, and other diverse diseases that eventually contribute to malaria. One debatable question is whether malaria in both the stable and unstable regions is a cause rather than a consequence of poverty. Malaria's pattern is somewhat different from the patterns of other diseases such as typhoid. By itself, it follows a continuous pattern of climate and ecology. Other minor determinants are bed nets, which apply to an urbanized area. However, these are not the main prevalent.

The economic issue, though emphasized in this paper is not the main effect. To support this fact, one such area is Kilifi which is a high tourist center and one of the stable malaria areas (Malinga et al., 2019) . The economic foundation of Kilifi is much better than compared of Kitui due to tourist activities. The only disadvantage that this area faces is its geography. As a country, Kenya has made a notable amount of progress in reducing the disease over the last twenty-six years, especially for the said regions. The Spatial maps applied that monitor malaria prevention is a considerable tool in pointing out other additional issues. Additionally, thirty-six years of spatial presentation gives an understanding of the prevalent variant of malaria otherwise known as plasmodium falciparum.

The method applied in the spatial distribution factored in the prevalent variant undertaken in both the stable and unstable regions. A Spatio-temporal geostatistical model was fit for this experiment especially with the sample study group being children from two to ten years of age (Odhiambo et al., 2020) . The age group was compared against all the explanatory variables. The model used categorized areas with alternating degrees of prediction from two crucial threshold policies that are less than one percent or greater and equal to thirty percent which is the exceedance probability. From the given regions, eighty-eight percent reduction dictated a mean model from a percentage statistic of an accurate twenty-one percent.

The last twenty-six years have seen the ASAL regions work towards reducing the spread of malaria as compared to the last twenty-six years. There remain certain areas where the current levels are alarming and therefore the methods might fail for example Machakos. The spatial modeling approach gives the ministry of health opportunities that are worth revising for the future pool of resources. Malaria risk mapping in the ASAL regions of Kenya is not a new tactic. Utilizing the pool of information provided by spatial resolution areas malaria risks for ASAL. Kenya holds a vast knowledge of resources due to its surveys, which is an additional opportunity to explore the initial patterns. The application of spatial methods is to understand the altering landscapes of malaria transmission and statistically represent the outcomes.

The measures put in place to combat the disease are at individual levels and more specifically apply to each region uniquely (Monroe et al., 2020) **.** This is because transmission is not always the same all over the country. At individual levels, areas such as the coastal region and Lake Victoria region factor in the use of insecticides, which are at relatively affordable prices. Such is the primary preventive tool. On the other hand, areas such as Nairobi which are rarely affected unless during rainy seasons factor in preventive measures by applying surveillance and treatment. Additionally, many people prefer the use of treated bed nets, especially for vulnerable people such as the old, pregnant women, and children.

The ministry of health advises pregnant women to at least take an intermittent preventive treatment that targets pregnant women and helps by giving preventive doses of antimalarial drug. If the parasite is already in the mother's bloodstream, severe cases result in miscarriage, which would have otherwise been prevented if the mother had taken an intermittent preventive treatment. The purchase of bed nets is seen as an underrated part of preventive measures since many people think that this is a waste of money. The strategy behind bed nets is not as effective but they have at least contributed to preventing the disease.

The preventive measures prove that mosquitos continually develop a resistance to the insecticides specifically applying to indoor spraying and bed nets. This has alarmed the public health officials who depend on the intervention. The ministry has additionally modified its insecticides through continuous research to combat mosquito**.** The inclusion of the government to fight the disease is an important facet of malaria prevention. The World Health Organization has supported efforts by the government to help Kenya towards the goal which is elimination. The ministry of health under the government in collaboration with the World Health Organization has introduced an anti-malarial vaccine that aims to combat the disease resistance (Kohler & Bowra, 2020).

The government has supported the foundations of laboratories that support new classes of vector insecticides to be used for bed nets and sprays. This is alongside approaches such as bait devices that kill mosquitoes. The government, through the ministry of health, reduced the tax on malaria preventive tools such as insecticides and indoor sprays. This is important since every person can afford to have one if not all of the tools. Mass education is another factor that the government has had to introduce especially with the spread of the disease. It is noted that most lack the proper knowledge, especially in the stable and unstable areas. The assumptions that the citizens have, especially towards the disease is the reason why it is still prevalent. Geographical regions are cited to be one of the contributing factors, however, such can be avoided with the right methods.

One of the preventive lessons taught in mass education is clearing of bushes and swampy areas which form a thriving basis for the mosquitoes (Kohler & Bowra, 2020). The government of Kenya has rolled out an anti-malaria vaccine free for all. This encourages a large number of people who show up just for the vaccine. Additionally, hospitals have nets that are given to pregnant mothers and their unborn children since this forms part of the vulnerable group of people. The ministry of health, under the government, has continually supported malarial research through setting aside funds that are specifically targeted at eliminate the diseases. Research is an important tool as is known all over the world. This is why the government has taken into account its benefits and used it to find solutions that would reduce the large statistics for the future generation.

2.5 Malaria Risk factors

2.5.1 Age

Age Is one of the key factors that contributes to malaria endemicity in many areas, and especially in tropical regions. From a study carried out in Zambia, it was found that increase in temperature and average humidity is associated with increased malaria incidences in children <5 years. In other studies, it has been found out that malaria prevalence increases with age especially in children. More children in the age bracket of 10-14 years suffer more due to high prevalence in this age set in Kenya (Sultana et al., 2017).

2.5.2 Region

According to (Sultana et al., 2017), in elevated areas where there are low temperatures, the rate of mosquito bites was twice as high in relation to low lying lands. This implies that topography of different regions has a great influence on the rate of replication of mosquitoes, thus the topography, complexity as well as the landscapes in the highlands influences the spatial heterogeneity in abundance of the vector as well as the intensity of transmission of malaria. Hence the survival rate of the vectors varies with intensity.

According to(Sultana et al., 2017), It was found that different Zones were a major factor in the way that malaria causing parasites are spread and the way malaria is distributed in some areas. In comparison to plains and urban areas, malaria was found to be more rampant in zones that are highly forested. Mosquitoes in these areas were also seen to have a larger life span in comparison to those in less forested areas. In other studies, they have shown that for instance, the spatial and temporal variation and distribution of the anopheles gambiae strain and the changes in the land use in some zones, especially in and areas around western Kenya highlands were mostly confined within the valley bottoms. This study also established that in areas that have been cleared for land use, especially in riparian lands and swampy areas had a high concentration of the disease. Thus, on studying the characteristic in these areas, it shows that the occurrence of the anopheline larva as statistically significant. In humid Zones, the mosquitoes in these areas are seen to have a longer lifespan than in arid and semi-arid areas. This can be attributed by the fact that the ecological factors in the areas of high humidity favor reproduction of these parasites.

2.5.3 Wealth distribution

One of the major risk factors for Malaria is the socio-economic position. It is an important observation that in many instances, malaria has been closely associated with poverty. On average, many cases of malaria have been reported in poor households and communities compared to the least poor(Tuyishimire, 2016). Household income is an important indicator to investigate the cases of malaria in many households in the country. Thus, it is important to point out that wealth indices in both households and communities have strong predictive values between health outcomes and socio-economic position. As such, wealth plays a major role on how health outcomes in relation to malaria compares in different regions around the country. In many major studies, the underlying findings has been the fact that most disease cases and overall effects affects poorest of the communities and malaria is not exceptional.

2.5.4 Place of residence

The areas of residence have been seen to have a major effect on the way malaria is spread in the country. There is a great variation in malaria prevalence between the rural and urban areas. For instance, studies have shown that the prevalence of malaria is high in rural than in urban areas accounting for 10.16% and 2.93% respectively. More so access to mediums of information is high in urban areas a factor that has greatly contributed to there being less cases of malaria especially in urban areas (Sultana et al., 2017).

2.6 Summary

We deduced from the study that malaria is a significant challenge which requires much effort and resources to fight the disease. Governments, especially those in developing countries, have to put resources into fighting the disease at the expense of other national development agendas. Most of these developing countries, especially Kenya, are in the initial stages of fighting the disease and have so much that they need to do to combat the disease entirely.

CHAPTER THREE

METHODOLOGY

3.1 Introduction

This chapter gives the model in the statistical application of malaria data to be used. The advancement in technology and the wide availability of data has brought a wide variety of data sets some of which has georeferenced sample locations.

3.2 Materials and Methods: Data

The study is based on secondary data. Data from malaria indicator survey of 2015 (KMIS 2015) in collaboration with Kenya National Bureau of Statistics (KNBS) was used for the study. The response variable of the study was malaria outcome. The predictor variables (χ_i)variables for the study included social-economic and demographic factors. The predictor variables included: Place of residence, wealth index, education level, Marital status and age. The dataset has both continuous and categorical variables. This dataset has a binary outcome (response, dependent) variable, malaria status (represented with 0s (no malaria) and 1s (has malaria). The predictor variables are factored to categorical variables—dichotomous and multiple categories except the age of the respondents, which is a continuous variable.

3.3 Statistical method: Logistic regression

A logistic regression model is ideal in cases where outcome variables are categorical. A univariate standard logistic model between each single covariate with the outcome variables (Malaria status). This model is appropriate in the case where the dependent variables are dichotomous. To investigate the status of malaria.

Let γ_{ij} be the status of the disease. For the individual j residing in the region ***i***. Therefore, i=*1, 2… 47*. Thus $\gamma_{ij} = 1$ **f**or an individual j recorded positive for malaria residing in county i, and 0 $otherwise$.The study assumes that $\gamma_{ij} = 1$ is a constant variable and a univariate Bernoulli distributed;

$$\gamma_{ij}|\rho_{ij} \sim Bernoulli(\rho_{ij}). \tag{1}$$

The ρ continuous independent variables are contained in the vector $\chi_{ijk} = (\chi_{ij1}, \chi_{ij2}, \dots \chi_{ij\rho})$whereas $\omega_{ijk} = (\omega_{ij1},\ \omega_{ij2}, \dots, \omega_{ijr})$ contains the r categorical independent random variables. In this model, the first component accounts for the intercept*. (p=1 (age), r = 0…)*

The unknown mean responses in the study: $\mathrm{E}(\gamma_{ij}) = \rho_{ij}$ relates to the independent variables as:

$$h(\rho_{ij}) = X^T \beta_1 + \omega^T \gamma \tag{2}$$

The logit link function is shown as h (.) for equation (2) above, the continuous independent variables, β represents the regression coefficients vectors of *p* dimension. The categorical independent variables are represented by γ which is a vector of r dimensions. A random walk model of order 2(RW2) accounts for the spatial autocorrelation and for non-linear effects of the continuous variables. The model relaxes the restrictive linear predictors to more semi-parametric predictors as;

$$h(\rho_{ij}) = \sum_{t=1}^{\rho} f t\ (\chi_{ijt}) + f_{\ s\rho\alpha t}(S_{i1}) + \omega^{\mathrm{T}} \gamma_1. \tag{3}$$

This model is used to determine the risk factors of malaria in Kenya. Objective (1).

For continuous covariates, function $ft(.)$ is a twice differentiable non-liner smooth function. $f_{\,sp\alpha t}(S_{ik})$ accounts for spatial effects for each of the county. The study used a convoluted structure, where the assumption is that spatial effects can be decomposed into spatially unstructured and spatially structured Components (Ngesa et al., 2014);

$$f_{\,sp\alpha t}(S_{ik}), = f_{\,str}(S_{ik}), (S_{ik}) + f_{\,unstr}(S_{ik}), \text{ k=1,0} \tag{4}$$

The spatially unstructured random effects cover for the correlation or the unobserved covariates inherent within the counties, like climate, culture or social-economic activity. The spatially structured random effects accounts for the un-observed covariates varying spatially in these counties. This defines the spatial autocorrelation. Technically, it refers to the dependence due to the geographical proximity. Therefore, the final model is expressed as:

$$h\left(\rho_{ijk}\right) = \sum_{t=1}^{\rho} ft\left(\chi_{ijt}\right) + f_{\,str}(S_{ik}) + f_{\,unstr}(S_{ik}) + \omega^{\mathrm{T}}\gamma_1 \tag{5}$$

The model is important in relaxing the stationarity assumption on the effects of risk factors on the prevalence of malaria in Kenya. Thus, helping meet the deliverable for objective (2).

Parameter Estimation:

The study used a fully Bayesian estimation approach: The parameters were assigned prior distributions in the study.

Non- linear effects

There are several methods that have been extensively used in estimating of smooth functions, $f(.)$. Among the most used model is the penalised regression splines model used by Eiliers and Marx. In this model the assumption is that the effects of the continuous covariates can be estimated using the polynomial spline (Eilers & Marx, 1996)**.** In the study, the random walk model was used in the estimation of the smooth function $ft(.)$

3.4 Spatial Model

In Spatial processes, the assumption that the relationship between the explanatory variable and the response variable is constant across the study regions does not hold. This relationship is affected by a number of factors in sampling variation like culture, attitude of people and in some area's different response to a similar stimulus as we move across the space. The conditional autoregressive (CAR) model relaxes this stationarity assumption allowing the covariates to vary spatially.

The spatial model specifies the distribution of data conditional on the unknown parameters. Subsequently the Unknown parameters are specified conditional on other parameters under study. Thus:

$$\gamma_{ij1}|\rho_{ij1} \sim Bernoulli(\rho_{ij1})$$

$$h(\rho_{ij}) = X^T\beta_1 + \omega^T\gamma \qquad (6)$$

Therefore, for the regression coefficients, $\left[\gamma \middle| u_{\gamma}, \Sigma_{\gamma}\right] = \mathrm{N}(1_{\eta\times 1} \otimes u_{\gamma}, \Sigma_{\gamma})$ defines the prior distribution:

$\mu_{\gamma} = (\mu_{\gamma 0}, \mu_{\gamma 1}, \dots, \mu_{\gamma \rho})T$ is the mean vector for regression coefficients corresponding to the explanatory variable ρ**.** The covariance Σ_{γ} takes into account the spatial dependence where the priors for γ are put into account / specified.

3.5 The Conditional Auto-Regressive (CAR) Model

The model describes observations varying over discrete sets of indices, like the number of disease cases recorded across regions and counties. They are extensively used to put into account correlations among the observations of interest in hierarchical models. Consider a random vector $\mu = (\mu_1, \dots, \mu_n)^{\mathrm{T}}$. Assuming that each of the components is univariate and fixed at a fixed site $i \in \{1,2, \dots, n\}$, these sites can represent either regions in space or points. The components of μ on the other hand can either be discrete or continuous. The CAR model allows to obtain the multivariate distributions for μ from univariate specifications based on local properties for regions of interest**.** Assuming that the conditional distribution $p(\mu_1|\mu_{j\neq i})$ Depends only on those sites that are neighbours of i. Only when j is defined as a neighbour of i if and only if the conditional distribution at site i depends on value at site j . For the Gaussian Conditional Auto-regressions:

A random vector $\mu = (\mu_1, \dots, \mu_n)T$ is the vector of means of the regression coefficients corresponding to each of n explanatory variables that follows the CAR model described if,

$\mu|\mu_{-1} \sim N(\sum_{j\in di} a_{ij}u_j,)$ where $\mu_{-1} = \{u_j, j \neq i\}$, (7)

a_{ij} denotes the sets that contain indices which are neighbours of i.

3.6 Posterior Distribution

The posterior distribution defines the way the parameters are distributed after observing the Data. Hence, once the prior distribution is updated with the observed data, the posterior distribution is obtained. Thus, sampling from the posterior distribution, it is then those inferences are made. The most common method for inferencing is the Markov Chain Monte Carlo (MCMC), however the method is very slow and performs poorly when such models are used. Thus, in order to go about these shortcomings, Integrated Nested Laplace Approximation (INLA) criteria is introduced (Rue et al., 2009)**.** Though a relatively new model, it works well in such cases. Therefore, for the latent Gaussian model, the Posterior Distribution becomes:

$$\pi(\chi, \theta|\gamma) \propto \pi(\theta)\pi(\chi|\theta) \prod_{\mathrm{i} \in \mathrm{I}} \pi(\gamma_i|\chi_i, \theta)$$

$$\propto \pi(\theta)|Q(\theta)|^{\frac{n}{2}} \exp\left(-\frac{1}{2}\chi^T Q(\theta)\chi + \sum_{\mathrm{i}\in\mathrm{I}} \log \pi(\gamma_i|\chi_i, \theta)\right) \qquad (8)$$

The class of latent fields is represented by χ, set of hyper parameters are represented by θ. The data is represented by . Therefore, the approach for INLA, the posterior marginal of interest is:

$$\pi(\chi_i|\gamma) = \int \pi(\chi_i|\theta, \gamma)\, \pi(\theta|\gamma) d\theta \qquad (9)$$

$$\pi(\chi_i|\gamma) = \int \pi(\theta|\gamma)d\theta_{\mathrm{J}} \qquad (10)$$

Therefore, these are used in the creation of nested approximations:

$$\tilde{\pi}(\chi_i|\gamma) = \int \tilde{\pi}(\chi_i|\theta,\gamma)\, \tilde{\pi}(\theta|\gamma)d\theta,\ \tilde{\pi}(\chi_i|\gamma) = \int \tilde{\pi}(\theta|\gamma)d\theta_{\mathrm{J}} \qquad (11)$$

3.7 Odds Ratio (OR)

Odds Ratio is the ratio that defines the probability of an event taking place or not happening. In Logistic regression, the Odds ratio refers to the exponential of the estimated coefficients exp $(\hat{\beta})$ and for each continuous covariate ***j***, where exp $(\hat{\beta})$ is the predicted change in Odds for the ***j*** predictor variable. The study has multiple independent variables; thus, they are categorized into ***k*** levels and their Odds ratios (OR) is subsequently determined,

$$OR= \left[\frac{P(Y=1/x_i)}{1-P(Y=1/x_i)}\right]= \left[\frac{\pi}{1-\pi}\right]=exp(\beta_o + \beta_1 X_1+, \ldots, +\beta_k X_k) \qquad (12)$$

Logit function= log (OR)

$$Log\ (OR)= \left[\frac{P(Y=1/x_i)}{1-P(Y=1/x_i)}\right]=Log\left[\frac{\pi}{1-\pi}\right]=(\beta_o + \beta_1 X_1+, \ldots, +\beta_k X_k)=\sum_{j=0}^{k} \beta_j X_j \qquad (13)$$

i =*1,2,… , n* and *j=0,1,2, ..., k*

$Log\left[\frac{\pi}{1-\pi}\right]$ is important in contingency table analysis ("log Odds") which has two columns and many rows of values of x.

3.8 Model Diagnostics

To come with the best model, the models will be compared using the Deviance information criteria (DIC). The model was proposed by Spiegelhalter et al, (2014). From the models tested, the model that will show the smallest DIC is the best fit of the models. The methods of obtaining the DIC is as:

$$DIC = \bar{D}\,(\theta) + P^D,$$

In the formula, the posterior means of the deviance that measure the goodness of fit is represented by $\bar{D}$, On the other hand, P^D will be used to give the number of parameters that is effective, that penalizes for the model complexity. In the model diagnostics, a better fit is indicated low values of $\bar{D}$, on the other hand, when there are low values of $\boldsymbol{P^D}$, it shows model parsimony.

3.9 Summary

The spatially structured random effects account for the unobserved covariates in these counties. This defines spatial autocorrelation. In Spatial processes, the assumption that the relationship between the explanatory variable and the response variable is constant across the study regions does not hold. It was observed that the most common method for inferencing is the Markov Chain Monte Carlo (MCMC); however, the technique is very slow and performs poorly when such models are used.

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1 Introduction

In this section, a logistic regression is used to explain each individual variable that determine the malaria condition. Each independent variable is fitted into the model and considered significant at 0.05 significance level and 95% confidence level. The results are as Presented.

Table 1. Malaria Prevalence Determining Factors

Malaria Risk Predictors

Variable	N	OR[1,2]	SE[2]	95% CI[2]	p-value
Age	6,481	0.98***	0.005	0.97, 0.99	<0.001
Net_used	6,481				
No		—	—	—	
Yes		0.99	0.101	0.81, 1.20	0.91
Education_level	5,226				
No_Education		—	—	—	
Primary		1.13	0.123	0.88, 1.43	0.33
Secondary		1.40	0.204	0.92, 2.06	0.10
Tertiary		1.01	0.180	0.70, 1.42	0.97
Wealth_index	6,481				
Middle		—	—	—	
Poorer		1.21	0.165	0.88, 1.68	0.24
Poorest		1.37*	0.155	1.02, 1.86	0.041
Richer		1.28	0.162	0.94, 1.77	0.12
Richest		1.26	0.164	0.91, 1.74	0.16
Endemicity_zone	6,481				
Coast endemic		—	—	—	
Highland Epidemic		1.12	0.189	0.78, 1.63	0.55
Lake endemic		1.68**	0.182	1.18, 2.43	0.004
Low Risk		1.29	0.180	0.91, 1.85	0.16
Semi-arid, Seasonal		1.80***	0.176	1.29, 2.56	<0.001
has_mosquito_net	6,481				
No		—	—	—	
Yes		1.02	0.102	0.83, 1.24	0.88
Residence	6,481				

Table 1. Malaria Prevalence Determining Factors

Malaria Risk Predictors

Variable	**N**	**OR[1,2]**	**SE[2]**	**95% CI[2]**	**p-value**
Rural		—	—	—	
Urban		0.84	0.096	0.70, 1.01	0.069
Marital_status	6,481				
Divorced		—	—	—	
Living Together		0.39***	0.242	0.25, 0.64	<0.001
Married		0.24***	0.209	0.16, 0.36	<0.001
Not Living together		0.25***	0.233	0.16, 0.40	<0.001
Widowed		0.59*	0.254	0.36, 0.98	0.040
County	6,481				
Baringo		—	—	—	
Bomet		0.55	0.521	0.19, 1.51	0.24
Bungoma		0.88	0.453	0.36, 2.20	0.77
Busia		0.40	0.574	0.12, 1.20	0.11
Elgeyo Marakwet		1.07	0.481	0.41, 2.79	0.89
Embu		0.40	0.617	0.11, 1.28	0.14
Garissa		3.07**	0.416	1.40, 7.28	0.007
Homa Bay		0.42	0.543	0.14, 1.20	0.11
Isiolo		0.83	0.525	0.29, 2.32	0.72
Kajiado		0.30	0.681	0.07, 1.05	0.079
Kakamega		0.17**	0.678	0.04, 0.59	0.009
Kericho		0.46	0.618	0.12, 1.48	0.21
Kiambu		0.57	0.466	0.23, 1.46	0.23
Kilifi		0.81	0.430	0.35, 1.95	0.62
Kirinyaga		0.76	0.478	0.30, 1.99	0.57
Kisii		0.73	0.490	0.27, 1.93	0.52
Kisumu		3.26**	0.393	1.57, 7.45	0.003
Kitui		1.11	0.482	0.43, 2.91	0.83
Kwale		0.16**	0.678	0.04, 0.56	0.007
Laikipia		0.99	0.461	0.40, 2.52	0.99
Lamu		1.65	0.435	0.72, 4.03	0.25
Machakos		0.47	0.520	0.16, 1.29	0.14
Makueni		0.94	0.492	0.35, 2.51	0.90
Mandera		2.51*	0.446	1.07, 6.25	0.039
Marsabit		0.22	0.795	0.03, 0.90	0.060
Meru		0.53	0.576	0.16, 1.58	0.27
Migori		1.54	0.435	0.67, 3.75	0.32
Mombasa		0.16*	0.793	0.02, 0.63	0.019
Murang'a		0.35	0.573	0.10, 1.03	0.064
Nairobi		0.96	0.441	0.41, 2.36	0.92
Nakuru		0.84	0.440	0.36, 2.06	0.69

Table 1. Malaria Prevalence Determining Factors

Malaria Risk Predictors

Variable	**N**	**OR**[1,2]	**SE**[2]	**95% CI**[2]	**p-value**
Nandi		1.30	0.443	0.55, 3.22	0.55
Narok		0.71	0.505	0.26, 1.93	0.50
Nyamira		0.33	0.616	0.09, 1.06	0.074
Nyandarua		1.14	0.455	0.47, 2.86	0.78
Nyeri		0.83	0.479	0.32, 2.17	0.70
Samburu		0.63	0.577	0.19, 1.89	0.42
Siaya		1.56	0.420	0.70, 3.71	0.29
Taita Taveta		0.48	0.502	0.17, 1.29	0.14
Tana River		1.12	0.494	0.42, 2.98	0.82
Tharaka Nithi		0.56	0.576	0.17, 1.69	0.32
Trans Nzoia		0.38	0.573	0.11, 1.15	0.095
Turkana		1.25	0.555	0.40, 3.68	0.68
Uashin Gishu		0.62	0.489	0.23, 1.64	0.33
Vihiga		0.15*	0.793	0.02, 0.62	0.019
Wajir		2.18	0.434	0.95, 5.33	0.072
West Pokot		0.72	0.490	0.27, 1.90	0.50

Data Source: Kenya malaria indicator survey of 2015

1 *p<0.05; **p<0.01; ***p<0.001

2 OR = Odds Ratio, SE = Standard Error, CI = Confidence Interval

The results show different analyses of the dataset using a logistics regression model. Other than the estimated value of individual variables, there are coefficients and their standard errors, the z value, the p-value, the odds ratio, and the confident intervals at 0.05. Since the variables are categorical, some terms have strong statistical significance, weak statistical significance, and others do not reached statistical significance. As such, some of these are brought about due to cases of missing data.

The study used the OR to define and conclude the relationships of independent variables to the logistics regression model of the outcome variable, malaria status. Considering the OR description of the individual variables, the study categorized them into three groups. The first group of OR greater than 1 (OR>1), second group OR = 1, and third group OR < 1. From the logistic regression model of malaria, Table 2, we get older age is a significant risk of malaria with Odds ratio =0.98*** 95% confidence interval (0.97, 0.99), and p-value <0.001 much less than 0.05. This is to mean that as one advances in old age, the odd is 0.98~1 times larger. The true p-value is between the 0.97 and 0.99 at 95% confidence interval. The chance of aged respondents contracting malaria increases significantly. Respondents in rural areas have odds of 1.32 times to malaria outcome effects versus no effect than those living in the urban areas and was statistically significant to the malaria outcome. The odds of getting (verse not getting malaria) in places of residence increases by 1.32, which is estimated to .28, CIs 95% (1.01, 1.72), and a p-value .04. Respondents in urban are less prone to malaria effects than those in rural areas, this could be attributed to the intervention measures and access of information in the respective areas.

The level of education (highest education level) odds given the presence of malaria verse no malaria are indirectly proportional to the level of education, respondents of primary level have odds of 1.13 and were statistical significance, CIs 95% (.88, 1.43), p-value .33. Respondents of education levels secondary and tertiary have the odds of (1.40 & 1.01), CIs 95% (.92, 2.06), (.70, 1.42) respectively and the p-value of .10 for secondary education level and .97 for tertiary level of education. Respondents with no education were used as default reference category with no effect on the outcome variable (malaria cases). in general, less educated respondents are reported having more exposure to malaria and its subsequent effects compared to people with higher levels of education; that is secondary and tertiary education.

Marital status (living together vs divorced, married vs divorced, not living together vs divorced, and windowed vs divorced) levels are significantly associated risk of malaria with Odds ratio as shown in the table above. Divorced level is at more risk than any other marital status. Living together, married and not living together are strongly significantly associated risk of malaria with p-value <0.001.

The odds of malaria in counties of residence are different; County levels include all 47 counties in Kenya with Baringo as reference category. Garissa, Kakamega, Kisumu, Kwale, Mandera, Mombasa, and Vihiga are significantly associated risk of malaria prevalence with Kisumu leading with Odds ratio = 3.26** , confidence interval (1.57, 7.45), and p-value 0.003.

The odds of malaria outcome to the endemicity zones varies significantly. In these zones (Highland Epidemic vs Coast endemic, Lake endemic vs Coast endemic, Low Risk vs Coast endemic, and Semi-arid, Seasonal vs Coast endemic), Lake endemic and Semi-arid, Seasonal levels are significantly associated risk of malaria with Odds ratio =1.68** confidence interval (1.18, 2.43), and p-value=0.004 <0.05, and Odds ratio =1.80*** confidence interval (1.29, 2.56), and p-value<0.001 respectively. Respondents in lake and coastal endemic zone are more prone to malaria compared to other zones. Those in semi-arid, seasonal and low risk zones are second in vulnerability to malaria. Those lake endemic zone are Siaya, Busia, Kisumu, Migori, Kakamega, Homa-bay, Bungoma, and Vihiga. As such, these areas recorded more malaria cases than any other region in the country. These findings are consistent with (Homan et al., 2016)**,** that occupation, population density, social economic status, and population density increased the risk of malaria, the model included environmental and household factors.

The categorical variables in the study of malaria outcome their terms/groups are not consistent with the dependent variable (malaria cases outcome). For those that reached statistical significance, some have a strong relationship, others weak, and no relationship to the outcome variables at all. The analysis is based on the OR, CIs, and P-value of the variables. The lake endemic zone residence has high exposure to malaria, these regions reported more cases compared to other zones. Other people prone to malaria effect are divorced and people with less education, primary level.

4.2 Spatial maps

In epidemiological modelling, Bayesian approach is essential as it allows the modelling of these epidemiological problems hierarchically. Employing the approach, in order to attain reliable estimates, the method was essential in determine the spatial distribution of Malaria in Kenya. As proposed by(Eilers & Marx, 1996), in order to perform a semi-parametric modelling to allow the spatial variation of the outcome variables, the study used B-splines, penalized likelihood as well as penalized regression splines, to determine the regional variation of malaria. The assumptions of linearity allowed some covariates like age to have a non-linear effect on prevalence of malaria. Using random walk model of Second order and the assumption of stationarity, this allowed covariates to vary spatially using conditional autoregressive model. Thus, in order to model the spatial effects in the model, Bayesian geostatistical models was used to the malaria risk data in quantifying the environmental-disease relations, identification of significant malaria predictors and transmission in the environment and provided a model-based malaria risk predictors as suggested by (Gosoniu et al., 2006). The models used in the study were based on the assumption of stationarity. In the study, the general assumption was that spatial correlation is a function of the distance between location and independence of location.

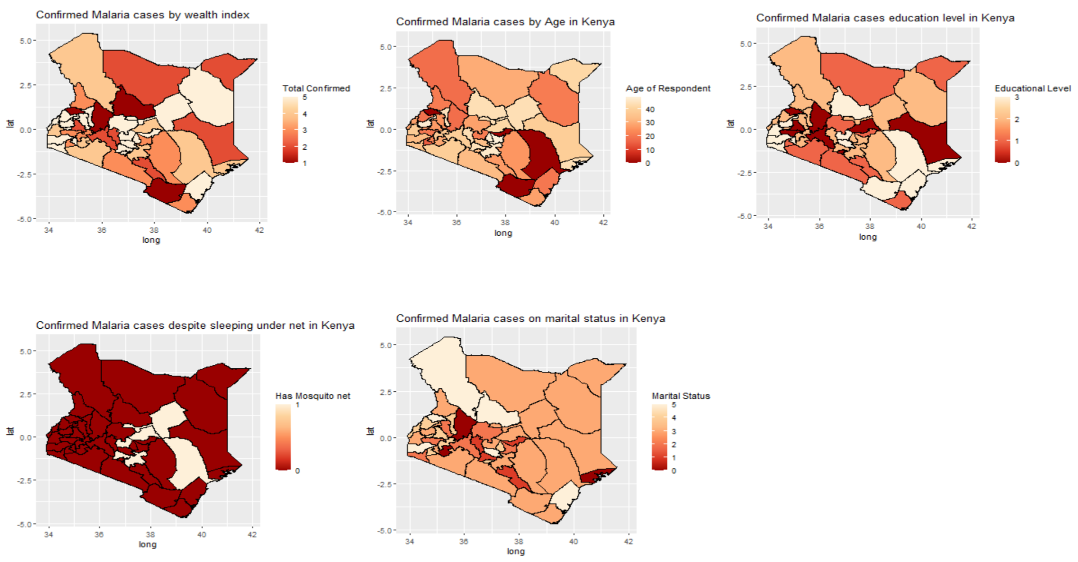

Fig 1: Spatially Varying effects of Covariates on Malaria

The spatial variation of Malaria in Kenya is shown in the maps. These effects are represented geographically as the map of Kenya is segmented into 47 counties. Each map represents each predictor variable under study. These variables are Age, wealth index, education level, Has Mosquitoes nets and marital status. From the first map on wealth index, which shows that as darker the color the lower the wealth index, it is clear that as we increase the wealth bracket the cases of malaria decreases, this may be because the wealthy have ways of prevention of mosquito into human contact either by using mosquito nets of other ways(Ssempiira et al., 2017).

Counties on lower index include Samburu, Baringo, Taita-Taveta. Consequently, these counties are experiencing a surge in malaria cases, in more wealthier counties of central Kenya like Nyeri, Kiambu, Murang'a, Meru, Tharaka-Nithi, Kirinyaga as well as the county of Nairobi, there are less cases Nairobi of malaria based on wealth distribution among inhabitants. These findings are consistent with (Gosoniu et al., 2006) that the results indicates that the stationarity assumption is a very important factor, since it had a major influence on the significance of environmental factors and the corresponding malaria risk maps.

The second map represents the distribution of malaria in Kenya based on Age of the respondent in each household surveyed, as age advanced, people become more prone to malaria, most of the counties reported high cases of Malaria among advanced age groups as compared to the other younger middle age groups. These are the youths age group and as such the cases of malaria increase as the age advances. In counties such as Mombasa, Tana River, Taita-Taveta, Tharaka Nithi, Trans-Nzoia, Kisumu, Homabay, Baringo and Kakamega. However, the severity of these cases varied significantly from one country to the other, with more severe cases being recorded around the lake region counties (Jenkins et al., 2015).

From the third map of education level, which shows darker shade from low education levels up to the tertiary education level, many counties reported more malaria cases among those counties where residents had minimal access to education. Fewer cases are recorded in counties registering high access to secondary and tertiary education with more cases recorded in those with primary education or none. Of such, counties in North rift like Baringo and Turkana and those in North Eastern Kenya like Garissa, Mandera, Wajir recorded More cases of malaria where access to education is minimal.

From the fourth map of cases despite sleeping under net, almost the whole country had cases of people getting malaria by not sleeping under net. But few counties like Isiolo, Meru, Nyeri, Machakos reported cases of malaria despite sleeping under net. Thus, in those regions where there are minimal cases of access to mosquito nets or where either deliberate or not people chose not to sleep under a treated mosquito net, there were more cases of malaria recorded. However, this variable seemed synonymous in almost all regions of the country. From the fifth map of cases on Marital status, most counties reported cases those on level 4 and 5. Counties like Lamu, Makueni, Kericho had many cases of malaria among the single people.

4.3 Summary

The results from the data analysis show that several factors are associated with risk of malaria, some of these factors includes wealth, education level as well as places of residence. For those risk factors that reached statistical significance, some showed a strong relationship and others had a weak relationship with the dependent variable.

CHAPTER FIVE

CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

The study found out that a significant relationship exists between malaria and socio-economic, demographic and environmental factors. Age, Wealth, Region, place of residence, marital status and education were significant factors in the distribution of malaria in Kenya. Some factors like risk in rainy season and gender were not considered due to large amounts of missing data. Wealthy household reported far less cases of malaria compared to their poor counterparts. This was largely due to the fact that most of these wealthy household had better capacity and resources to manage and also prevent fatalities caused by malaria. As such mm, it could be attributed to better housing facilities, access to improved healthcare and living in good sanitary environments, of which, such resources were scarce in poor households. Similarly, education levels in households were seen as another major factor. In those households recording improved access to education, secondary and tertiary institutions, that recorded lower cases of malaria compared to the illiterate households. Education plays a key role in how culture and beliefs are shaped. Those more educated are most likely to adopt new and improved practices compared to less educated households. Such households are most likely to visit health centers to manage conditions in comparison. Thus, as the literacy levels in households increases, they tend to have more ability to access information and control measures as they emerge, this has had a direct impact on lowering the cases of malaria.

Place and region of residence was another important factor that showed a significant relationship with the prevalence of malaria. People living in urban areas recorded fewer cases of malaria compared to those living in rural areas. This observation could be attributed to access to better health facilities in urban areas compared to rural areas. More so, people in urban areas to have a better access to information compared to the rural dwellers. On the other hand, region of residence was an important covariate on the spread on malaria. Some regions are more prone and high cases of malaria in comparison to the others. For instance, coastal and lake region counties recorded more cases of malaria compared to others. This could be, to a large part attributed to weather patterns in these counties. They were found to have many ideal places and weather conditions that harbored the breeding of mosquitos, thus a rise in malaria cases in these regions. However, on the other part, some other counties like northern Kenya also recorded higher cases of malaria, this could be attributed also to the climatic patterns in those regions, Mores, lack of access to better health infrastructure and information contributed greatly to many malaria cases in these regions. On major observation was the fact that in most of the regions experiencing high malaria cases, multiple covariates/variables are more pronounced here; some of these includes, minimal wealth distribution, poor access to education, low access to mosquito nets.

5.2 Recommendations

It is evident that from the study that there is a spatial variation of malaria prevalence in Kenya. A number of factors contributes to this, to the large degree, this can be attributed to uneven distribution of key resources in Kenya. Those counties with improve infrastructure and resources were seen to record minimal cases of malaria. Lack of access to basic infrastructure like healthcare, improved living conditions, better economic environment were seen to largely cause this variation. Similarly, poor sensitization campaigns, diet as well as lack of control to other infectious diseases had a major role on the spread of malaria. Those regions sharing common neighborhoods were also found to have similar malaria patterns. This could be attributed to factors like wealth distribution, access to education and health facilities as well as weather patterns, which to large degree led to higher prevalence of malaria in those regions, like lake region counties, western highlands and coastal regions.

In order to curb the menace that malaria is, there is need to have a tailor-made approach from the government and private sector as well. This study recommends that, both levels of government increase funding on malaria control initiatives. It also recommends that both levels of government to improve on existing and developed new infrastructure in healthcare and sanitization. There should be an initiative to push for access to improved housing facilities. There is also a recommendation for a community level outreach programs for those in rural areas to sensitize them on the dangers of malaria and the best strategies to control and subsequent eradication of malaria. more so, this study recommends a custom approach, where region specific initiatives are modelled specific to each region, since a wholistic approach has failed to recognize regions-specific challenges. Similarly, the study recommends that more research and resources to be put in place, borrowing best practices from regions that have successfully fought the pandemic, for instance China which has recently been declared Malaria free by the Word health Organization (WHO).

The study also established a strong correlation on regions sharing common boundaries. For example, the lake region and coastal region counties. These counties have people with similar cultural practices, weather patterns and socio-economic practices, a such, heightened campaigns on adoption and use of treated mosquito nets in these regions as well other endemic regions should be a priority for both levels of government.

Malaria control programs, availability of well-trained health personnel to help in managing the problems, improved sanitary facilities, improved wealth distribution and programs to improve literacy levels in households should be prioritized. That way, the knowledge gap on both the population and health personnel will be bridged. This will cause a ripple effect overall on governments effort to curb the prevalence and overall eradication of Malaria in Kenya.

5.3 Future Work

Based on the findings from the study, the following recommendations are made for the future work;

(i) A more localized study which is county-based should be considered to ascertain whether the counties have the same challenges as those seen at the country level.

(ii) With rapid development in technology, there has been a gradual development in exposure modelling and mapping, improved study designs, coupled with the improved and new methods used for surveillance in health databases, the ability to understand environment-health relations has been improved, as such, the study recommends the use of these improved methods of study.

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APPENDICES

APPENDIX I: PUBLICATION

John, M. M., Luchemo, E., & Anapapa, A. (2021). Spatial Modelling of Malaria Prevalence in Kenya. *Asian Journal of Probability and Statistics*, *14*(3), 8-21. https://doi.org/10.9734/ajpas/2021/v14i330328

Appendix 1I: Malaria Data Summary

Table 1. Malaria Data Summary

Variable	**N = 6,481**[1]
Participant_ID	3,241 (1,621, 4,861)
Status	465 (7.2%)
Education_level	
No_Education	2,578 (49%)
Primary	1,680 (32%)
Secondary	346 (6.6%)
Tertiary	622 (12%)
Unknown	1,255
Wealth_index	
Middle	1,203 (19%)
Poorer	1,230 (19%)
Poorest	1,528 (24%)
Richer	1,289 (20%)
Richest	1,231 (19%)
Endemicity_zone	
Coast endemic	894 (14%)
Highland Epidemic	1,369 (21%)
Lake endemic	1,182 (18%)
Low Risk	1,605 (25%)
Semi-arid, Seasonal	1,431 (22%)
has_mosquito_net	4,258 (66%)
Residence	
Rural	2,985 (46%)
Urban	3,496 (54%)
Risk_in_rainy_season	
Somewhat Agree	864 (13%)
Somewhat Disagree	923 (14%)
Strongly Disagree	3,603 (56%)
Strongly Agree	1,091 (17%)
Marital_status	
Divorced	151 (2.3%)
Living Together	606 (9.4%)
Married	4,255 (66%)
Not Living together	1,128 (17%)
Widowed	341 (5.3%)
Net_used	2,274 (35%)
County	
Baringo	105 (1.6%)
Bomet	144 (2.2%)
Bungoma	171 (2.6%)
Busia	138 (2.1%)
Elgeyo Marakwet	110 (1.7%)

Appendix 1I: Malaria Data Summary

Table 1. Malaria Data Summary

Variable	N = 6,481[1]
a	110 (1.7%)
Garissa	112 (1.7%)
Homa Bay	158 (2.4%)
Isiolo	97 (1.5%)
Kajiado	109 (1.7%)
Kakamega	190 (2.9%)
Kericho	96 (1.5%)
Kiambu	216 (3.3%)
Kilifi	242 (3.7%)
Kirinyaga	150 (2.3%)
Kisii	141 (2.2%)
Kisumu	171 (2.6%)
Kitui	106 (1.6%)
Kwale	201 (3.1%)
Laikipia	141 (2.2%)
Lamu	127 (2.0%)
Machakos	167 (2.6%)
Makueni	111 (1.7%)
Mandera	84 (1.3%)
Marsabit	97 (1.5%)
Meru	106 (1.6%)
Migori	135 (2.1%)
Mombasa	138 (2.1%)
Murang'a	159 (2.5%)
Nairobi	182 (2.8%)
Nakuru	206 (3.2%)
Nandi	138 (2.1%)
Narok	128 (2.0%)
Nyamira	132 (2.0%)
Nyandarua	135 (2.1%)
Nyeri	138 (2.1%)
Samburu	90 (1.4%)
Siaya	165 (2.5%)
Taita Taveta	186 (2.9%)
Tana River	95 (1.5%)
Tharaka Nithi	100 (1.5%)
Trans Nzoia	144 (2.2%)
Turkana	57 (0.9%)

Appendix 1I: Malaria Data Summary

Table 1. Malaria Data Summary

Variable	**N = 6,481**[1]
Uashin Gishu	164 (2.5%)
Vihiga	140 (2.2%)
Wajir	106 (1.6%)
West Pokot	143 (2.2%)
Age	31 (24, 41)
Region	
Central	798 (12%)
Coast	989 (15%)
Eastern	894 (14%)
Nairobi	182 (2.8%)
North Eastern	302 (4.7%)
Nyanza	902 (14%)
Rift Valley	1,775 (27%)
Western	639 (9.9%)
Country	
Kenya	6,481 (100%)
Age_group	
(15,20]	740 (11%)
(20,25]	1,332 (21%)
(25,30]	1,071 (17%)
(30,35]	876 (14%)
(35,40]	781 (12%)
(40,45]	616 (9.5%)
(45,50]	485 (7.5%)
(50,55]	314 (4.9%)
(55,60]	181 (2.8%)
(60,65]	60 (0.9%)
Unknown	25

[1] Median (IQR); n (%)

Appendix III: R-codes: Linear Regression

```
library(tidyverse)
library(gtsummary)
library(survival)
library(rio) # used to import data from the directory



#import data

malaria<-read.csv("C:\\Post Grad Final\\malaria_complete.csv",header=T,sep=",")

attach(malaria)

##format categorical and level variables as factor.
malaria$Education_level <- as.factor(malaria$Education_level)
malaria$Country <- as.factor(malaria$Country)
malaria$Wealth_index <- as.factor(malaria$Wealth_index)
malaria$Endemicity_zone <- as.factor(malaria$Endemicity_zone)
malaria$has_mosquito_net <- as.factor(malaria$has_mosquito_net)
malaria$Residence <- as.factor(malaria$Residence)
malaria$Marital_status <- as.factor(malaria$Marital_status)
malaria$Net_used <- as.factor(malaria$Net_used)
malaria$Region <- as.factor(malaria$Region)
malaria$Risk_in_rainy_season <-as.factor(malaria$Risk_in_rainy_season)


#group age , Mutate age
malaria$Age_group <- cut(malaria$Age,c(15,20,25,30,35,40,45,50,55,60,65))

############################initial data formatting############################
malaria$Education_level[malaria$Education_level == 0] <-"No_education"
malaria$Education_level[malaria$Education_level == 1] <-"No_education"
malaria$Education_level[malaria$Education_level == 2] <-"Primary"
malaria$Education_level[malaria$Education_level == 3] <-"Primary"
malaria$Education_level[malaria$Education_level == 4] <-"Secondary"
malaria$Education_level[malaria$Education_level == 5] <-"Tertiary"
```

```
malaria$Education_level[malaria$Education_level == 5] <-"Tertiary"

malaria$Education_level <- as.factor(malaria$Education_level)
summary(malaria$Education_level)

write_csv(malaria, file = "data/malaria.csv")
###########################        end          ############################


##malaria data summary
tbl_summary(malaria) %>%
  bold_labels() %>%
  modify_header(label ~ "**Variable**") %>%
  as_gt() %>%
  gt::tab_header(
    title = gt::md("**Table 1. Malaria Data Summary**")
  )



#build logistic model
malaria_md <- glm(Status ~ Age + Age_group + Net_used + Education_level +
                    Wealth_index + Endemicity_zone + has_mosquito_net + Residence +
                       Marital_status + County, malaria, family = binomial()
           )

```

```

##Create publication table
malaria_md %>%
  tbl_regression(exponentiate = TRUE,) %>%
  bold_labels() %>%
  modify_header(label~"**Variable**") %>%
  add_significance_stars(
    hide_ci = FALSE,
    hide_p = FALSE
      ) %>%
   as_gt() %>%
  gt::tab_header(
    title = gt::md("**Table 2. Malaria Prevalence Determining Factors**")
  ) %>%
  gt::tab_options(
    table.font.size = "small",
    data_row.padding = gt::px(.3),
  ) %>%
  gt::tab_source_note("Kenya malaria indicator survey of 2015")




###uvregression--univariate reg.
malaria %>%
  select(Status, Age, Net_used, Education_level,
         Wealth_index, Endemicity_zone, has_mosquito_net, Residence,
         Marital_status,County) %>%
  tbl_uvregression(
    method = glm,
    y = Status
```

```
    method = glm,
    y = Status,
    method.args = list(family = binomial),
    exponentiate = TRUE,
    pvalue_fun = ~style_pvalue(.x, digits = 2)) %>%
  bold_labels() %>%
  modify_header(label~"**Variable**") %>%
  add_significance_stars(
    hide_ci = FALSE,
    hide_p = FALSE
  ) %>%
  as_gt() %>%
  gt::tab_header(
    title = gt::md("**Table 2. Malaria Prevalence Determining Factors**"),
    subtitle = gt::md("**Malaria Risk Predictors**")
  ) %>%
  gt::tab_options(
    table.font.size = "small",
    data_row.padding = gt::px(.3),
  ) %>%
  gt::tab_source_note("Data Source: Kenya malaria indicator survey of 2015")
```

Appendix IV: R-Codes: Spatial Analysis

```
library(rgdal) #reading shapefiles
library(plotly) #interactive visualization
library(tmap)
library(rgdal)    # for readOGR and others
library(sp)       # for spatial objects
library(leaflet)  # for interactive maps (NOT leafletR here)
library(dplyr)    # for working with data frames
library(ggplot2)  # for plotting
library(sf)
library(ff)       # for memory allocation. not necessary for now


#Loading the Data

#Notice the function setNames used below.
#It is a convenience function that sets the names on an object and returns the object.
malaria <- read.csv("C:/Msc Project/anaZip/Malaria analysis Kenya/malaria-analysis-kenya map/MalariaAGE.csv")

head(malaria)
str(malaria)

#GROUPING THE DATA

labs <- c(paste(seq(0, 30, by = 5), seq(0 + 5 - 1, 35 - 1, by = 5),
                sep = "-"), paste(35, "+", sep = ""))
labs

#To add the ages to age groups, we create a new column AgeGroup
#and use the cut function to break Age into groups with the labels we defined in the previous step

missing.age <- is.na(malaria$age.of.respondent)
malaria <- malaria[!missing.age,]  # Remove NA

#OR REPLACE IT WITH 0
malaria[is.na(malaria)] = 0
```

```

x_num <- as.numeric(malaria$age.of.respondent)
malaria$AgeGroup <- cut(x_num, breaks = c(seq(0, 35, by = 5), Inf), labels = labs, right = FALSE)

head(malaria[c("age.of.respondent", "AgeGroup")], 15)

head(malaria)
#Loading the Shapefiles
kenyaShp1<- readOGR("./www/shp/county.shp")

##Converting the Shp to a data frame
kenyaShpdf <- fortify(kenyaShp1)

library( plyr)
malaria_count<-count(malaria, c("age.of.respondent", "county.of.residence"))
head(malaria_count)
#TOTAL COUNT BY COUNTY
malaria_count$total <- cumsum(malaria_count$county.of.residence)
head(malaria_count)

#Merging the Shapefiles and the data frame

popDF <- merge(kenyaShpdf, malaria_count, by.x = "id", by.y = "county.of.residence")

library(ggmap)
library(scales)
```

```
library(ggmap)
library(scales)
#LOADING A PRETTY THEME
theme_opts<-list(theme(panel.grid.minor = element_blank(),
                       panel.grid.major = element_blank(),
                       panel.background = element_blank(),
                       plot.background = element_blank(),
                       axis.line = element_blank(),
                       axis.text.x = element_blank(),
                       axis.text.y = element_blank(),
                       axis.ticks = element_blank(),
                       axis.title.x = element_blank(),
                       axis.title.y = element_blank(),
                       plot.title = element_blank()))

#PLOTTING
png("map.png")
map<- ggplot() +
  geom_polygon(data = popDF, aes(x = long, y = lat, group = group, fill =
                                   total),color = "black", size = 0.25) +
  theme(aspect.ratio=1)+
  scale_fill_distiller(name="Total Confirmed", palette = "YlGn", breaks = pretty_breaks(n = 5))+
  labs(title="Confirmed Malaria cases in Kenya")
print(map)
dev.off()

#using different themes
library(ggthemes)

map+ theme_igray() + scale_colour_colorblind()

```

```

#MALARIA BY AGE
png("map1.png")
map1<- ggplot() +
  geom_polygon(data = popDF, aes(x = long, y = lat, group = group, fill =
                                   age.of.respondent),color = "black", size = 0.25) +
  theme(aspect.ratio=1)+
  scale_fill_distiller(name="Age of Respondent", palette = "OrRd", breaks = pretty_breaks(n = 5))+
  labs(title="Confirmed Malaria cases by Age in Kenya")
map1
print(map1)
dev.off()

#MALARIA BY EDUCATION LEVEL

#It is a convenience function that sets the names on an object and returns the object.
malaria1 <- read.csv("C:/Users/Kireru's/Documents/R list/kenya map/Malaria.csv")
head(malaria1)
#OR REPLACE IT WITH 0
malaria1[is.na(malaria1)] = 0

labs <- c(paste(seq(0, 30, by = 5), seq(0 + 5 - 1, 35 - 1, by = 5),
                sep = "-"), paste(35, "+", sep = ""))
labs

#To add the ages to age groups, we create a new column AgeGroup
#and use the cut function to break Age into groups with the labels we defined in the previous step

missing.age <- is.na(malaria1$age.of.respondent)

#OR REPLACE IT WITH 0
malaria1[is.na(malaria1)] = 0
```

```r
malaria1[is.na(malaria1)] = 0

x_num <- as.numeric(malaria1$age.of.respondent)
malaria1$AgeGroup <- cut(x_num, breaks = c(seq(0, 35, by = 5), Inf), labels = labs, right = FALSE)

head(malaria1[c("age.of.respondent", "AgeGroup")], 15)

head(malaria1)
#Loading the Shapefiles
kenyaShp1<- readOGR("./www/shp/county.shp")

##Converting the Shp to a data frame
kenyaShpdf <- fortify(kenyaShp1)

library( plyr)
malaria_count1<-count(malaria1, c("highest.education.level", "county.of.residence"))
head(malaria_count1)
#TOTAL COUNT BY COUNTY
malaria_count1$total <- cumsum(malaria_count1$county.of.residence)
head(malaria_count1)

malaria_count2<-count(malaria1, c("wealth.index", "county.of.residence"))
head(malaria_count2)

malaria_count2$total <- cumsum(malaria_count2$county.of.residence)
head(malaria_count2)

malaria_count3<-count(malaria1, c("has.mosquito.net", "county.of.residence"))
head(malaria_count3)

malaria_count3$total <- cumsum(malaria_count3$county.of.residence)
head(malaria_count3)

malaria_count4<-count(malaria1, c("marital.status", "county.of.residence"))
head(malaria_count4)

malaria_count4$total <- cumsum(malaria_count4$county.of.residence)
head(malaria_count4)


popDF1 <- merge(kenyaShpdf, malaria_count1, by.x = "id", by.y = "county.of.residence")
head(popDF1)

popDF2 <- merge(kenyaShpdf, malaria_count2, by.x = "id", by.y = "county.of.residence")
head(popDF2)

popDF3 <- merge(kenyaShpdf, malaria_count3, by.x = "id", by.y = "county.of.residence")
head(popDF2)

popDF4 <- merge(kenyaShpdf, malaria_count4, by.x = "id", by.y = "county.of.residence")
head(popDF2)


library(ggmap)
library(scales)

#LOADING A PRETTY THEME
theme_opts<-list(theme(panel.grid.minor = element_blank(),
                       panel.grid.major = element_blank(),
                       panel.background = element_blank(),
                       plot.background = element_blank(),
                       axis.line = element_blank(),
                       axis.text.x = element_blank(),
                       axis.text.y = element_blank(),
                       axis.ticks = element_blank(),
                       axis.title.x = element_blank(),
                       axis.title.y = element_blank(),
```

```r
                              axis.title.x = element_blank(),
                              axis.title.y = element_blank(),
                              plot.title = element_blank()))
png("map2.png")
map2<- ggplot() +
  geom_polygon(data = popDF1, aes(x = long, y = lat, group = group, fill =
                                    highest.education.level),color = "black", size = 0.25) +
  theme(aspect.ratio=1)+
  scale_fill_distiller(name="Educational Level", palette = "Blues", breaks = pretty_breaks(n = 3))+
  labs(title="Confirmed Malaria cases education level in Kenya")

map2+ theme_igray() + scale_colour_colorblind()
print(map2)
dev.off()

library(ggthemes)

map2+ theme_igray() + scale_colour_colorblind()

#Having plots in All in One
#Grid arrange

library(cowplot)
library(grid)
library(gridExtra)
library(patchwork)


#MAP
map<- ggplot() +
  geom_polygon(data = popDF2, aes(x = long, y = lat, group = group, fill =
                                     wealth.index),color = "black", size = 0.25) +
  theme(aspect.ratio=1)+
  scale_fill_distiller(name="Total Confirmed", palette = "OrRd", breaks = pretty_breaks(n = 5))+
```

```r
  theme(aspect.ratio=1)+
  scale_fill_distiller(name="Total Confirmed", palette = "OrRd", breaks = pretty_breaks(n = 5))+
  labs(title="Confirmed Malaria cases by wealth index")

#MAP 1

map1<- ggplot() +
  geom_polygon(data = popDF, aes(x = long, y = lat, group = group, fill =
                                   age.of.respondent),color = "black", size = 0.25) +
  theme(aspect.ratio=1)+
  scale_fill_distiller(name="Age of Respondent", palette = "OrRd", breaks = pretty_breaks(n = 5))+
  labs(title="Confirmed Malaria cases by Age in Kenya")

#MAP 2
map2<- ggplot() +
  geom_polygon(data = popDF1, aes(x = long, y = lat, group = group, fill =
                                   highest.education.level),color = "black", size = 0.25) +
  theme(aspect.ratio=1)+
  scale_fill_distiller(name="Educational Level",palette = "OrRd", breaks = pretty_breaks(n = 3))+
  labs(title="Confirmed Malaria cases education level in Kenya")

#MAP 3
map3<- ggplot() +
  geom_polygon(data = popDF3, aes(x = long, y = lat, group = group, fill =
                                   has.mosquito.net),color = "black", size = 0.25) +
  theme(aspect.ratio=1)+
  scale_fill_distiller(name="Has Mosquito net",palette = "OrRd", breaks = pretty_breaks(n = 1))+
  labs(title="Confirmed Malaria cases despite sleeping under net in Kenya")

#MAP 4
map4<- ggplot() +
  geom_polygon(data = popDF4, aes(x = long, y = lat, group = group, fill =
                                   marital.status),color = "black", size = 0.25) +
  theme(aspect.ratio=1)+
```

```
                                 marital.status),color = "black", size = 0.25) +
  theme(aspect.ratio=1)+
  scale_fill_distiller(name="Marital Status",palette = "OrRd", breaks = pretty_breaks(n = 5))+
  labs(title="Confirmed Malaria cases on marital status in Kenya")


png(file="Malaria Plot.png",width=1200,height=800)
grid.arrange( map, map1, map2, map3, map4,ncol=3,nrow=2)
dev.off()

#saving each map(MAP1)
png(file="Malaria1 Plot.png",width=1200,height=800)
grid.arrange( map,ncol=1)
dev.off()
#MAP2
png(file="Malaria2 Plot.png",width=900,height=500)
grid.arrange( map1,ncol=1)
dev.off()
#MAP2
png(file="Malaria3 Plot.png",width=900,height=500)
grid.arrange( map2,ncol=1)
dev.off()
#MAP3
png(file="Malaria4 Plot.png",width=900,height=500)
grid.arrange( map3,ncol=1)
dev.off()
#MAP4
png(file="Malaria5 Plot.png",width=900,height=500)
grid.arrange( map4,ncol=1)
dev.off()
```

```

# calculate cumulative sum of mass by species
sw <- malaria_count %>%
  group_by(species) %>%
  mutate("cm_mass" = cumsum(mass))






#ALLOCATE MORE MEMORY FIRST
if(.Platform$OS.type == "windows") withAutoprint({
memory.size()
memory.size(TRUE)
memory.limit()
})
memory.limit(size=7000)


#DOING WALD.TEST
library(mdscore)

malaria <- read.csv("C:/Users/Kireru's/Documents/R list/kenya map/KMalaria.csv")
str(malaria)
data(strength)
str(strength)
#example from package
fitf <- glm(y ~ cut * lot, data = strength,family = inverse.gaussian("inverse"))
wald.test(fitf,term=9)

```

```r
wald.test(fitf,term=9)

#MY DATA

malaria[sapply(malaria, is.character)]<-lapply(malaria[sapply(malaria, is.character)],as.factor)

fitf <- glm(age.of.respondent ~ has.mosquito.net * highest.education.level , data = malaria,family = inverse.gaussian("inverse"))
wald.test(fitf,term=9)

#EXAMPLE2
data(esoph)
head(esoph)
str(esoph)
 model1 <- glm(cbind(ncases, ncontrols) ~ agegp + tobgp *
     alcgp, data = esoph, family = binomial())
 anova(model1)
wald.test(model1,term=9)
data(api)

model2<-svyglm(I(sch.wide=="Yes")~ell+meals+mobility, design=dclus2, family=quasibinomial())
regTermTest(model2, ~ell)
 regTermTest(model2, ~ell,df=NULL)
 regTermTest(model2, ~ell, method="Wald")
 regTermTest(model2, ~ell+meals, method="LRT")


#DOING MINE
 model1 <- glm(cbind(ncases, ncontrols) ~ agegp + tobgp *
     alcgp, data = malaria, family = binomial())
```