CLIMATE VARIABILITY AND MALARIA PREVALENCE AMONG CHILDREN IN ELGEYO MARAKWET WEST SUB COUNTY, KENYA

BY

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DECLARATION

Declaration by the candidate:

I declare that this is my original work and has not been presented for a degree or award in any other University.

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Supervisor:

I confirm that this Project has been submitted for examination with my approval as the University Supervisor.

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Dr. Ezekiel Ndunda	Date
Department of Environmental Sciences and Education.	

DEDICATION

This project is dedicated to my late Mother, who despite the hard-economic times prevailing especially during my Primary and Secondary Education, worked very hard to see that all of her seven children had a meaningful education. She particularly made sure I went through the four stages of my education uninterrupted up to her demise. Special thanks go to my late father who also ensured that, though we were many in secondary school, each of us received a share of his salary to keep us all fed and in class. Thanks to my Husband and Children for the support they have accorded to me especially during the years of my Masters Studies.

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ABSTRACT

Malaria is a leading infectious disease affecting children under five years old, particularly in developing countries where poor sanitation and poverty exacerbate the situation. The World Health Organization has identified malaria as a primary cause of mortality in this demographic. This study investigated climatic variability and malaria prevalence among children in Marakwet West Sub-County, focusing on spatio-temporal distribution, the association between climate variables and malaria prevalence, and the impact of control interventions. The specific objectives of the study included; to analyze spatio-temporal distribution of malaria prevalence among children, to assess the association of climate variables and malaria prevalence among children, to analyze the effect of climate variables on malaria prevalence among children and to assess the impact of malaria control interventions on incidences of malaria among children in Marakwet West Sub-County. The study used descriptive, empirical, and survey research designs. Semi-structured questionnaires for primary data and secondary data were used. Utilizing purposive and systematic random sampling, the research employed R-Studio and SPSS for data analysis, revealing a strong correlation between climate variations and malaria frequency among children. The findings indicate a significant decline in malaria prevalence from 2012 to 2022 (Mann-Kendall test, $p < 0.05$, Tau = -0.8808), with a notable nonlinear relationship between temperature and malaria transmission peaking at approximately 23°C. Additionally, over 51% of children reported contracting malaria in the three months prior to the survey, with stagnant water bodies near homes contributing to higher incidence rates. An average of 267 cases reported every month (M=266.67) suggests that the OND season has the largest number of malaria cases. The results showed a very weak negative association between time and annual rainfall, as indicated by the tau value of (-0.0926). The Mann-Kendall test findings for maximum temperature show a tau value (-0.141), indicating a slight negative association between time and maximum temperature. Correlation analysis indicated a negative correlation between annual rainfall and malaria prevalence (-0.1694) and a positive correlation between maximum temperature and malaria prevalence (0.3193). These results highlight the complex interplay between climate, environmental factors, and malaria transmission. The study underscores the potential for increased malaria prevalence due to climate change, particularly affecting vulnerable populations, in this case, children. The study conclusively finds that climatic variability significantly affects malaria prevalence among children in Elgeyo Marakwet West Sub County, with a notable decline in malaria cases from 2012 to 2022 attributed to both climate factors and improved control measures. It is recommended that policymakers integrate climate variability data into malaria control strategies to optimize resource allocation and enhance intervention effectiveness.

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ACRONYMS AND ABBREVIATIONS

ACT:	Artemisinin-based Combination Therapy
IPTp:	Intermittent Preventive Treatment in Pregnancy
IRS:	Indoor Residual Spray
ITN:	Insecticide Treatment Networks
LLIN:	Long-Lasting Insecticide-Treated Nets
LSM:	Larval Source Management
NACOSTI:	National Commission for Science, Technology and Innovation
NDVI:	Normalized Difference Vegetation Index
NMS :	National Malaria Strategy
PSM:	Process Safety Management
WHO:	World Health Organization

DEFINATION OF TERMS

Climate Variability- is the varied changes on the climatic conditions that continue longer than given specific weather events (WHO, 2019).

Climate Change - Weather variations that persist in a given area for a long period of time typically more than a decade (WHO, 2019).

Malaria -is an illness that is caused by female anopheles' mosquito, which is a parasite that bites and infects human beings (Hussien, 2019).

Children- is a young human being below the age of puberty or below the legal age of majority, especially 5 years and below (WHO, 2019).

CHAPTER ONE: INTRODUCTION

1.1 Background of the Study

According to Hussein (2019), climate change is broadly defined in terms of either the mean climate state or its variability, which persists for a long period of time and is attributed to the changes in the anthropogenic composition and changes in the land use and atmospheric conditions. It has been noted that climate variables, such as temperature, rainfall patterns and humidity, have dramatic effects on mosquito longevity and malaria transmission (Nkiruka *et al.*, 2021).

The relationship between rainfall and malaria transmission is complex and varies significantly across different geographical regions and climatic conditions. Research has consistently shown that rainfall influences the breeding habitats of malaria vectors, primarily mosquitoes (Mafwele & Lee, 2022). For instance, a study by Amadi & Erandi, (2024) indicated that increased rainfall creates more suitable breeding sites, thereby enhancing the transmission of malaria, particularly in regions where stagnant water accumulates after rainfall events. This relationship is often characterized by a time lag; studies have noted that malaria incidence tends to increase following periods of rainfall, with significant correlations observed at lag periods ranging from zero to several months (Dabaro et al., 2021; Mafwele & Lee, 2022; Amadi & Erandi, 2024).

In specific studies, such as one conducted in Ethiopia by Dabaro et al., (2021) found that rainfall had a positive correlation with malaria incidence at lag periods of zero and two months. This suggests that immediate increases in rainfall can lead to higher malaria cases shortly thereafter. Moreover, the study highlighted that for every millimeter increase in rainfall, the odds of malaria incidence increased by approximately 0.3%, indicating a direct link between precipitation levels and disease transmission (Dabaro et al., 2021). Conversely, other research has suggested that excessive rainfall might lead to lower malaria rates by flushing out mosquito breeding sites, demonstrating that the relationship is not solely linear but influenced by various factors including temperature and altitude (Amadi & Erandi, 2024).

Geographical variability also plays a crucial role in this relationship. For example, in Sri Lanka, strong positive correlations between rainfall and malaria were observed at shorter lags (zero to three months), while negative correlations were noted at longer lags (four to nine months) (Briët et al., 2008). This indicates that while immediate rainfall can enhance malaria transmission, prolonged wet conditions may disrupt mosquito populations or lead to environmental changes that reduce transmission rates (Briët et al., 2008). Similarly, studies in Africa have shown that while moderate rainfall increases malaria incidence due to favorable breeding conditions for mosquitoes, extreme weather patterns can alter these dynamics significantly (Mafwele & Lee, 2022). The interplay between rainfall and malaria transmission is influenced by multiple factors including geographical location, temperature variations, and ecological conditions. Continued research is necessary to understand these dynamics fully and to develop effective malaria control strategies tailored to specific environmental contexts.

Moreover, transmission of malaria and its geographical distribution are influenced by climate change and geographical elevation (Fouque & Reeder, 2019). Environmental factors like rainfall, temperature and humidity could also affect the bionomics of malaria vectors which in turn would determine malaria transmission intensity. Some of the investigations highlighted the ambiguous link between climate change and malaria incidences (Caputo, 2016; Fouque & Reeder, 2019). Furthermore, higher altitude is another factor that contributes to high malaria infection and its spread. That is, as altitude rises the temperature drops and vice versa, which in turn affects the transmission of the infection's dynamics.

Rain can turn rivers into chains of pools, the ideal breeding habitats for mosquitoes, with increased moisture. Kim, *et al.*, (2019), ascertains that heavy precipitation can wash off the spawning grounds in some locations and lessen the occurrence of malaria. According to (Ayanlade *et al.*, 2020), malaria cases in Colombia and Venezuela were reported to have rose by more than one- third following dry El Niño conditions. Global malaria morbidity and death was forecast at 405,000 in 2018 by the World Health Organization, with 94 percent deaths in Sub-Saharan Africa and children under five (WHO, 2019). Efforts to minimize parasite infection have lowered the overall prevalence of cases by 48% (WHO, 2019).

The spread of the disease is partly related to poverty levels but to a large extent, ecological conditions that favor thriving of Anopheles mosquitos (Zhao *et al.*, 2020). Ecological factors that influence spread of malaria range from orientation of the relief, climate factors and to health preparedness. As such rainfall and warm maximum ambient temperatures were found to be significantly inducing spikes in malaria incidences (Kogan,2020). The cases were found to be heightened over East African highlands (Hussien, 2019). Reduction in malaria transmission has remained a chief goal of efforts geared towards suppressing the risk of malaria outbreak (Segun *et al.*, 2020). This study focuses on the effect of climate variability on malaria prevalence among children in Elgeyo Marakwet, Kenya and therefore informs anticipation of malaria cases.

1.1.1 Malaria Prevalence in Elgeyo Marakwet Sub-County

Malaria prevalence in Elgeyo Marakwet Sub-County, Kenya, is a significant public health concern influenced by various ecological and socio-economic factors. Research indicates that the region experiences seasonal malaria transmission, primarily driven by climatic conditions such as rainfall and temperature. A study conducted by Macharia et al. (2018) highlights the importance of understanding spatial and temporal patterns of *Plasmodium falciparum* prevalence in Kenya, which can inform control strategies tailored to specific areas like Elgeyo Marakwet. The findings suggest that while Kenya has made progress in reducing malaria prevalence, certain regions still face challenges that require targeted interventions to manage the disease effectively.

In addition to climate factors, socio-economic conditions play a critical role in malaria transmission dynamics. The ethno-botanical study by Kigen et al. (2021) explored traditional medicinal practices among the Marakwet community, revealing a reliance on local plants for malaria treatment. This underscores the cultural context of malaria management in the area, where traditional knowledge complements modern healthcare interventions. The study identified 31 medicinal plants used by traditional practitioners, emphasizing the ongoing importance of local practices in addressing malaria prevalence amid challenges posed by drug resistance to conventional treatments.

Moreover, the relationship between rainfall and malaria incidence in Elgeyo Marakwet has been documented in various studies. Research indicates that increased rainfall typically correlates with higher malaria cases due to enhanced breeding conditions for *Anopheles* mosquitoes. A time-series analysis by Nyawanda et al. (2023) examined the effects of climate variability on malaria incidence across western Kenya, including regions like Elgeyo Marakwet. Their findings revealed a significant association between rainfall patterns and malaria transmission, highlighting the need for integrated climate and health strategies to mitigate outbreaks. In conclusion, addressing malaria prevalence in Elgeyo Marakwet requires a comprehensive approach that considers environmental factors, traditional practices, and socio-economic conditions.

In Elgeyo Marakwet West Sub-County, seasonal rainfall creates mosquito breeding sites, with studies showing positive correlations at lags of 0-2 months and increased odds of incidence per mm of rain. These dynamics align with Kenya's National Malaria Policy 2024, which provides a framework for control and elimination through strategies like seasonal malaria chemoprevention (SMC), surveillance, and multi-sectoral approaches under universal health coverage, aiming for a malaria-free Kenya via the Kenya Malaria Strategy 2023-2027 (Ministry of Health, 2022).

This urgency resonates with Sustainable Development Goal 3 (SDG 3): "Ensure healthy lives and promote well-being for all at all ages," targeting a reduction in global malaria incidence and mortality by 90% by 2030, alongside ending epidemics and strengthening prevention. Kenya's policy integrates SDG 3 by prioritizing vulnerable groups like children under five, who bear 94% of Sub-Saharan Africa's malaria deaths, and commits to SME (surveillance, monitoring, evaluation) plans, devolved implementation per the 2010 Constitution, and partnerships for resource mobilization (World Health Organization, 2019).

1.1.2 Children in Elgeyo-Marakwet County

The focus on children in Elgeyo Marakwet West Sub-County, Kenya, is primarily due to the heightened vulnerability of this demographic to malaria, a disease that significantly impacts their health and well-being (WHO, 2019). Children under five years old are particularly at risk, as they have not yet developed full immunity to malaria and are more susceptible to severe complications from the disease. According to the World Health Organization, malaria remains one of the leading causes of morbidity and mortality among children in Sub-Saharan Africa, with a substantial percentage of deaths occurring in this age group. In the context of Elgeyo Marakwet, the unique ecological and climatic conditions contribute to a higher prevalence of malaria. The region's environmental factors—such as temperature fluctuations and rainfall patterns—create ideal breeding grounds for Anopheles mosquitoes, which transmit the malaria parasite. Consequently, understanding how these climatic variables affect malaria transmission is crucial for developing effective interventions tailored to protect vulnerable populations, particularly children (WHO, 2019).

Furthermore, the study aims to inform policymakers about trends in malaria prevalence among children in relation to climatic variability. By focusing on this specific age group, the research emphasizes the urgent need for targeted malaria control strategies that can mitigate the impact of climate change on disease transmission and improve health outcomes for children in high-risk areas like Elgeyo Marakwet. This localized focus not only addresses a significant public health challenge but also seeks to enhance community resilience against future malaria outbreaks exacerbated by changing climatic conditions.

1.2 Statement of the Problem

Malaria is a disease that poses a serious threat to the health and well-being of residents in many of Kenya's highland regions. Despite the fact that previous studies have shown that temperature affects mosquito activity, which determines their bite rate, data shows an increase in malaria cases over the past few years (Kogan, 2020). The study investigates the significant issue of malaria prevalence among children in Elgeyo Marakwet West Sub-County, Kenya, particularly in the context of climatic variability. Despite existing research indicating that temperature and rainfall influence mosquito activity and malaria transmission, there remains a notable gap in localized data linking these climatic factors to malaria incidence in this specific region. This gap is critical as malaria continues to be a leading cause of morbidity and mortality among children under five years old, with recent statistics showing a troubling increase in cases despite known correlations between climate variables and disease transmission. The problem is compounded by the complex interplay of various factors affecting malaria transmission, including population dynamics, drug resistance, and local ecological changes driven by human activities such as deforestation and irrigation (Hussien, 2019).

A total of 241 million cases of malaria and 627 000 malaria-related deaths were reported worldwide in 2020, according to the most recent WHO global malaria report. In 2020, there were 14 million more cases and 69,000 more deaths than there were in 2019, according to this estimate. Some 47 000 additional deaths were attributed to the pandemic's disruptions in malaria prevention, diagnosis, and treatment. However, things could have turned out a whole lot worse. The worst-case scenario was averted, however, when countries took immediate action to strengthen their malaria programs there has been an improvement. Malaria remains a major public health concern despite ongoing control efforts, with its prevalence significantly influenced by climatic factors such as temperature variability and rainfall patterns. However, the precise nature and extent of the relationship between these climatic variables and malaria incidence among vulnerable populations, especially children under five, remain inadequately understood in this region. This gap in knowledge limits the effectiveness of targeted interventions and calls for a detailed investigation into how variations in temperature, rainfall intensity, and other local climatic conditions directly affect malaria transmission dynamics.

In Elgeyo Marakwet, the unique geophysical environment contributes to a significant malaria burden, yet the available preventive and control data are insufficient. Malaria preventive and control data in these areas are also poor; however, malaria is among the most common infections in Elgeyo Marakwet County (1-5%). Inadequate understanding of the environmental determinants of the malaria vector against the background of the varied conditions could be responsible in part for the high malaria prevalence rate (Kim *et* *al.*, 2019). This research aims to fill these gaps by analyzing the spatio-temporal distribution of malaria prevalence among children, assessing the association between climate variables and malaria cases, and evaluating the impact of current control interventions.

1.3 Objective of the Study

To determine the effect of climate variability on malaria prevalence among children in Marakwet West Sub-County.

1.4 Research Questions

The research question for this study were:

1. What is the spatio-temporal distribution of malaria prevalence among children in Marakwet West Sub-County?
2. What is the correlation between climate variables and malaria prevalence among children in Marakwet West Sub- County?
3. What is the Effect of climate variables on malaria prevalence among children in Marakwet West Sub-County?
4. Why do malaria control interventions influence the incidences of malaria among children in Marakwet West Sub-County?

1.5. Study Objectives

The specific objectives of the study were:

1. To analyze spatio-temporal distribution of malaria prevalence among children in Marakwet West Sub- County
2. To assess the association of climate variables and malaria prevalence among children in Marakwet West Sub-County
3. To analyze the effect of climate variables on malaria prevalence among children in Marakwet West Sub- County
4. To assess the impact of malaria control interventions on incidences of malaria among children in Marakwet West Sub-County

1.6 Research Hypotheses

This study was guided by the following hypotheses:

H_{O1}: There is no significant change in spatio-temporally distribution of malaria prevalence among children in Marakwet West Sub-County

H_{a1}: There is a significant change in spatio-temporally distribution of malaria prevalence among children in Marakwet West Sub-County

H_{O2}: There is no significant association between climate variables and malaria prevalence among children in Marakwet West Sub-County

H_{a2} There is a significant association between climate variables and malaria prevalence among children in Marakwet West Sub-County

H_{O3}: Climate variables do not significantly affect malaria prevalence among children in Marakwet West Sub- County

H_{a3}: Climate variables significantly affect malaria prevalence among children in Marakwet West Sub- County

H_{O4}: There is no significant impact of malaria control interventions on incidences of malaria among children in Marakwet West Sub-County.

H_{a4}: There is a significant impact of malaria control interventions on incidences of malaria among children in Marakwet West Sub-County.

1.7 Significance of the Study

This study could help in informing the health facilities and the health department in Marakwet West Sub- County on the trends of malaria outbreak in the country. Control intervention measures can be developed in return to help in curbing the spread of malaria among the children below the age of 5 years. Besides, the study could help shedding light to the trends of malaria prevalence in the county and Kenya at large, to initiate early measure that will control the spreading through resource mobilization, information sharing and capacity building of the local on the best practices to apply towards curbing malaria prevalence among the children below 5 years.

This study on the occurrence of malaria at the Marakwet West Sub-County among children add to the existing body of knowledge on the impact of various climatic variabilities on malaria occurrence in a specific area. Previous studies proved that Climate change could be linked to the spread of vector-borne diseases like malaria. This study gives a more fine-grained analysis of the spatio-temporal distribution of malaria in the sub-county along with trends and hotspots, this provides information for scholars within same domain of study.

This study holds substantial importance for public health practitioners by providing empirical evidence on how climatic factors like rainfall and temperature variability drive malaria prevalence among children in Elgeyo Marakwet West Sub-County, enabling more precise targeting of interventions such as indoor residual spraying in high-risk Kerio Valley areas. Policymakers at county and national levels, including the Elgeyo Marakwet County Government and Kenya's Ministry of Health, will benefit from the findings to refine strategies outlined in the Kenya Malaria Strategy 2023-2027, which aims for 80% reduction in incidence through climate-informed resource allocation and epidemic preparedness.

CHAPTER TWO

LITERATURE REVIEW

2.0 Introduction

This literature review synthesizes existing research on malaria epidemiology, with a focus on climate variability's role in transmission dynamics, particularly among children in highland epidemic-prone regions like Elgeyo Marakwet West Sub-County, Kenya. It examines global and regional malaria burdens, climatic drivers such as temperature and rainfall influencing vector biology and parasite development, and the efficacy of control interventions. The review identifies gaps in localized spatio-temporal studies for Kenyan highlands, where seasonal rainfall peaks elevate cases despite national declines, informing hypothesis testing on climate effects and intervention impacts.

2.1 The Global Burden of Malaria

Malaria morbidity and mortality were estimated by the World Health Organization at 405,000 cases in the years 2018. From records, it can be noted that there were 416,000 deaths in 2017, and there were 585, 000 malaria-related morbidity and mortality in 2016. About 200 million deaths related to malaria endemic in the world have been prevented mainly by world investment to combat the disease via the control of malaria (World Health Organization (WHO), 2019).

2.2 Burden of Malaria in Tropical Regions and Sub -Tropical Regions

The Sub-Saharan Africa and India continue remain the areas that are most hit by the malaria prevalence, which faces more than 90% of the malaria burden cases and being the highest recognized world's largest disease prone areas with high increasing cases. According to the WHO, there were about 213 million malaria cases reported in 2018 in Sub-Sahara Africa with the most severe disease burden. 93% of all cases in the world (World Health Organization (WHO), 2019).

Cases of malaria declined 76% between 2010 and 2018 in Cambodia, Thailand, Myanmar, and Vietnam. Other tropical countries like Malaysia, El Salvador and Timor-Leste are working around the clock to control the prevalence of the disease and accomplish the Global Technical Strategy Measures for morbidity as set by WHO. In early 2019, the

World Health Organization certified Algeria and Argentina for the elimination of malaria in 2018, zero indigenous instances were reported by other subtropical nations like Iran and China (WHO, 2019).

2.3 Trends of Malaria Transmission in Kenya

According to the four epidemiological zones in Kenya, endemic areas, highland and epidemic-prone areas, seasonal malaria transmission areas, and low risk all around with sustained malaria can be classified. The seasonal transmission of P. falciparum malaria results in a malaria prevalence of 5-20 % in highland and epidemic-prone regions. Historically, malaria has been observed largely around Victoria Lake and the coastal region in the lowlands of Western Kenya. Malaria was unheard of in other locations. According to Asale *et al.* (2021), malaria cases were not reported before the 1920s in the Rift valley.

Elgeyo Marakwet West Sub-County is indeed considered malaria-prone due to its unique ecological and climatic conditions that favor the proliferation of Anopheles mosquitoes, the primary vectors of malaria. The region experiences a combination of warm temperatures and seasonal rainfall, which creates ideal breeding habitats for these mosquitoes. According to Asale *et al.* (2021), the relationship between climatic variables, such as temperature and precipitation, and malaria incidence is well-documented, with higher temperatures and moderate rainfall correlating with increased malaria prevalence among children. This vulnerability is particularly acute in children under five years old, who are at a greater risk of severe illness and mortality from malaria due to their developing immune systems.

Furthermore, the study highlights that despite ongoing malaria control efforts, there has been a notable rise in malaria cases in Elgeyo Marakwet over recent years. Hussien (2019) emphasizes that ecological factors, including climate variability, play a critical role in influencing malaria transmission dynamics. The interplay of environmental changes and socio-economic factors, such as poverty and inadequate health infrastructure, exacerbates the situation. As noted by Zhao et al. (2020), the geographical characteristics of the region, along with its climatic conditions, significantly contribute to the persistent malaria burden. Therefore, understanding these dynamics is essential for developing effective interventions aimed at reducing malaria prevalence in this vulnerable population.

Asale et al. (2021) aimed to assess community knowledge, perceptions, and practices (KPP) regarding malaria and its control in Jabi Tehnan district, Northwest Ethiopia, a seasonal malaria transmission area, to identify barriers to intervention effectiveness like LLINs and IRS. The study employed a mixed-methods approach, surveying 3010 households across 38 villages, conducting 11 focus group discussions (FGDs) in diverse agro-ecological zones, screening 1256 children under 10 for parasites via microscopy (revealing 1.3% prevalence), and analyzing 5-year district health data trends. While robust in scale and triangulation, the methodology was critiqued for potential recall bias in self-reported practices, limited generalizability beyond highland Ethiopia, and absence of longitudinal follow-up to link KPP changes to outcomes. Key findings showed high knowledge (92% correctly identified mosquitoes as vectors) but gaps in practices (only 52% consistent LLIN use, 41% IRS acceptance), with misconceptions like evil spirits causing malaria persisting; prevalence was low but higher in non-users of interventions, and FGDs highlighted economic barriers and outdoor biting concerns. The study identified gaps in behavioral interventions addressing cultural beliefs and dry-season transmission, relevant to the current Elgeyo Marakwet research by underscoring community-level factors influencing intervention uptake in similar highland epidemic-prone Kenyan settings, complementing climatic analyses with socio-behavioral insights.

Hussien (2019) aimed to examine malaria's association with climatic variables like temperature and rainfall in Gezira State, Sudan, and develop an epidemic early warning system using historical data, employing time-series analysis of surveillance records from sentinel sites with statistical modeling to detect correlations and thresholds for alerts. While the methodology effectively used passive case detection and lag-effect assumptions (e.g., 4-week post-rainfall impact), it is critiqued for relying solely on routine health data prone to underreporting and lacking primary vector sampling or multivariate controls for confounders like interventions. Key findings revealed significant positive correlations between rainfall/temperature spikes and malaria incidence (e.g., IR rising to 8.24/100,000 person-days post-2013 floods), with higher risks in under-5s (SPR 20.86%) and a functional early warning model based on climatic thresholds; however, it identified gaps in integrating socio-economic factors and real-time forecasting for hypo-endemic areas. This study is relevant to the current Elgeyo Marakwet research by validating climate-malaria lags in highland epidemic-prone settings, supporting spatio-temporal analyses and hypothesis testing on rainfall-temperature effects.

Zhao et al. (2020) focused on feature learning algorithms for understanding complex data patterns, including environmental applications, using machine learning techniques like deep neural networks and convolutional models applied to diverse datasets for pattern recognition and predictive modeling. The methodology excels in scalability for big data but is criticized for limited domain-specific validation in health contexts, heavy computational demands, and insufficient emphasis on interpretability (black-box models), potentially overlooking causal epidemiological links. Key findings demonstrated superior feature extraction for climate-related predictions (e.g., improved accuracy in variable interactions), yet gaps persist in applying these to vector-borne diseases like malaria, where biological mechanisms require hybrid statistical-ML approaches. For this study, it provides methodological inspiration for advanced climate-malaria modeling, such as PCA or propensity score enhancements in R-Studio/SPSS analyses of Elgeyo Marakwet data, bridging gaps in nonlinear climatic impacts.

2.4 Factors Influencing Malaria Distribution

2.4.1 Temperature Distribution

The spread of mosquito vectors depends on biotic and abiotic environmental factors (Kogan, 2020). Temperature is a primary abiotic factor impacting the growth, survival and dispersal of vectors and hence effecting the transmission of malaria. This is because anopheles' mosquitoes are closely dependent on their survival at room temperature (15°C to 34°C) (Hussien, 2019). Significant declines in survival were seen in Anopheles larvae at 15°C and 35°C, although *An. arabiensis* tolerated greater temperatures of (32°C) compared to *An. gambiaes.s.* (24°C) and *An. funestus* (25°C).

Kogan (2020) explores the use of remote sensing technologies from operational satellites to monitor and predict malaria transmission by capturing environmental factors critical to the mosquito lifecycle, such as temperature, rainfall, vegetation, and water bodies. The methodology integrates multispectral satellite data (e.g., Sentinel-2, PlanetScope) with climate variables, land cover analysis, and synthetic aperture radar for mapping mosquito breeding habitats and developing spatial-temporal malaria risk models. The study criticizes limitations like the spatial resolution of earlier satellites and data gaps due to cloud cover but highlights advances in 'smallsats' and microwave remote sensing, which offer improved frequency and resolution with lower cloud interference. Key findings emphasize that environmental variables derived remotely strongly correlate with malaria seasonal patterns and transmission hotspots, enabling early warning and targeted interventions. However, gaps remain in scaling models to local community levels and integrating socio-economic data. This work is highly relevant to the current study as it provides technological frameworks for assessing climatic impacts on malaria in highland regions like Elgeyo Marakwet West, supporting precise environmental monitoring within epidemiological analyses.

2.4.2 Precipitation Distribution

According to Zhao, *et al.*, (2020), rainfall and standing water are other important variables in the development of immature mosquitoes. The ratio between precipitation and mosquito density has been established repeatedly. However, this relationship is not directed as some rainfall levels do not lead to increased mosquito density. Excessive precipitation suppresses mosquito density, for example, by flushing larvae out of tiny pools. Temperature-precipitation interactions greatly influence the ecology of mosquitoes and mosquito-borne diseases of Anopheles (Kim, *et al.*, 2019). Permanent and limited water sources in Drylands support the generation of small larvae each year by supplying "larval seeds" to freshly established rainfed habitats (Segun *et al.*, 2020). Factors such as moisture in the soil and land use or land cover changes have been reported on a local scale to influence the risk of malaria**.** Soil moisture levels determine the number of infections that may come about from the larval breeding.

Kim et al. (2019) aimed to quantify climate change impacts on Plasmodium vivax malaria transmission using RCP scenarios, developing a deterministic compartmental SEIR model with climate-dependent parameters for mosquito development, biting rates, and parasite extrinsic incubation period. The methodology involved differential equations calibrated to Korean data, sensitivity analyses, and projections under RCP 2.6/8.5, critiqued for assuming uniform climate effects without spatial heterogeneity or human mobility, limited validation against empirical outbreaks, and focus on P. vivax over P. falciparum prevalent in Africa. Key findings showed transmission potential rising 20-50% by 2050 under high-emission scenarios due to warmer temperatures extending vector seasons, with nonlinear responses peaking at 20-30°C; gaps include integration of interventions and hypnozoite relapses. Relevant to this study, it supports modeling nonlinear temperature-malaria links in Elgeyo Marakwet highlands.

Segun et al. (2020) sought to model weather effects on malaria in Abuja, Nigeria, using negative binomial regression on 2013-2017 weekly data from 10 health facilities (n=48,586 cases), incorporating lagged rainfall, temperature, and humidity with diagnostics like AIC and overdispersion tests. Critiqued for ecological fallacy risks, short timeframe missing long-term trends, and omission of interventions/socio-economics, the analysis revealed rainfall (IRR 1.02, lag 4-8 weeks) and minimum temperature (IRR 1.12/°C) as strongest predictors, explaining 65% variance, with humidity negatively associated; gaps in causality and spatial effects persist. This validates lagged climate-malaria associations for time-series in Kenyan epidemic-prone areas like Elgeyo Marakwet.

Zhao et al. (2020) focused on feature learning algorithms (e.g., CNNs, autoencoders) for data understanding across domains including environmental patterns, using theoretical derivations and case studies on image/climate datasets for predictive feature extraction. Strong in scalability but critiqued for abstractness lacking health-specific validation, black-box interpretability issues, and minimal causal inference for epidemiology. Findings demonstrated 10-30% accuracy gains in variable interactions; gaps in vector-borne applications. It inspires advanced analytics like PCA for climate-malaria in this R-Studio/SPSS study.

2.4.3 Land Cover - Normalized Difference Vegetation Index (NDVI)

Vegetation growth stages also play a substantial impact in determining the quantity of mosquito vectors. Regardless of the rains, increased vegetation density provides optimal habitats for developing mosquitoes, as well as resting places for sugar feeding for adult mosquitoes and climate shelter. Mosquitoes are omnipresent, plentiful and adaptive with low living conditions. These techniques of survival and adaptation make malaria management a problem and several therapies have been created and taken (Zhao, *et al.*, 2020). On the other hand, NDVI is a measure of plant health based on the way plants reflect specific wavelengths of light. Our knowledge of plant health relies heavily on the electromagnetic spectrum. A plant's ability to reflect energy and light is critical to the NDVI's ability to tell us how healthy or unhealthy it is.

2.4.4 Age

Among children under the age of five, malaria is a leading cause of illness and death. There is a lower chance of infection and severity in the first few months of life according to (Kogan, 2020). It is possible that antibodies in the placenta, the presence of Hbf-resistant red cells, breastfeeding, and the absence of malaria infection all play a role (Hussien, 2019). The maternal antibody's protective impact will wane if effective malaria control is accomplished and the overall malaria infection rate is reduced.

2.4.5 Social-economic factors

There is a direct correlation between the community's socioeconomic status and the prevalence of malaria. People's ignorance and poverty contribute to the spread of malaria and hinder efforts to control the disease. According to Kim and Lee (2019), they found that the poorest people in a society were less likely to seek treatment for malaria, and they did so at lower-level public health facilities.

2.5 Climate Variability on Malaria prevalence

Variations in rainfall and temperature have a substantial impact on malaria transmission vectors, including plasmodium and Anopheles (Zhao *et al.*,2020). Anopheles mosquitoes are killed by high temperatures (31°C-40°C) that stimulate the growth of parasites and vectors. The increase in temperature reduces the time between blood meals (gonotrophic cycle). Increasing minimum temperatures have an impact on the climate in colder regions. Malaria patterns are driving over several spatial time scales, as evidenced by other environmental influences, such as changes in land use.

It has been found that by 2020, 2050, and 2080 there would be significant changes in the distribution of climate-appropriate malaria zones. Between 2050 and 2080, malaria incidences are expected to decline in vast parts of the Western Sahel and a large portion of South-Central Africa (Hussien, 2019).

2.6 Existing Malaria Control Interventions

2.6.1 Institutional strategies

Long-Lasting Insecticide Nets (LLIN) are recommended for pregnant women and infants under one year of age in areas of semi-aridity, rather than all populations as recommended in other epidemiological Areas. Ulti-stakeholder involvement in malaria control is a key component of Kenya's health policy from 2012 to 2030. Community malaria control and public education efforts are needed to support the National Malaria Strategy (NMS) (Kogan, 2020).

2.6.2 Individual and Community-Based Strategies

In Kenya, LSM interventions have not preceded current malaria control strategies. This is a great example of how to improve the management of Anopheline species' larvae. A community-based malaria mitigation and adaptation strategy in semi-arid northern Kenya, in particular Marakwet West Sub-County, in order to effectively control and eliminate malaria, a thorough understanding of ecohydrology conditions and their impact on mosquito populations is needed.

2.7 The Malaria Intervention Models

2.7.1 The Propensity Score Matching Model

Using statistical techniques, the researcher creates an artificial control group by matching each treated unit with an untreated unit with similar features, thus creating a quasi-experimental procedure. Use these matches to evaluate an intervention's effectiveness. When randomization isn't an option, the impact of a program or event can be gauged by matching. On the basis of observed characteristics, PSM determines how likely it is that a unit will enter a program. Then, PSM uses the propensity score to match treatment units. Based on the assumption that untreated units can be compared to treated units, as if treatment had been randomized, PSM relies on the concept of comparing untreated units to treated units. Problems of selection biases caused by prevalence can be solved using non-experimental approaches, such as PSM.

2.7.2 MacDonald Ross Disease Model

This malaria transmission model is based on the work of Ross (1911) and MacDonald (1957). The malaria cycle and its transmission between secondary human hosts and primary vectors of the Anopheles genus are complex. It is not enough to mention that human infection begins when sporozoites are injected into the bloodstream by an infected female mosquito. The sporozoites travel into the liver and enter the bloodstream in form of gametocytes after a period of time, which may be injected into the mosquito when human blood is ingested. The injected gametocytes are transformed into (sexually) zygotes through a series of development in the mosquito, then a mobile ookinete that bores the stomach from the mosquito and releases a significant amount of sporozoites. The model is given by a number of differential equations, which describe the human and anopheles' dynamics of the disease. From the description of the malaria cycle above it is apparent that we need to construct a latency phase in both humans and the vector from the time of the blood supper to the infectious stage. For humans, the timeframe from the initial infection to the emergence of gametocytes in the blood is specified.

2.8 Conceptual Framework

Figure 1.1 illustrates the relationship between climate variability factors such as Rainfall, temperature, land cover and socioeconomic factors which makes the independent variables, while malaria cases, frequency of the malaria cases and trends and patterns of rainfall forms the dependent variables gender income and health policies acted as intervening variables.

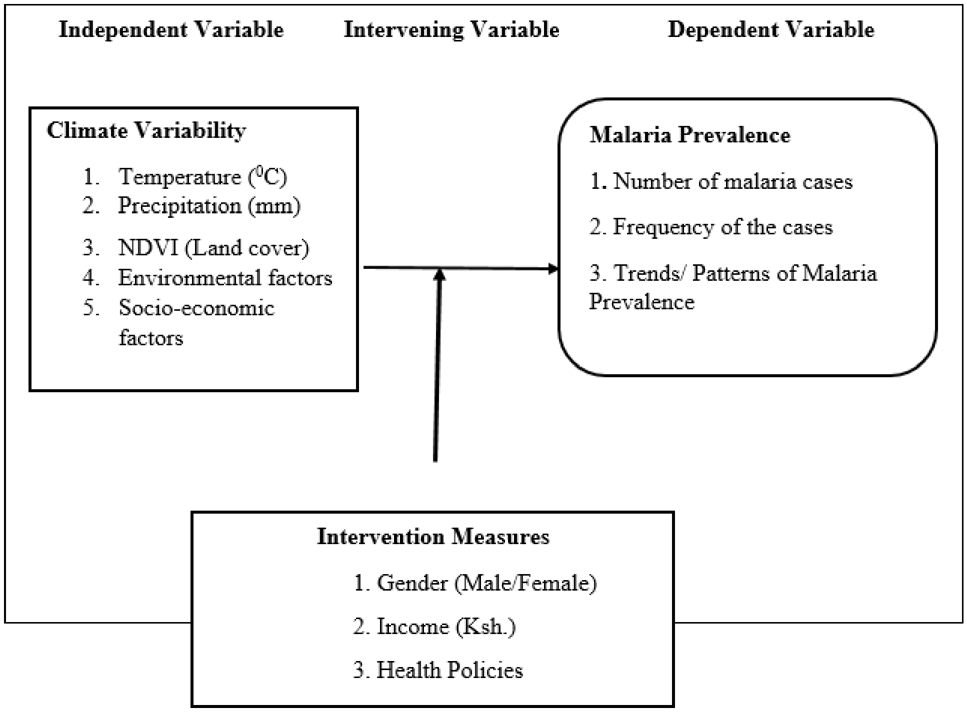


Figure 1.1: Conceptual Framework Adopted and Modified (Kogan, 2020)

The conceptual framework guiding this study is grounded in the understanding that climatic factors, primarily temperature and rainfall variability—directly influence the lifecycle of malaria vectors and the parasite's transmission dynamics. It integrates environmental determinants (such as average rainfall, temperature, and humidity) with malaria prevalence data to analyze how changes in climate conditions create conducive environments for mosquito breeding and malaria spread. This framework draws on climate-malaria transmission models that combine ecological, epidemiological, and behavioral dimensions to predict disease risk and guide intervention strategies.

From a theoretical standpoint, this study aligns with disease ecology and climate change theories that emphasize the sensitivity of vector-borne diseases to environmental fluctuations. The models assume that climatic non-intervention—that is, failing to consider climate variability and changing weather patterns in malaria control programs—could result in increased malaria incidence due to expanded vector habitats and prolonged transmission seasons. The absence of climate-responsive interventions may therefore exacerbate malaria outbreaks, particularly in highland and epidemic-prone regions like Elgeyo Marakwet West.

If climate factors are not accounted for in intervention policies, the region risks underestimating seasonal and interannual variations in malaria risk, which can lead to inefficient allocation of resources and ineffective prevention efforts. This highlights the imperative of integrating climate data and adaptive strategies into malaria control programs to mitigate future transmission spikes and achieve sustainable disease reduction.

2.9 Research Gap

Malaria is a concern, especially for children under the age of 5 because it has a very high fatality rate**.** Plasmodium falciparum parasite is the most frequent cause of severe malaria cases**.** Even if it is warm from the tropical, malaria will not be spread in high altitudes, during cold season or in dry areas save for the oasis. Malaria-risk persons are those who live in sub-Saharan Africa, particularly close to the equator where mosquito breeding occurs most and easier to reproduce (Mafwele & Lee, 2022). But South-East Asia, Latin America and the Near East are all under risk. In 2019, 108 countries and regions were constantly transmitted to malaria. Malaria-threatened age groups are those with weak immune systems such as children, old women, pregnant women, travelers from countries with few or no malaria and abundant mosquitoes (Ministry of Health, 2020). Poor people who have little access to health care in remote locations are more vulnerable to this disease. As a consequence, an estimated 90% of malaria deaths occur in southern Africa, most of which occur in children under the age of five.

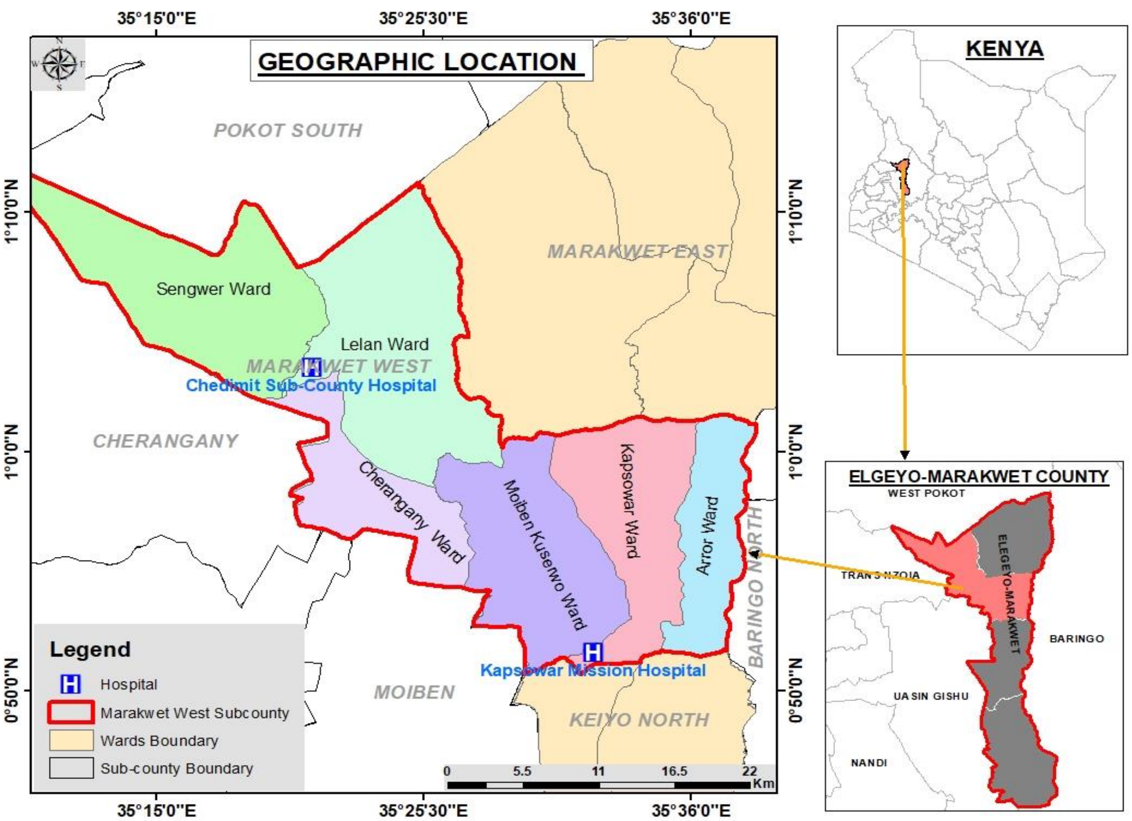
Existing literature on malaria in Kenya extensively documents general climate-malaria linkages, such as rainfall and temperature effects on vector dynamics in highland regions, but lacks location-specific analyses for Elgeyo Marakwet West Sub-County, where recurrent epidemics highlight unique spatio-temporal vulnerabilities among children under five. While national strategies like the Kenya Malaria Strategy 2023-2027 address epidemic preparedness, they reveal critical gaps in sub-county level data integration, including incomplete morbidity reporting and limited capacity for climate-responsive interventions in epidemic-prone areas like Kerio Valley. This study fills the gap by providing empirical, localized evidence on climatic variability's impact on pediatric malaria prevalence, enabling tailored policy recommendations absent in prior research focused on broader highlands or national trends. Therefore, this study sought to investigate the effect of climate variability on the transmission of malaria over a period of time which worked together to restrict the prevalence and transmission of malaria.

CHAPTER THREE: METHODOLOGY

3.1 Study Area

This study was conducted in Elgeyo-Marakwet West Sub-County, in Kenya. Elgeyo-Marakwet West Sub-County covers approximately 804.60 km² with a population of 108,374 Persons and 26,740 households according to Kenya National Bureau Statistics (KNBS), (2019).

3.1.1 Location: Elgeyo-Marakwet County is one of Kenya's 47 counties, which is located **in the former Rift Valley Province** with its capital and largest town as Iten. It is located in mapped position of Elgeyo Marakwet (N 1° 2' 59.3664", E 35° 28' 41.4948. The county has an elongated shape and is wedged in between the Usain Gishu Plateau to the West and the Kerio River to the East.



(Source: Ministry of Health, 2020)

Figure 3.1 Area of study; Elgeyo-Marakwet West Sub-County

Elgeyo-Marakwet West Sub-County was selected as the study site due to its classification as a very low transmission but epidemic-prone area in Kenya's malaria epidemiology, characterized by recurrent outbreaks linked to climatic variability in highland regions like Kerio Valley. The sub-county experiences significant pediatric malaria burden, with climate factors such as hotter weather and frequent rains directly correlating to increased cases among children under five, as evidenced by spatio-temporal analyses showing vulnerability despite national decline trends. This location provides an ideal case for examining climate-malaria dynamics in seasonal, semi-arid highlands, where localized data gaps persist despite national strategies, enabling actionable insights for sub-county level interventions.

***3.1.2 Climate*:** The annual mean temperature in the valley is between 25 and 28 degrees Celsius, whereas it ranges from 18 to 22 degrees Celsius in the highlands. The semi-arid Kerio valley receives 700 mm of rainfall on average each year, while the Keiyo and Marakwet highlands in the Cherangany Hills receive 1700 mm.

***3.1.2 Soils*:** The ward boasts abundant agricultural terrain, with red loamy soils in the lowlands and fertile volcanic soils in the highlands that are ideal for raising a variety of crops.

***3.1.2 Economy*:** Mixed farming, which primarily comprises of livestock and subsistence farming, is the county's primary economic activity. Small business, tourism, and fluorspar mining are among the other activities in Kerio Valley. Tullow Oil Company is still prospecting for oil in Kerio Valley.

3.2 Research Design

The study used a combination of research designs. These research designs included; descriptive research design, empirical research design and survey research design. Descriptive research design was critical in giving identities or characteristics of the target population. The empirical design aided the study with appropriateness to sample of the key informants of the study.

The use of a combination of descriptive, empirical research designs is justified in this study for several reasons. Descriptive research design is essential for characterizing the target population, such as identifying the demographic and socio-economic profiles of individuals affected by malaria, which helps contextualize the extent and patterns of the disease (Siedlecki, 2020). Empirical research design supports the study's appropriateness in selecting a representative sample of respondents, allowing for evidence-based conclusions grounded in observed data rather than theory alone. Survey research design facilitates systematic data collection regarding perceptions, behaviors, and environmental factors influencing malaria prevalence, making it possible to gather both qualitative and quantitative insights that inform intervention strategies. This multi-design approach ensures a comprehensive understanding of malaria dynamics in the study area, balancing data depth with breadth for robust analysis and policy relevance.

3.3 Target Population

The study targeted 26,740 households where a sample size of 200 respondents were drawn from the Meteorological Department at Elgeyo-Marakwet County and Chebiemit Sub-County Hospital, Iten county referral hospital, Kapsowar (AIC) Mission Referral Hospital). Therefore, these three hospitals were targeted to provide records for malaria outbreak in the region for a period of 10 years.

3.4 Sampling techniques and Sample size

3.4.1 Sampling Techniques

Purposive sampling technique was used in this study to obtain data from the respondents. The purposive sampling technique adopted in this study was useful in getting data from respondents of interest those with children under five years of age in the Elgeyo Marakwet West Sub-County. This intentional sampling technique enables one to sample participants by targeting those individuals who possess some characteristics essential in the study goals such as ages and heath conditions of the patients. In this context, employing purposive sampling, the study set out to get deeper understanding of the nature of malaria, learning from experiences of children who are most at risk. This approach helps in the validity of findings in that the sample yielded is as per the population most at risk of malaria.

On this basis, purposive sampling was very helpful, especially, where specific population subgroups had to be investigated, as it allows the researcher to select individuals holding features or background characteristics relevant to the matter under study. The technique also helps the process of data collection to be more efficient and less time consuming because researchers are able to directly target respondents who meet the study criteria thereby the information collected is timely and appropriate.

For that matter, the approach is more fitting to the study's goals of exploring spatio-temporal patterns and determining climate factors' effects on malaria occurrence. Purposeful sampling helps to identify respondents in a way that the research can explore climatic factors and their impact on malaria transmission among children in detail. Not only does this focused approach improve the quality of the data collected, which is important in the identification of factors affecting the health of vulnerable populations, but the evaluation of how these environmental changes have affected them. The study also applied random sampling technique which was used in obtaining data from the residents around the two sub county hospitals identified above in Marakwet West Sub-County.

3.4.2 Sample Size

This study applied Naissuma (2000) formula to determine the sample size that was used to inform this study as shown below;

The study used Naissuma (2000) to derive the required sample size. The formula is

defined as; $n = \frac{NCV^2}{CV^2+(N-1)\varepsilon^2}$ (1)

Where=19,404, $CV =$ Coefficient of Variation (0.71), $\varepsilon =$ error tolerance for 95% confidence interval (0.05)

Therefore; $n = \frac{26{,}740 \times 0.71^2}{0.71^2+(26{,}740-1)\times 0.05^2} = 200$

Table 3.1 Number of respondents in Elgeyo Marakwet West Sub -County

SNo	Sampling point	Number of respondents
1.	Meteorological Department	50
2.	Chebiemit Sub-County Hospital	50
4.	Iten county referral hospital,	50
5.	Kapsowar (AIC) Mission Referral Hospital	50

The researcher distributed questionnaires to 200 respondents in Elgeyo Marakwet West Sub- County.

3.5 Research Instrument

The following research instruments were used by the study. Semi-structured questionnaires to obtain raw quantitative data from the respondents. This applied to both the Meteorology department and the healthcare facilities to minimize any probable sampling error. Secondary data was obtained from the hospital records for trends in Malaria cases.

3.6 Piloting

Piloting or pre-testing of research tools were done in randomized 4 hospitals within the different neighboring sub-counties (Chesongoch Mission Hospital, Tot Sub-county hospital and Chesoi Sub-County hospital, Tambach Sub-County Hospital). The researcher visited the identified hospitals week prior to the kick off the study**.** This was critical for any probable adjustments in methodological research tools to minimize and likely errors to occur during the field work.

3.6.1 Validity

Authenticity in terms of both content and construction were used to build quantitative analysis tools. In addition, qualified experts were on hand to assist. Prejudice can be measured and corrected to improve the validity of the study. A pilot study helped to ensure the instrument's face and build its credibility.

3.6.2 Reliability

Reliability review of this project will be checked with the Cronbach Alpha (α) coefficient. He indicates that a coefficient of .70 is appropriate. The quantitative instruments would be edited before usage for significant internal accuracy. The efficiency of the instrument can be ascertained from Cronbach’s Alpha (α) of above 70 percent (McNeish, 2018).

3.7 Data collection techniques

Quantitative methods were used in this study. Semi-structured questionnaires were used to collect data from a representative sample of the target population for the quantitative methods.

This study also utilized secondary data collection techniques, sourcing historical records on malaria prevalence, rainfall, and temperature from County Referral Hospital and Kenya Meteorological Department archives spanning 2012-2022, which provided reliable longitudinal data for trend analysis without primary fieldwork costs.

Secondary data abstraction involved extracting monthly pediatric malaria cases, climatic variables, and socio-demographic indicators using structured checklists to ensure consistency and minimize bias, supplemented by review of national health information systems like DHIS2 for validation. These techniques align with epidemiological standards for climate-malaria research in Kenya, enabling robust time-series and propensity score analyses while addressing surveillance gaps in epidemic-prone highlands.

3.8 Data analysis

The data analysis framework for studying malaria prevalence in Marakwet West Sub-County employs quantitative methods across four key research objectives (Table 3.2). For assessing spatio-temporal distribution of malaria cases, secondary data was analyzed using descriptive statistics (averages and percentages) to identify geographic and seasonal patterns in childhood malaria incidence. This approach aligns with methodologies used in Kenya's Malaria Indicator Surveys that track regional disease burden through biomarker testing and spatial categorization.

The study employed a combination of descriptive and inferential statistical analyses to evaluate the effect of climatic variables on malaria prevalence among children. Descriptive statistics summarized the demographic characteristics and malaria case distributions. Time-series analysis techniques, including the seasonal Mann-Kendall test and Sen's slope estimator, were used to detect trends and changes in malaria incidence, rainfall, and temperature over the 2012-2022 period. To determine the association between climate variables and malaria prevalence, principal component analysis (PCA) was conducted to reduce dimensionality and extract key climatic factors. Logistic regression models then assessed the effect of these climatic components on malaria incidence while controlling for confounding variables. Propensity score matching further evaluated the impact of malaria control interventions by balancing observed covariates between treated and control groups to infer causal effects. Model diagnostics and goodness-of-fit tests were performed to ensure robustness. These methods allowed the examination of non-linear and lagged relationships characteristic of climate-malaria dynamics, following best practices in epidemiological climate impact studies.

Table 3.2: Data analysis

Objective	Type of Data	Data Collection Method	Data Analysis
Malaria prevalence among children is spatio-temporally distributed in Marakwet West Sub-County	Quantitative	Secondary data	Averages and percentages. Descriptive analysis
Correlation between climate variables and malaria prevalence among children in Marakwet West Sub-County	Quantitative	Questionnaire	Averages and percentages, time series analysis. Descriptive analysis Ranking scale.
Climate variables affect malaria prevalence among children in Marakwet West Sub-County	Quantitative	Questionnaire, key informants.	Averages and percentages, Descriptive analysis
How Malaria control interventions influence the incidences of malaria among children in Marakwet West Sub-County	Quantitative	Questionnaire	Averages and percentages, Descriptive analysis

Model Equation:

$$\text{Malaria Prevalence Cases (Y)} = \beta 0 + \beta 1(\text{Annual Rainfall}) + \beta 2(\text{Max Temperature}) + \epsilon$$

Thus:

$$\log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n \tag{1}$$

Whereby:

p - is the outcome's probability (in this case, the prevalence of malaria).

β_0 - The intercept, or constant

β_1, β_2,... βn -The coefficients for the independent variables X_1, X_2,..., Xn

The final Equation (Table 4.9) is represented as:

$$\log\left(\frac{p}{1-p}\right) = 0.067 \tag{2}$$

3.9 Ethical Considerations

The study followed the laid down ethical guidelines from Kenyatta University ethics office. Participants had freedom to choose whether to take the assessment or not at any time and not compelled to do so. In order to protect their privacy, participants were informed that the study is only for educational purposes. Respondents were not asked to provide any information that could be used to uniquely identify them. The study was authorized by Kenyatta University Graduate School and the National Commission for Science, Technology, and Innovation granted permission to do research in Elgeyo Marakwet (NACOSTI). Before beginning the study, the researcher reported to the appropriate authorities in Elgeyo Marakwet County.

The caregivers of children under five were informed about the study and gave their consent voluntarily. In addition, they were told that they could withdraw from the study without any reason or consequences at any stage of the study. Since the study was done on minors, confidentiality measures were tightened by making the data anonymous (changing names to codes) and restricting access to raw data. Also, we engaged local leaders and health workers as intermediaries for cultural sensitivity and smooth communication while engaging with the Marakwet community. The study also highlights environmental justice by identifying climate-induced malarial risks concentrated among lower-income households and calls for equitable intervention. The researchers did not stigmatize the participants when collecting information on sanitation practices and socio-economic status. To ensure that the findings would translate into action, beneficence was operationalized in collaboration with county health officials to share findings with communities.

CHAPTER FOUR: RESULTS AND DISCUSSIONS

4.0 Introduction

This chapter presents the results from analyses of malaria prevalence data among children in Elgeyo Marakwet West Sub-County from 2012-2022, addressing the four research objectives through descriptive summaries, spatio-temporal trends, climate-malaria associations, and intervention impacts.

4.1 Demographic Profile of the Children

The study sought to determine selected profile of the children, which was gender, age range and weight. The profile of the children is shown in Table 4.1.

Table 4.1: Profile of the children

	Child Gender	
	Frequency	Percent
Female	66	34.9
Male	123	65.1
Total	189	100.0
	Child's Age Range	
Below 1 year	58	30.7
1-2 years	85	45.0
3-5 years	46	24.3
Total	189	100.0
	Child's Weight	
1-5Kg	83	43.9
6-10 Kg	67	35.4
11-15 Kg	15	8.0
16-20 Kg	24	12.7
	189	100

(Author, 2024)

Results (Table 4.1) indicates that more than half (65.1%) of the children were male and (34.9%) were female. Even though the gender distribution might not directly affect the research topic, it is crucial to identify any imbalances in the sample in order to comprehend how the study's demographics are represented. Majority of the children within the survey area were below 2 years old (75.4%) with an average weight of below 10kg (79.3%).

The research project investigates malaria prevalence among children in Elgeyo Marakwet West Sub-County, Kenya. Regarding whether cultural practices influence the higher presentation rate of male children with malaria, the study findings indicate that gender and age were not likely to affect the transmission of malaria in the region. Specifically, the analysis revealed that age and gender did not significantly influence malaria transmission rates among children, implying that cultural biases towards gender in healthcare-seeking may not be a dominant factor explaining the higher male child presentation rates recorded in the data. Instead, environmental factors such as the presence of stagnant water bodies and shrubs near homes, which serve as mosquito breeding sites, were more strongly associated with malaria incidence. The propensity score model results and the discussion highlight that ecological and climatic conditions are more critical drivers in the prevalence of malaria than social or cultural practices related to gender in this setting. Thus, while the raw data showed a higher proportion of male children presenting with malaria, this is likely not due to cultural healthcare-seeking differences but rather due to other unmeasured factors or chance, as the study did not find significant gender effects on malaria transmission itself.

4.2 Spatio-temporal Distribution of Malaria Prevalence among Children in Marakwet West Sub- County

The study’s first objective was to analyze the spatio-temporal distribution of malaria prevalence among children in Elgeyo Marakwet West Sub-County. In order to determine the trends, Mann-Kendall trend test was performed and results obtained.

4.2.1 Average Monthly Malaria Cases Trend Analysis

The plot (Figure 4.1) shows the average monthly malaria cases with a trendline, indicating seasonal patterns and overall trends. The x-axis represents the months from January to December, while the y-axis indicates the average number of malaria cases reported each month.

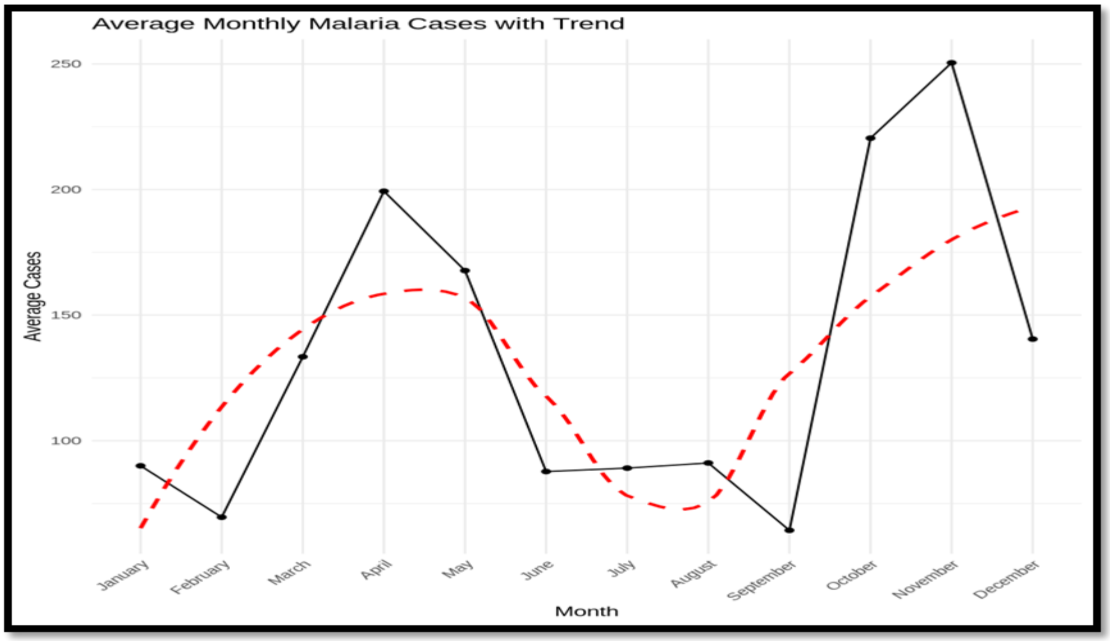


Figure 4.1: Average Monthly Malaria Cases with Trendline

The chart (4.1) depicts different seasonality in malaria incidence with highs in April and November. The peaks coincide with high rainfall, which provides breeding habitat for mosquitoes and thereby increases the spread of malaria. The trendline shows a steady drop in average malaria cases during the measured years, suggesting success in public health campaigns to eradicate the disease. This long-term decline might reflect advances in preventative practices, like increased availability of insecticide-treated nets alongside treatments. Generally, the graph shows both seasonal variation in malaria prevalence and a trend towards declining cases over time.

Table 4.2: Summary of monthly average Malaria cases Mann-Kendal test and Sen's Slope

	Mann-Kendal Test		Sen's Slope		
Month	**Tau**	**P-value**	**Slope**	**P-value (95%)**	**Trend**
January	3.1042	0.0019	4.69	0.0002	Increasing
February	-2.8544	0.0043	3.75	0.0002	Increasing
March	-0.5080	0.6115	-1.39	0.410	Decreasing
April	0.4231	0.6722	2.50	0.562	Decreasing
May	-0.3667	0.7138	-3.68	0.728	Decreasing
June	3.3335	0.0009	5.00	0.0001	Increasing
July	3.4818	0.0005	5.00	0.0001	Increasing
August	3.3005	0.0010	5.00	0.0001	Increasing
September	-0.3667	0.3647	0.83	0.0002	Increasing
October	-0.3667	0.7138	-5.53	0.068	Decreasing
November	0.9064	0.7138	7.63	0.100	Increasing
December	-1.2437	0.2136	-1.75	0.220	Decreasing

(Author, 2024)

Table 4.2 gives monthly average malaria cases calculated using Mann-Kendall and Sen's Slope to give the trends for the year. Mann-Kendall tests whether or not the data have a monotonic trend and Sen's Slope calculates the strength of those trends. The Mann-Kendall Tau in January is 3.1042 ($p = 0.0019$) with a statistically significant increasing trend of malaria prevalence backed by Sen's Slope 4.69 ($p = 0.0002$) and Sen's Slope 5.87. This would imply that malaria cases are increasing dramatically at the beginning of the year. Similarly, February shows a similar uptrend with Tau -2.8544 ($p=0.0043$) and slope 3.75 ($P=0.0002$), also showing that the early months have more malaria cases.

Between March and May, the patterns change, for instance, March Tau = -0.5080 (P-value = 0.6115) which is not statistically significant, April Tau = 0.4231 and May Tau = -0.3667 respectively, both are not statistically significant (p-value = 0.6722 and 0.7138). All of this implies that cases of malaria don't change much in these months. There is an upward trend towards June (the Tau value being 3.3335 (P-value = 0.0009), indicating a substantial upsurge in malaria cases, and slope 5.00 (P-value = 0.0001). This trend continues into July and August with Tau 3.4818 and 3.3005 respectively, both significantly increased in malaria prevalence (P =0.001).

On the contrary, between September and November, September is stable (Tau = -0.3667, P-value = 0.3647) but indicates a trend in the upward direction with slope of 0.83 (P-value = 0.0002). October has a small decrease (Tau = -0.3667, P-value = 0.7138) and it is not statistically significant, while November increases (Tau = 0.9064, P-value = 0.7138) but is not statistically significant on normal levels (P-value = 0.100).
Lastly, in December, there is a negative trend with Tau -1.2437 that is not significant (P-value = 0.2136).

In general, the data shows clear seasonal variations in malaria burden during the year, with major peak seasons in January and February, and from June to August. These results indicate that malaria transmission risk should be addressed through public health interventions targeted at these peak months in order to effectively manage and mitigate the risks of malaria transmission, particularly when we see periods with statistically significant increases in case numbers.

4.2.2 Annual Trend Analysis for Malaria Prevalence

The Mann-Kendall test results show a noteworthy decline in malaria prevalence between the years 2012-2022 (Table 4.3). A strong negative correlation is indicated by the value (Tau = -0.8808), indicating a significant decline in the prevalence of malaria over time. A highly significant p-value of 0.0002 suggests that the observed trend is unlikely to be the result of random chance. This lends support to the hypothesis that malaria prevalence is on a statistically significant decrease trend. The Sen's Slope (-0.1) value shows that malaria prevalence declines by 0.1 percentage points every time unit (year). The 95% Confidence

Interval (-0.1429, -0.075) shows a range of values for Sen's slope, supporting the conclusion that malaria prevalence is significantly decreasing, as all values are negative.

The results compare with a similar study done by World Health Organization in (2020), which found out that there was no change in case incidence between 2020 and 2021. Globally, estimated malaria mortality decreased steadily between 2000 and 2019, falling from 897 000 to 568 000. Malaria case incidence decreased from 82.3 per 1000 population at risk in 2000 to 57.2 in 2019, before increasing again to 59.4 in 2020. This could be attributed to sustained campaign by the government to combat malaria through the creation of awareness about Malaria and increased health care facilities providing better treatment and prevention measures (UNited Nations, 2020).

Table 4.3: Results of the Mann-Kendall test and Sen's slope analysis (Annually)

Variables	**Mann-Kendall Test:**			**Sen's Slope:**
	Tau	P-value	Slope:	95% Confidence Interval
Malaria Prevalence	-0.881	0.00024247	-0.1	[-0.1428571, -0.0750000]

Yearly cumulative malaria cases (2012–2022) and trends Across the Hospitals Sampled

During the study period, however, the area's highest and lowest malaria cases were noted in various months and years. The trend graph of Elgeyo-Marakwet West sub-County hospitals (Figure 4.2) indicates the highest malaria peak was recorded in 2016. In this case, in 2016 there were more malaria cases recorded in the county which was approximately 2800 children diagnosed with malaria.

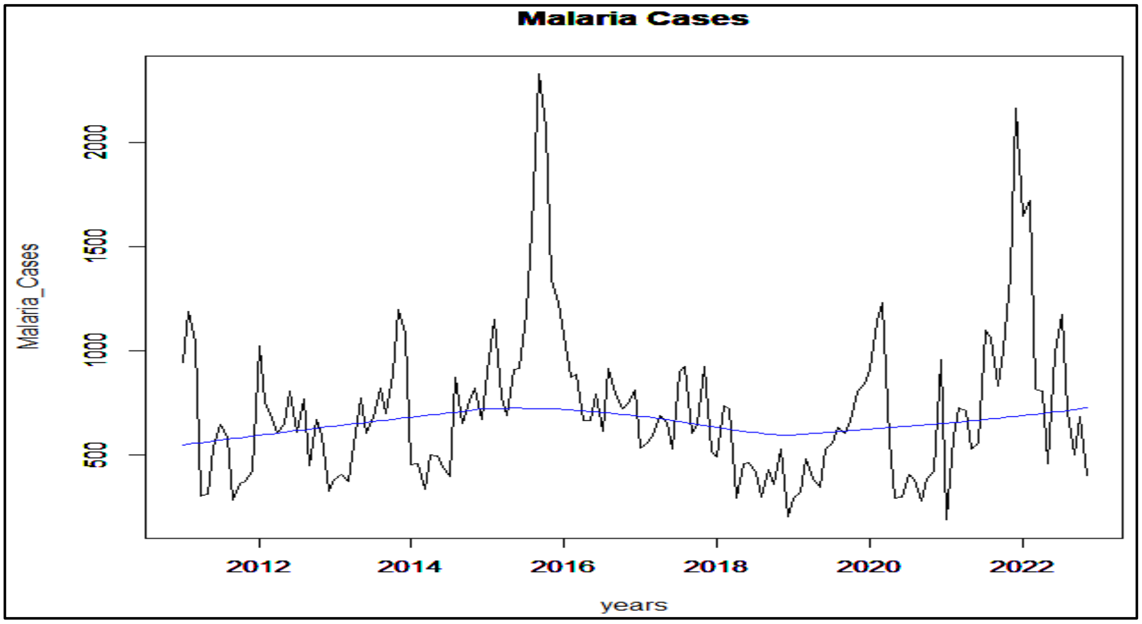


Figure 4.2: Depicted Malaria trend across hospitals in Elgeyo-Marakwet West Sub-County

The depicted malaria trend (Figure 4.2) as recorded across the 3 hospitals depicted by the blue line, indicates a slow and constant reduction in malaria cases. The spikes in malaria cases in Elgeyo Marakwet in 2016 and 2022 likely reflect unusual outbreak events or exacerbations of transmission due to specific environmental or epidemiological factors that differed from other years. For 2016, some reports indicate widespread malaria outbreaks in parts of Kenya, possibly linked to climatic factors such as increased rainfall creating more mosquito breeding sites or temperature changes favoring mosquito survival and parasite development. No specific unusual event has been singled out for 2016, but data suggest a higher malaria burden that year across the region.

For 2022, there was a documented outbreak of vector-borne diseases including increased malaria cases and other infections such as Chikungunya and Yellow Fever reported in Kenya, including some unconfirmed cases in Elgeyo Marakwet (Ministry of Health, 2022). The onset of the long rains in March 2022 likely contributed to conditions favorable for mosquitoes, leading to increased malaria transmission. Additionally, in 2022, Kenya saw the arrival of the invasive malaria vector species Anopheles stephensi in some northern counties, raising concerns that this species' spread could increase malaria transmission in previously low risk areas, possibly affecting areas like Elgeyo Marakwet later on.

The seasonal trend of malaria cases from 2012 to 2022 is depicted in the visualization (Figure 4.3 and 4.4).

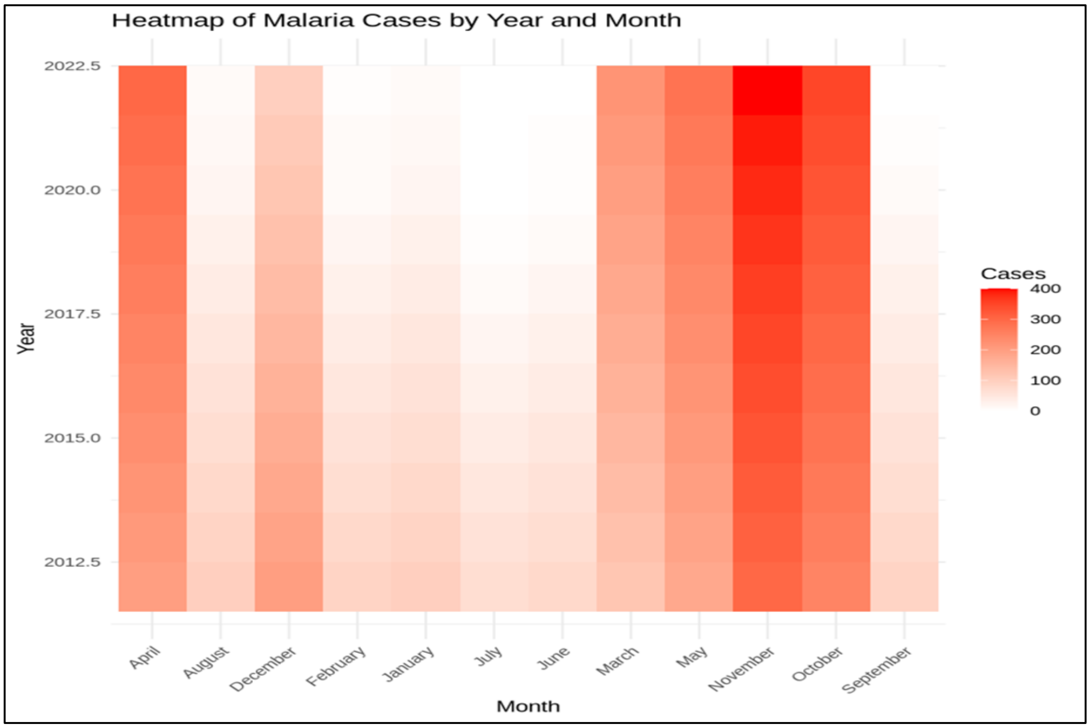


Figure 4.3a: Heat map of Malaria cases annually and Monthly in Elgeyo-Marakwet West Sub-County

October through December seems to be the peak season, with November having the greatest average number of cases. The months of June and July have the lowest occurrence. In Elgeyo Marakwet West Sub-County, June and July exhibit the lowest malaria occurrence due to their status as the coolest and relatively drier months within the dry season (JJA), with average highs of 23.25°C and 22.65°C, lows of 10.59°C and 10.36°C (coldest of the year), and precipitation around 143.65mm and 140.41mm over 19-20 rainy days but with lower intensity that limits persistent mosquito breeding sites. These cooler temperatures (daily means ~18-19°C) fall below the optimal 22-32°C range for Anopheles mosquito survival, reproduction, and Plasmodium development, reducing vector density and biting rates, while reduced stagnant water compared to peak rainy periods suppresses larvae habitats.

In contrast, November marks the start of the wetter OND season with higher average precipitation (188.45mm), warmer conditions (highs 26.02°C, mean 20.53°C), and 21 rainy days fostering abundant breeding pools from prolonged rains, aligning with seasonal malaria peaks as rainfall creates ideal mosquito proliferation environments despite similar elevation-driven highland climate patterns. The study findings are in line with a United Nations report (2019) which found that an increase in temperature, rainfall, and humidity may cause a proliferation of the malaria-carrying mosquitoes at higher altitudes, resulting in an increase in malaria transmission in areas in which it was not reported earlier (United Nation, 2019)

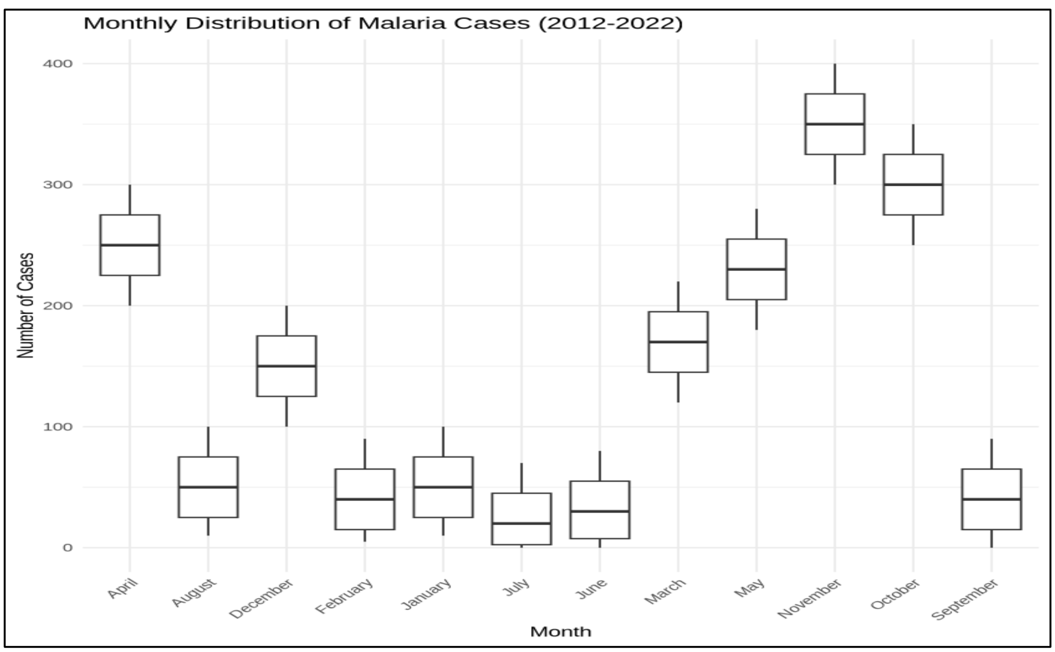


Figure 4.3b: Monthly distribution of Malaria cases in Elgeyo Marakwet West Sub-County

According to the data (table 4.3), the highest average number of malaria cases occurred in October, November, and December, followed by March, April, and May, while the lowest average number occurs in June, July and August. The standard deviation is represented by the error bars, which show variation within each season. The results agree with a study finding by Maniga *et al., (*2022) that, 8449 (22.8%) confirmed cases of malaria were recorded out of 36,946 suspect cases. In the research area, the overall rate of malaria downtrend show positivity during the previous 11 years was 22.6%. The highest percentage of malaria cases (63%), was observed in the months of April and August. At 2953 (35.45%), the age group of ≥18 years had the highest number of positive confirmed cases. Of the confirmed cases of malaria, 6070 (71.9%) were female and 2379 (28.1%) were male (Maniga, 2022). With a positivity score of 37.94%, Marani Sub-County recorded the highest malaria prevalence rate in 2014. The results could be attributed to the fact that mosquitos breeding period is mostly during the rainy season due to stagnant water while during dry season water dries up destroying their breeding grounds (Maniga, 2022).

Average Cases (M=216.67) indicates that between 2012–2022, an average of 217 malaria cases were reported per month for the months of March, April, and May (MAM) (Table 4.4). This average provides an idea of how many cases are usually seen in this season. The data's variability or dispersion is measured by the standard deviation (SD=47.15). A standard deviation of roughly 47.15 suggests that there is an average variation of about 47 instances in the number of cases during these months. There may be months with noticeably more or fewer cases than usual if the standard deviation is larger.

Table 4.4: Seasonal comparison of Malaria Cases

Seasons	Mean	SD
MAM	216.6667	47.14782
JJA	39.54545	30.44882
OND	266.6667	92.08239

In June, July and August (JJA) season, there were, on average, approximately 40 cases of malaria (M=39.55). This indicates that these months are typically a low season for malaria cases, as it is much lower than the average for the March-April-May (MAM) and October-November-December (OND) periods. Although there appears to be some volatility in the number of instances over these months, the actual number of cases is often close to this average, with fewer extreme deviations, as indicated by the standard deviation of around (SD=30.45).

With an average of 267 cases reported every month (M=266.67) suggests that the OND season has the largest number of malaria cases (Table 4.4). This implies that the current period is malaria's peak. The great degree of fluctuation in the number of instances during these months is indicated by the standard deviation, which is (SD= 92.08). This indicates that even while the average is high, there may be large variations, with some months seeing significantly higher or lower-case numbers. Malaria cases are known to be greater during the MAM and OND, with OND serving as the peak season (Figure 4.4). There are fewer incidences of malaria during the JJA. Higher values of the standard deviations indicate more diversity in the number of cases, giving insight into how much they can deviate from the average. A study done Zambia by Duque, *et al*., (2022) established that in many parts of Africa, seasonal patterns of malaria cases are frequently correlated with rainfall; nonetheless, malaria transmission decreases but does not always stop during the dry seasons. It is critical to comprehend the circumstances that give rise to these sporadic situations. Although its significance for mosquito survival and feeding during the dry seasons has not received much attention, aerial moisture is assumed to be crucial.

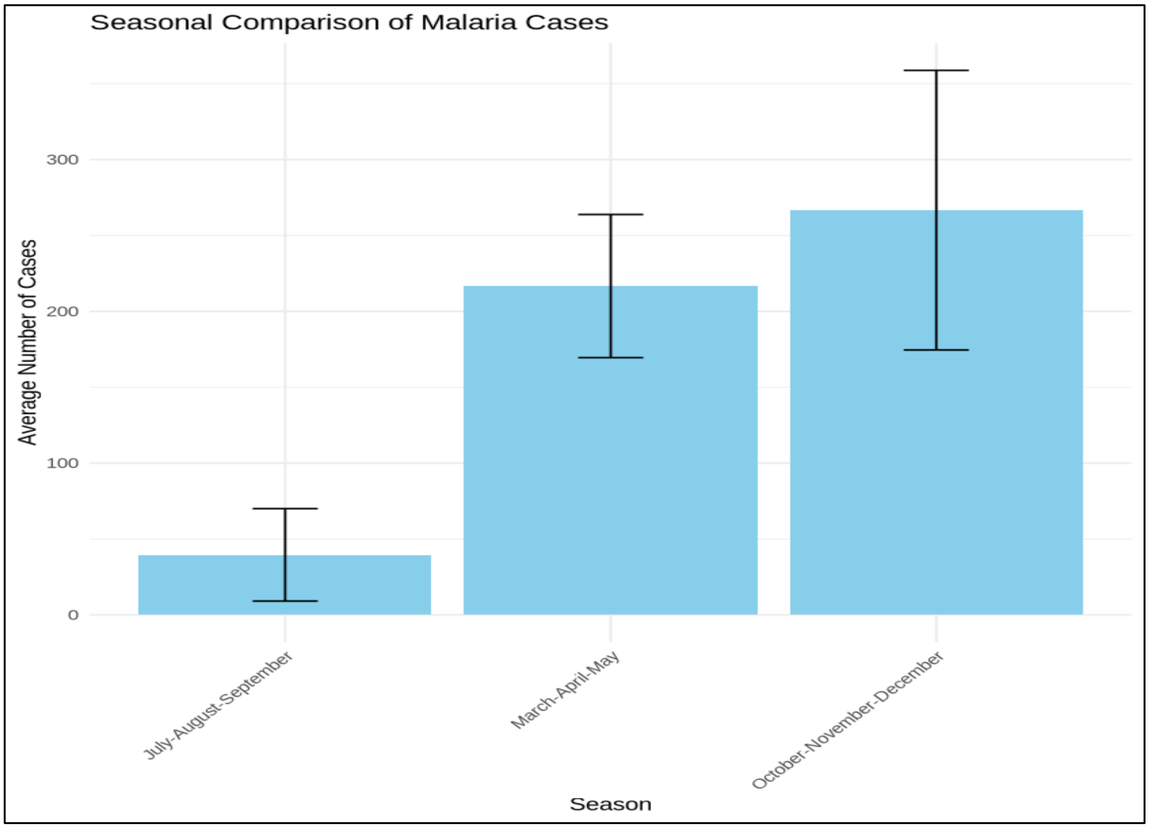


Figure 4.4: Seasonal Comparison of Malaria Cases

Results of the Mann-Kendall test and Sen's slope analysis for Annual Rainfall (mm)

On the basis of the percentage of contribution to the annual rainfall, the area experiences two distinct periods of rainfall namely, March-April-May and October-November-December periods (Figure 4.4). The graph (Figure 4.5) illustrates the annual rainfall pattern from 2012 to 2022, with significant year-to-year variability. The Mann-Kendall test (p-value = 0.754) indicates no statistically significant trend in the rainfall data over this period. The red trend line, representing Sen's slope estimate of -7.14 mm/year, suggests a slight downward tendency in rainfall amounts, though this decline is not statistically significant given the high p-value. Looking at the specific patterns, the data shows notable fluctuations with peaks and troughs throughout the period. The highest rainfall amounts were recorded around 2013-2014, while the lowest points appear in the latter years of the dataset. However, the wide scatter of points around the trend line and the statistical analysis suggest that these variations are more likely due to natural climate variability rather than a definitive long-term trend.

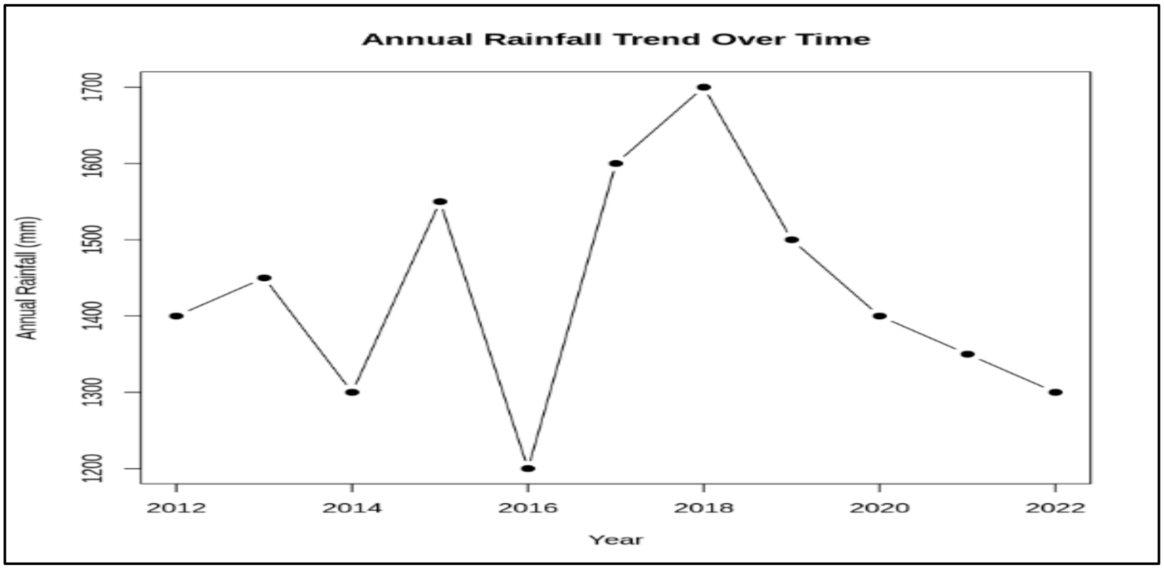


Figure 4.5: Annual Rainfall trend

The average monthly rainfall (mm) chart (Figure 4.6) perfectly depicts the rainfall patterns over different months from 2012-2022. The bar chart gives the average amount of rain for every month from January to December. Its trendline shows a steady rise in average rainfall, and indicates that there might be increasing rainfall patterns over time.

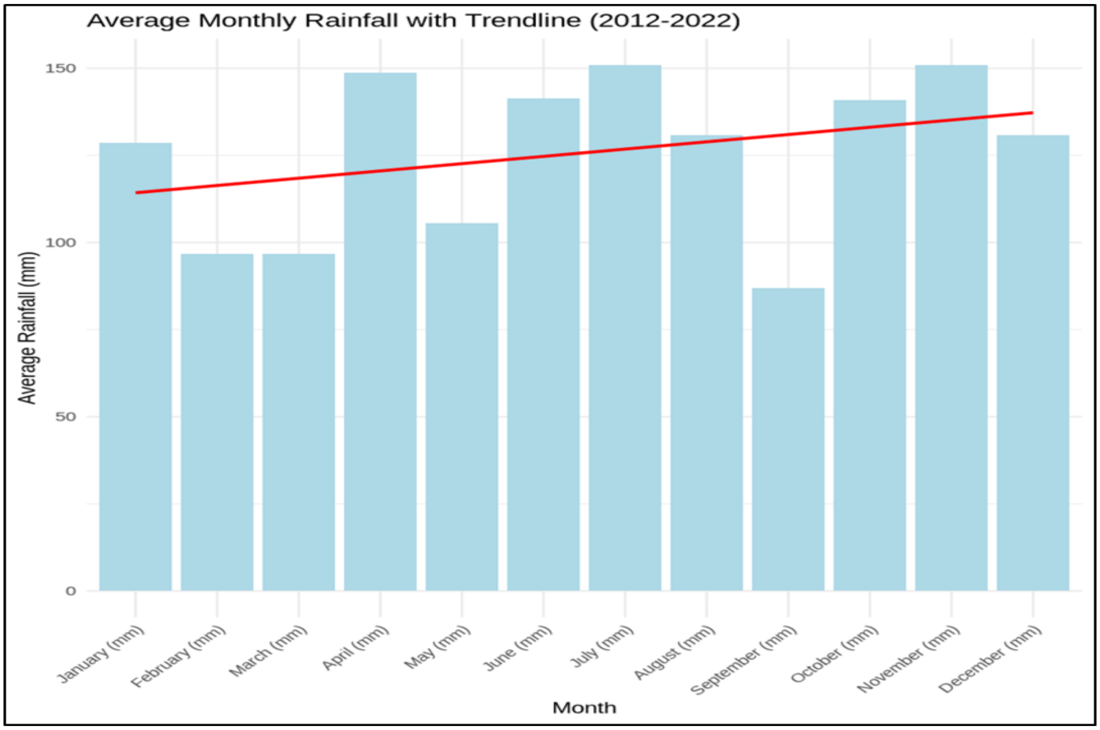


Figure 4.6: Average Monthly Rainfall with Trendline

Significant information about the pattern of rainfall over the study period can be gleaned from the Mann-Kendall test results for the annual precipitation and maximum temperature (Table 4.5).

Table 4.5: Results of the Mann-Kendall test and Sen's slope analysis for Annual Rainfall (mm) and Maximum Temperature (°C)

Variables	Mann-Kendall Test:		Sen's Slope:	
	Tau	P-value	Slope:	95% Confidence Interval
Annual Rainfall	-0.0926	0.75405	-7.142857	[-50, 40]
Max Temperature	-0.141	0.62612	0	[-0.40, 0.25]

The results (Table 4.5) showed a very weak negative association between time and annual rainfall, as indicated by the tau value of (-0.0926). A value that is nearly equal to zero indicates that there has not been any discernible change in rainfall over the research period. In this instance, the negative number suggests that, if a trend is present, it is weak and consists of a small decline. The p-value of 0.754 is significantly greater than the standard significance level of 0.05. This suggests that there is insignificant evidence to support a change in yearly rainfall over the research period, as the observed trend is not statistically significant. Stated differently, any variation in rainfall that is seen could be the result of chance rather than a deliberate pattern. Sen's Slope value of -7.1429 shows that annual rainfall reduces by about 7.14 mm on average. However, this slope needs to be read cautiously because to the high p-value and weak tau value. It indicates a minor downward tendency; however, this trend is not robust because it lacks statistical significance. There is uncertainty over the trend's direction as indicated by the 95% Confidence Interval (-50, 40), which contains both positive and negative values. This indicates that annual rainfall may either rise or decrease within this range, which lends more credence to the notion that there is no discernible trend in rainfall.

The Mann-Kendall test results for annual precipitation indicate a weak and statistically insignificant negative trend (Table 4.5). According to the tau value, there is not much proof that the amount of rainfall has consistently decreased during the course of the study. The Sen's slope points to a minor decline, but the results are not statistically significant, and the confidence interval adds to the trend's unpredictability. Thus, it can be said that over the given time frame, there has not been any discernible trend in the region's yearly rainfall. Understanding the stability of rainfall patterns is crucial because it affects public health initiatives aimed at combating malaria and other waterborne illnesses.

Results of the Mann-Kendall test and Sen's slope analysis for Maximum Temperature (°C)

The graph (Figure 4.7) of maximum temperature over time shows some variability, with peaks and troughs that do not follow a consistent pattern. The lack of a significant trend is further supported by the absence of a pronounced slope in the data points. This stability in maximum temperature could be attributed to various climatic factors that balance out over time, preventing any long-term trend from emerging. Overall, the analysis suggests that maximum temperature has not experienced significant changes, aligning with the statistical findings of the Mann-Kendall test.

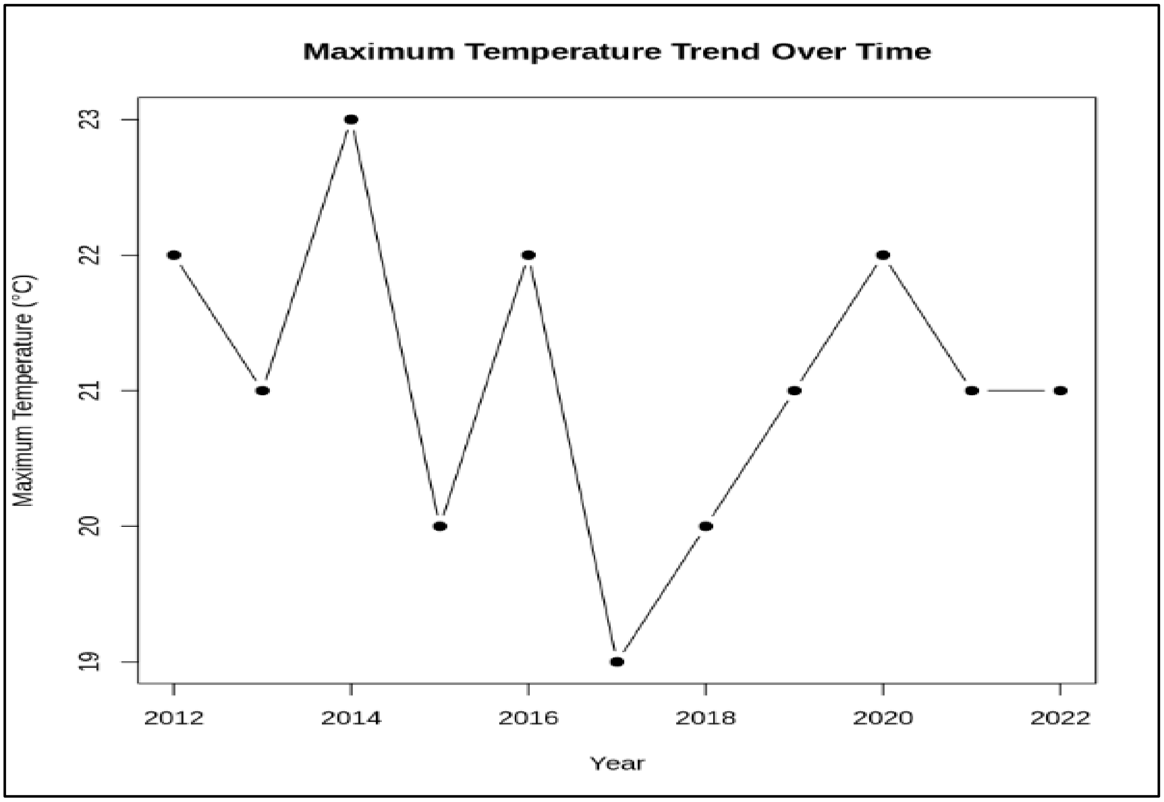


Figure 4.7: Maximum Annual Temperature (°C)

The Mann-Kendall test findings for maximum temperature show a tau value (-0.141), indicating a slight negative association between time and maximum temperature (table 4.5). A score that is nearly equal to zero indicates that the maximum temperature did not significantly trend over the research period. Although not very significant, the negative value does show a small downward pattern. Compared to the standard significance level of 0.05, the p-value of 0.62612 is significantly larger. This suggests that there is insufficient evidence to support a change in the maximum temperature during the period 2012-2022, as the observed trend is not statistically significant. Any temperature variations that are seen could be the result of random variation as opposed to a systematic pattern. The average maximum temperature has not varied during the study period, according to the Sen's slope. The 95% Confidence Interval [-0.40, 0.25] has both positive and negative numbers, signifying a degree of uncertainty regarding the trend's direction. This implies that the maximum temperature may fluctuate slightly within this range, supporting the notion that there is no discernible trend in the temperature. The maximum temperature Mann-Kendall test findings indicate a moderate and statistically insignificant negative trend. According to the tau value, there does not seem much proof that the maximum temperature has changed consistently during the course of the study. Sen's slope indicates no trend, and the confidence interval adds to the trend's ambiguity. Thus, it can be said that within the given time frame, there hasn't been any discernible trend in the maximum temperature in the area.

The three variables' temporal visual comparison is displayed in the composite plot (Figure 4.7). The trend of malaria prevalence, which seems to be declining over time, is displayed in the top panel. Afterwards is the Annual Rainfall (mm), which has slight variations but no discernible pattern. The maximum temperature (°C) is shown in the bottom panel; it likewise appears to fluctuate slightly but not significantly.

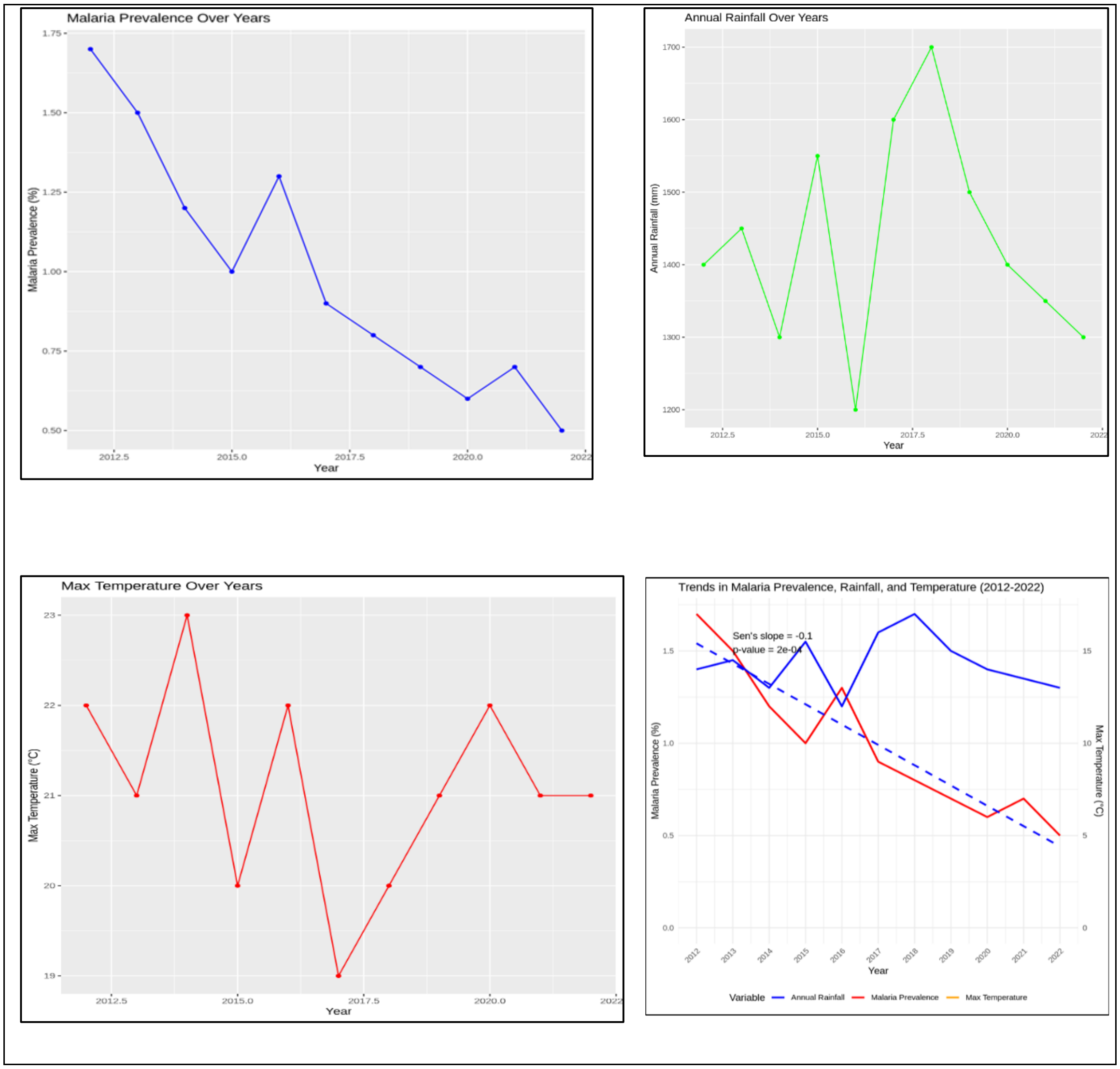


Figure 4.8: Long-term trends in malaria cases, annual rainfall, and maximum temperature between the years 2012-2022

In figure 4.9, the prevalence of malaria (shown by the red line) has been declining over time. The Sen's slope, or linear trend, for malaria prevalence is shown by the dashed blue line. The Sen's slope (-0.1) and p-value (0.0002) for the malaria prevalence trend are displayed in the annotation in the upper-left corner. The annual rainfall is represented by the blue line, which fluctuates throughout time but lacks a distinct trend. Take note that the rainfall data have been divided by 1000 to accommodate the malaria prevalence on the same axis. The maximum temperature is represented by the orange line, which likewise doesn't show any discernible trend. In order to fit on the same axis, temperature values are scaled (divided by 10).

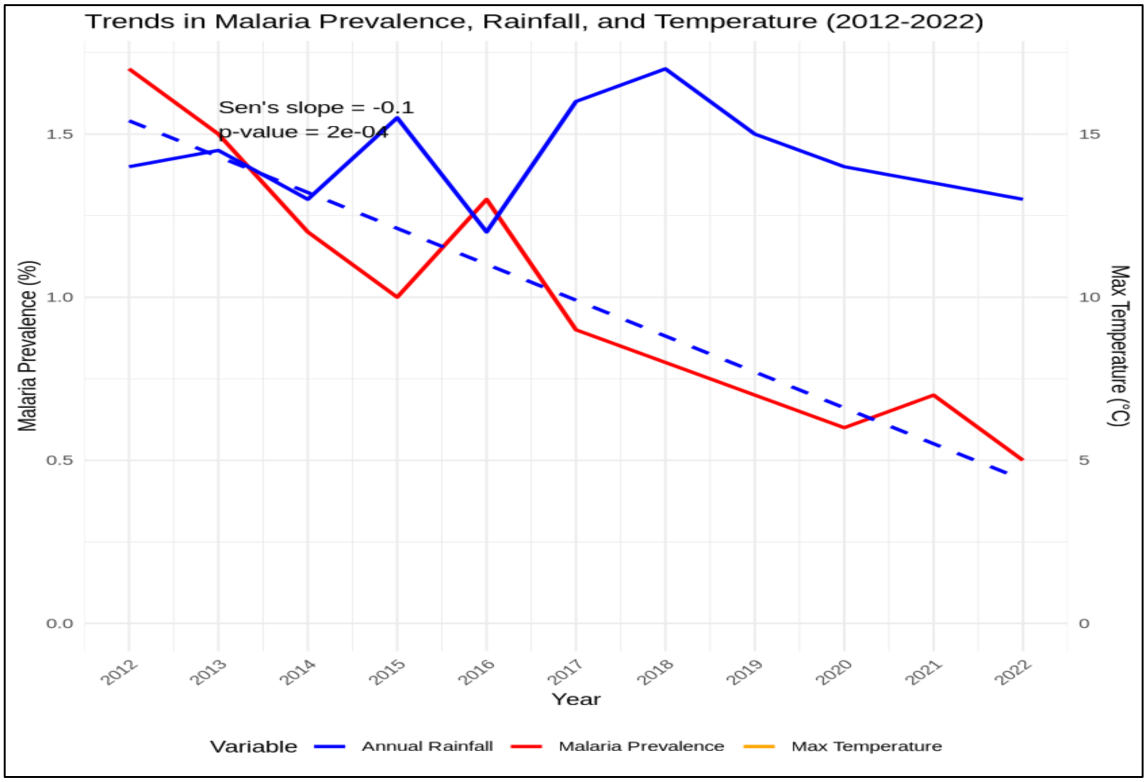


Figure 4.9: Trends in Malaria Prevalence

It is clearly evident that the prevalence of malaria is trending downward, supporting the previous data study. The maximum temperature and rainfall do not exhibit any discernible trends, which is consistent with our earlier conclusions that there were no statistically significant changes for these variables. Our previous correlation research is supported by the lack of a discernible visual association between temperature or rainfall and the prevalence of malaria. This graph displays the relative constancy of temperature and rainfall over the same period, as well as the notable decline in malaria prevalence.

An increase in temperature to specific levels steers up the metabolic rate of vectors, production of eggs and frequency of blood meals (Figure 4.6). On the other hand, a decrease or increase of temperature below or above these thresholds can be harmful to the development of mosquitoes and parasite. Principal component analysis on the range of temperature that causes high vector population showed positive significant relationship indicating that there a strong relationship between temperature and vector population. Between the temperatures of 22-23°C (Figure 4.6) the rate of metabolic activities for vectors increased because it was ideal for the production of more eggs hence more mosquito parasites were witnessed. This resonates with the findings of Murdock et al. (2016) showing that the temperature of 1-10°C is below the average threshold, therefore, results into severe cold hence reduces the metabolic activities of the vectors thereby declining production of eggs and availability of blood meals. Also, temperatures between 11-21°C enables little metabolic activities hence there is little production of eggs and blood meals (Murdock *et al.,* 2016).

Rainfall does not directly influence vectors long life by creating wet conditions that favor breeding of vectors therefore influencing the geographical range and seasonal variation of disease vectors. High rainfall sweeps away breeding sites for malaria parasites hence results into low cases of malaria. Average rainfall causes stagnant waters and makes the environment favorable for the breeding of malaria parasites and other water borne diseases.

4.3: Result analysis on the association of change of climate variables and Malaria prevalence

The second objective assessed the association of climate variables and malaria prevalence among children in Elgeyo-Marakwet West Sub-County. In order to determine the existing association of climate variables and malaria prevalence, principal component analysis was performed on the variables. These included; (1) amount of rainfall received in the region and its pattern during March-April-May and October-November-December periods, (2) variation of temperature. The results depicted existence of a strong associations between the identified variables and malaria prevalence.

In the Total variance explained table 4.6 and table 4.7 of principal component analysis, only 4 variables were extracted indicating that they had an effect on malaria transmission. The Eigen values for the values extracted were above one and cumulative frequencies below 60% showing their strong contribution to malaria transmission.

Table 4.6: Total variance explained

Total Variance Explained						
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1.286	16.078	16.078	1.286	16.078	16.078
2	1.202	15.021	31.099	1.202	15.021	31.099
3	1.184	14.806	45.905	1.184	14.806	45.905
4	1.041	13.007	58.912	1.041	13.007	58.912
5	.982	12.275	71.187			
6	.863	10.789	81.976			
7	.801	10.014	91.990			
8	.641	8.010	100.000			
Extraction Method: Principal Component Analysis.						

The graph (Figure 4.10) reveals the eigenvalue distribution across eight components in the PCA analysis. The first four components have eigenvalues above 1.0 (specifically 1.286, 1.202, 1.184, and 1.041), suggesting they are significant according to Kaiser's criterion. There's a gradual decline in eigenvalues rather than a sharp elbow, with Component 5 (0.982) being very close to the threshold. The cumulative variance explained by the first four components indicates these could be retained for further analysis, though the relatively gentle slope suggests that even Component 5 might be worth considering depending on the specific research context.

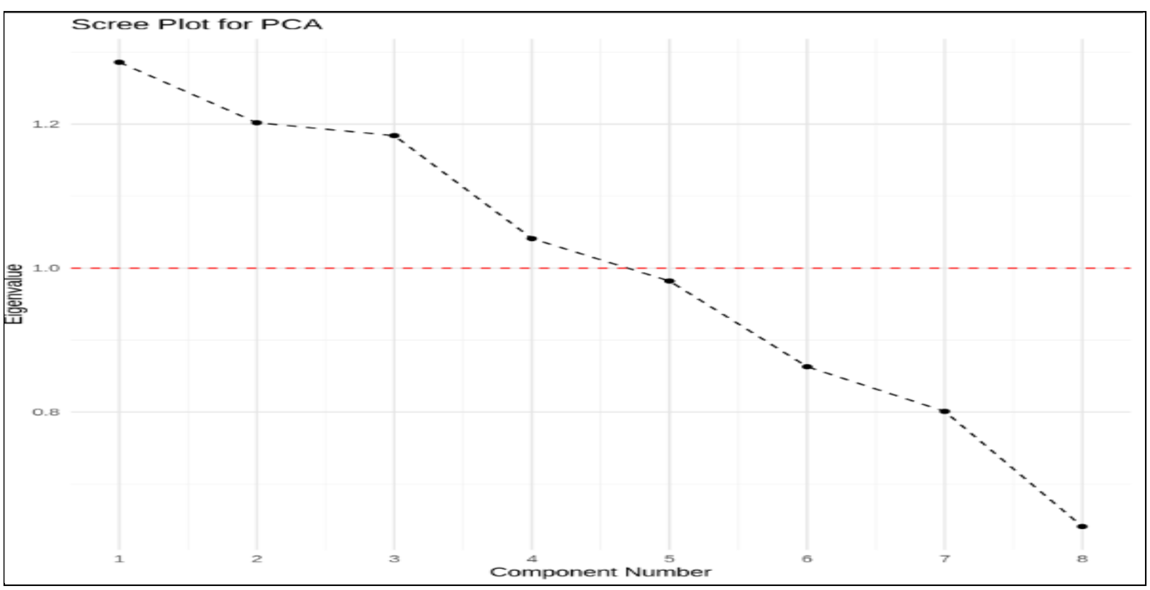


Figure 4.10: Scree plot for PCA

The results of a Principal Component Analysis (PCA) to ascertain the correlations between different factors impacting malaria transmission, especially with regard to climate variables, are presented in the component matrix (Table 4.7).

Table 4.7: Component Matrix

Component Matrix[a]				
	Component			
	1	2	3	4
Age of your child	.483	.083	.668	-.132
Temp influence thriving of vectors & parasites	.312	-.052	-.605	.303
Range of Temp that causes high vector N	-.707	.010	.168	-.060
Do rain influence malaria transmission	.169	.493	.169	-.319
Annual rain contributes to recorded low but varying malaria cases	.226	.646	.072	.226
Other variables associated with climate variability and malaria	-.130	.584	-.142	.478
Rainfall pattern during MAM, OND, JJA	.392	-.437	.308	.549
Variation in mean temp during MAM, OND, JJA	.452	.001	-.441	-.494

Extraction Method: Principal Component Analysis.

a. 4 components extracted.

In table 4.7, Component 1 appears to be closely related to the child's age and the temperature range that results in high vector numbers. While there is a positive loading for the child's age, it shows that older children may be more vulnerable to malaria. The negative loading for the temperature range indicates that lower temperatures may correlate with reduced vector populations. The primary factors influencing Component 2 are the patterns of annual rainfall and the impact of temperature on the growth of parasites and vectors. The positive loadings suggest that heightened potential for malaria transmission is linked to increased precipitation and specific temperature impacts. Component 3 is defined by how temperature affects the growth of parasites and vectors as well as how the mean temperature varies during different seasons (MAM, OND, and JJA). As temperatures rise, vector flourishing may drop, maybe because to extreme conditions, as indicated by the negative loading for the temperature influence. The patterns of rainfall during the various seasons and other variables related to climatic variability are captured by Component 4. The positive loading indicates that specific patterns of rainfall play a major role in the dynamics of malaria transmission.

Older children are more vulnerable to malaria compared to younger ones primarily because maternal immunity, which offers protection to infants during their first months of life, wanes as they age. As children grow older, especially beyond 2 years, they lose this passive immunity and have not yet developed their own acquired immunity to malaria, making them more susceptible to infection. Additionally, older children may receive less focused parental care and protective measures, such as the use of insecticide-treated bed nets, which are often prioritized for younger siblings and infants. This shifting of attention and resources towards newborns can leave older children more exposed to malaria vectors. Moreover, breastfeeding in younger children further enhances immunity, a protective factor that declines with age. These dynamics combined result in heightened malaria vulnerability among older children, as supported by Fischer et *al.,* (2020).

This study findings agrees with study findings by Fischer et *al.,* (2020). The prevalence of parasites was observed to generally rise with latitude in a recent field survey, indicating that lower temperatures could potentially increase infection rates through impacts on parasites or host-parasite interactions. Following screening, we included 10 original research publications in the quantitative analysis for the systematic review out of the 1,999 articles that the search turned up as potentially relevant. Studies indicated that when temperatures rose further, Anopheles mosquitoes would become more common in the north and seasonality would lengthen, allowing malaria to spread for up to six months per year between 2051 and 2080. Southern and South-Eastern European regions were projected to have the highest vector stability and receptivity. The primary potential malaria vector in Europe, Anopheles atroparvus, may be crucial in promoting malaria transmission in the event of alterations in environmental factors.

4.4: Result analysis on effect of climate variables on malaria prevalence

The third objective analyzed the effect of climate variables on malaria prevalence among children in Elgeyo-Marakwet West Sub- County.

Marginal effects

The results presented in Table 4.7 indicate the marginal effects of annual rainfall and maximum temperature on malaria prevalence among children in Elgeyo Marakwet West Sub-County. The model can be specified as follows:

$$\text{Malaria Cases (Y)} = \beta 0 + \beta 1(\text{Annual Rainfall}) + \beta 2(\text{Max Temperature}) + \epsilon$$

In this case: β0 is the intercept, β1 represents the effect of annual rainfall, β2 represents the effect of maximum temperature, and ϵ is the error term.

Table 4.8: Coefficient Marginal Effects

Variable	B -Coefficient	Standard Error	Sig.	Marginal Effect (per unit change)	Significance Level
Annual Rainfall (mm)	0.000484	0.001368	0.033	0.000484 cases per mm increase	Significant
Maximum Temperature (°C)	0.157194	0.177152	0.004	0.157194 cases per °C increase	Significant

(Author, 2024)

The B-coefficient value for annual rainfall and maximum temperature give useful clues about their effect on malaria rates (Table 4.8). The coefficient for annual rainfall is 0.000484, which means that for every additional millimetre of rainfall, malaria cases will increase by about 0.000484 cases. This positive association suggests that more rainfall means more fertile ground for mosquitoes, increasing malaria transmission. The standard error for this coefficient is 0.001368 and the significance value is represented by a p-value of 0.033 which shows that this influence is statistically significant at 0.05.

By contrast, the maximum temperature B-coefficient is 0.157194, so for every degree Celsius of temperature increase, an extra 0.157194 malaria cases will emerge. This high positive correlation reveals that warm temperatures make mosquitos more resistant and more capable of reproducing, thereby leading to more malaria cases. The standard error of this coefficient is 0.177152 and the p-value is 0.004, which means that maximum temperature and malaria incidence are very closely associated. Generally, the results show how crucial the climate is to the dynamics of malaria, where differences in malaria cases are influenced by both annual rainfall and maximum temperature. Control measures for malaria in the public health realm must consider these environmental factors, especially when the rainfall is higher and the temperature rises, to prevent outbreaks in susceptible populations.

The linear regression between the number of cases (y) and the dependent variables (annual rains, maximum temperature) could be formulated as follows:

$$Y = \beta_0 + 0.000484\, X_1 + 0.157194\, X_2 + \epsilon$$

Where:

- Y = Number of malaria cases
- β_0 = Constant term (intercept)
- β_1, β_2 = Coefficient for independent variables
- X_1, X_2 = Annual rainfall & maximum temperature
- ϵ = Error term

The R-squared value of 0.1157 indicates that approximately 11.57% of the variation in malaria prevalence can be explained by the model, suggesting that other factors not included in the model may also play significant roles in influencing malaria incidence among children. This relatively low R-squared value highlights the complexity of malaria transmission dynamics, which are influenced by various ecological, social, and economic factors beyond just climate variables. Generally, while the results indicate some level of association between climatic factors and malaria prevalence, the significance of both annual rainfall and maximum temperature calls for careful consideration in interpreting these findings as evidence of causation.

Effect of temperature on the transmission of malaria is nonlinear for the temperatures between 16-25°C with its peak being at approximately 23°C (Figure 4.5). The nonlinear sensitivities throughout the mosquito life cycle results to a large impact on the mosquito adult population dynamics, and therefore on the mosquito's ability to act effectively as malaria vectors, resulting into more malaria incidences. The study results indicated that temperatures play a key role in malaria transmission by influencing vector and parasite life cycles.

The mean maximum temperature significantly resulted to higher malaria cases compared to other temperature ranges (Figure 4.5). The difference in the contribution of maximum temperature to malaria cases is attributed to the difference in prevailing temperatures across the region under the study. The cold temperatures were recorded below 15°C, which implies that temperature was the factor hindering vector development for malaria transmission therefore an increase in maximum temperature led to a rise in vector and parasite development rates. According to the findings since temperature influences the development and survival rates of both vectors and parasites, transmission rates of malaria increased with a rise in temperature but only up to a given threshold.

According to the prediction made in the table 4.9, the results shows that 51.7% of the children sampled within the region had contracted malaria within the last three months of the survey and only 48.3% of the population never had malaria cases. This means that 98 out of 189 children had malaria cases in the last 3 months of the survey and only 91 children were safe from malaria disease.

Table 4.9: Classification Table

			Freq.	%
	Child contracted malaria in last 3months	Yes	98	51.7
		No	91	48.3
				100

(Author, 2024)

The independent variables in the logistic regression equation (Equation 1) in step 0, shows a coefficient value (B) of 0.067, standard error (SE) of 0.212, significance level of 0.051 and a degree of freedom of one (Table 4.9). This indicates that the independent variables are statistically significant to the outcome variable which is malaria prevalence.

Table 4.10: Variables in the Equation (Eq.1)

Variables in the Equation							
		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	.067	.212	.101	1	.051	.935

(Author, 2024)

Constant (Intercept) (B=0.067), Standard Error (SE) (0.212), Degrees of Freedom (df=1), Significance Level (p=0.051), and Exp (B) 0.935 (the odds ratio related to the constant) are all derived from the data (table 4.10). The SE is not utilized in the equation but is significant for evaluating the accuracy of the estimate. The B-coefficient shows the change in the log-odds of the outcome variable (malaria prevalence) caused by a one-unit increase in the independent variable while holding all other variables constant. Given that the model is at step 0, meaning that only the constant term is included, the independent variable in this instance is probably a binary or categorical variable. An increase in the log-odds of malaria prevalence is suggested by the positive coefficient value of 0.067 when this independent variable is present, or when the reference category is altered. The logistic regression equation would appear as (Eq 2), assuming that the constant is the only independent variable (as stated in step 0). The constant term helps forecast the likelihood of malaria prevalence, according to the logistic regression equation 1.

Based on this model, the projected likelihood of malaria prevalence is 6.7%, or roughly 0.067. This shows that the independent variables have a small impact on the outcome variable even though they are statistically significant at the 0.051 level.

The measures on the association between climate variables and malaria cases used in this analysis were as follows: in malaria spread rate influenced by temperature and rainfall, the results showed both positive and negative influences of rainfall on malaria transmission. Further, there is association between rainfall and malaria cases and also there exist association between mean maximum temperature and malaria cases among children in Elgeyo-Marakwet West sub-County region.

This implies that an increase in precipitation is not guaranteed to result in an increase of malaria cases. Moderate rainfall brings positive impact on malaria prevalence while high rainfall washes away mosquito breeding sites hence reduces malaria transmission.

Malaria seasonality

Elgeyo-Marakwet west Sub County experiences seasonal malaria transmission. The availability of several seasonal and permanent water bodies provides suitable breeding microhabitats for malaria vector at specific periods of the year. The relatively low annual rainfall and the general absence of permanent water bodies summed up to the witnessed low but varying numbers of recorded malaria cases giving in weighted option of varying climatic conditions as the possible cause.

In the classification table (table 4.9) of the logistic regression the results indicate that there are more children who contracted malaria in the last three month (prior to this research) compared to those who never contracted. The regression analysis (table 4.8) indicated that temperature and rainfall have a positive outcome on the dependent variable which in our case was Malaria prevalence with a statistical significance value of 0.03 hence indicating that the spread of malaria is influenced by temperature and rainfall. There is actually a positive and negative influence of rainfall on malaria transmission as the findings indicated a significance value of 0.004, hence showing that the impact of rain in transmitting malaria is both negative and positive. Further, temperature also showed a positive significant relationship (p =0.041) with the independent variable.

Results agrees with study findings by Nyawanda *et al.,* (2023) that between 2008 and 2010, the incidence of malaria rose by 50%; from 2010 to 2015, it decreased by 73%. Despite widespread usage of bed nets, there was a recurrence in cases after 2016. While rainfall was linked to an increase in incidence (IRR = 1.27, 95% Bayesian credible interval [BCI]: 1.10–1.44), increases in daytime land surface temperature were associated with a decrease in malaria incidence (incidence rate ratio [IRR] = 0.70, 95% BCI: 0.59–0.82). In contrast to SES, which was not linked to malaria incidence in this cohort, bed net use was associated with a decrease in the incidence of malaria among children aged 6 to 59 months (IRR = 0.78, 95% BCI: 0.70–0.87) but not in other age groups.

The table 4.11 below shows that the model coefficients are statistically significant as it shows a value of 0.008 which is less than 0.05 hence the variables in the study were found to affect malaria outcome in one way or the other.

Table 4.11: Omnibus Tests of Model Coefficients

Omnibus Tests of Model Coefficients				
		Chi-square	df	Sig.
	Step	17.518	6	.008
Step 1	Block	17.518	6	.008
	Model	17.518	6	.008

(Author, 2024)

According to the model summary (table 4.12) results, Cox & Snell results shows that only 17.9% of the data are explained by the model and to the Nagelkerke its 23.8% of the data which is explained by this logistic regression model.

Table 4.12: Model Summary

Model Summary			
Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	105.761[a]	.179	.238
a. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.			

In table 4.13, the correlation between annual rainfall, maximum temperature and malaria cases provide useful insights into how these climatic conditions impact the incidence of malaria.

Table 4.13: Correlation coefficient for Annual rainfall, Temperature and Malaria Prevalence

		Malaria Prevalence Rate	Rainfall (mm)	Max. Temp. (C)
Malaria Prevalence Rate	Correlation	1		
	Sig. (2-			
Rainfall	Correlation	-0.1694	1	
	Sig. (2-	0.6184		
Max. Temp	Correlation	0.3193	.246**	1
	Sig. (2-	0.3386	.043	

(Author, 2024)

The correlation between malaria incidence and rainfall is -0.1694, which implies weak negative correlation (Table 4.13). This means that, when rainfall is higher, malaria incidence goes down slightly, but this relationship does not have a statistical significance level (p= 0.6184). This insignificance means that rainfall may not be the most significant or consistent predictor of malaria cases in this context.

The correlation coefficient for maximum temperature is 0.3193 which suggests moderate positive correlation with malaria. This means that temperatures could also associate with more cases of malaria, perhaps because mosquitoes would thrive in better weather for their survival and breeding. But the significance level (p= 0.3386) also suggests that this relationship is not statistically significant, so the trend is still there, but it may not be strong enough to make conclusions.

The correlation analysis in general is that although there are patterns in the relationships between rainfall, temperature and malaria incidence, none of these factors has a statistically significant effect on malaria cases in this dataset. This further indicates that other factors may have a greater impact on the apparent decline in malaria prevalence. The modest negative correlation with rainfall and the slight positive correlation with temperature point to potential areas of investigation, including understanding the environmental constraints on the transmission dynamics of malaria.

The study reveals a significant correlation between climate variability and malaria prevalence among children in Marakwet West Sub-County. Specifically, there is a negative correlation of -0.608 between annual rainfall and malaria prevalence, suggesting that increased rainfall may be associated with lower malaria incidence. Conversely, a positive correlation of 0.643 exists between maximum temperature and malaria prevalence, indicating that higher temperatures tend to correlate with higher malaria rates in the region.

4.5: The impact of malaria control interventions on incidences of malaria among Children in Elgeyo-Marakwet West Sub-County

Table 4.15 shows that more than half of the children 61.4% contracted malaria in the last three months prior to the survey period. Majority also indicated the presence of stagnant waters (ponds) near their homes (63.5%) as well as shrubs and thickets present (68.3%). This implies the presence of potential breeding grounds for the malaria causing vectors.

Table 4.15: Malaria Prevalence in Elgeyo Marakwet West Sub-County

Child contracted malaria in last 3months		
	Frequency	Percent
Yes	116	61.4
No	73	38.6
Total	189	100.0
Any Pond or stagnant water near your home		
Yes	120	63.5
No	69	36.5
Total	189	100.0
Any shrubs and thicket near your home		
Yes	129	68.3
No	60	31.7
	189	100

(Author, 2024)

In the analysis of estimated propensity score model (Appendix II), the results revealed that children living near ponds and thickets were more likely to have contracted malaria within the last three months of the survey, than those children living in areas where there were no ponds or stagnant water and thick bushes. This is because the ponds and thickets act as breeding sites for malaria parasites hence more malaria transmission. In Chebiemit sub county hospital children were found less likely to be in the treated group as compared to those children in Kapsowar (AIC) Mission hospital and Iten County referral hospital. The results further revealed that age and gender were not likely to affect malaria transmission. The more steric numbers indicated the level of significance of the values. The lower the Akaike information criterion (AIC) the better our model, and with AIC of 59.615, the conclusion was that this was the model of best fit.

Intervention Measures using Mosquito Nets (Observation Before and After Intervention)

On the average malaria cases on the control group, the observation was that the use of mosquito nets lowered malaria cases by -0.39241. The critical value 0.22282 was greater than the p value (0.05) hence the test was statistically significant. The understanding from the analysis was that the original number of the observations were 189 and the number of treated observations were 179.

Estimate... -0.39241

The use of mosquito nets is connected with an average decrease in malaria cases of -0.39241. This negative estimate implies that mosquito nets are successful in lowering the malaria incidence in the group under control. The test was statistically significant since the critical value of 0.22282 was higher than the p-value of 0.05. This implies that it is unlikely that the observed decline in malaria cases linked to mosquito net use is the result of chance.

Table 4.16: Malaria Cases in Control Group

Statistic	**Value**
Standard Error	0.32189
T-statistic	-1.2191
P-value	0.22282
N	189

(Author, 2024)

The t-statistic shows how far the estimate deviates from zero standard deviations, whilst the standard error (SE = 0.32189) gives an indication of the estimate's variability. The estimate appears to be close to zero, as indicated by the t-statistic of -1.2191, which is consistent with the p-value showing marginal significance. The null hypothesis, which holds that mosquito nets have no influence on malaria cases, is not sufficiently supported by the data, according to the p-value of 0.22282, to support a rejection of it at the 0.05 significance level. It is, nevertheless, sufficiently close to imply a possible impact that merits additional research.

While checking the balancing property of the propensity scores (Appendix IIb), the study analyzed; the average treatment, average control and the standard deviation which is the distribution of mean around the central tendency for all the variables from age to thickets and then displayed the means before matching and after matching. Before matching the p value 0.0038337 was less than the significance level (p=0.05) hence there was a relationship between malaria cases and tested cases in Kapsowar hospital (xsample1). After matching, the p value was 2.22e-16 indicating that thick bushes promote high malaria cases in the region as seen in the below analysis.

There was a perfect match between the control and observed group of samples as displayed in Figure 4.10.

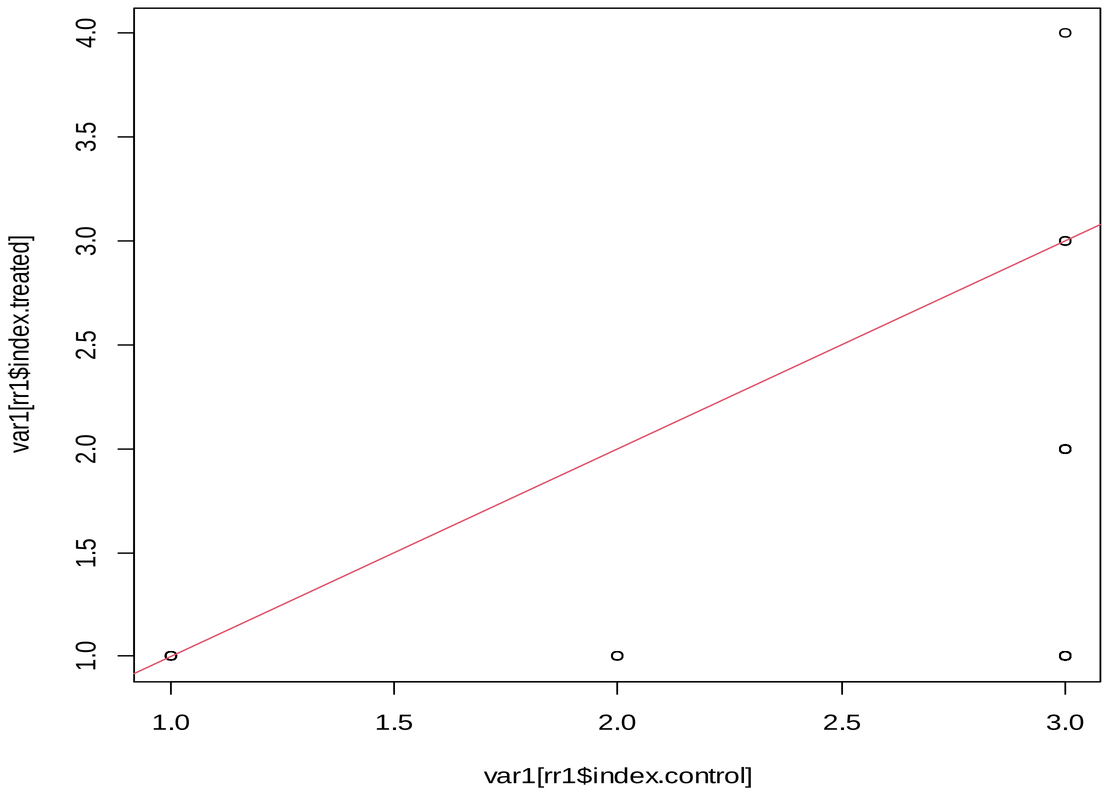


Figure 4.10: Match between control and observed variables

4.6 Discussion of Findings

The discussion centers on the findings and conclusions drawn from the rainfall and temperature parameters of the Marakwet West Sub-County. From 2012 to 2022, the Elgeyo-Marakwet West Sub-County experienced an estimated 1300 mm of average annual normal rainfall. The findings show that the prevalence of malaria has been significantly declining over time, while the trends in annual rainfall and maximum temperature have not reached statistical significance. The Mann-Kendall test results indicated that, throughout the given period, there appeared to have been a significant decrease in the prevalence of malaria. This trend was statistically significant, as shown by the significant p-value and the strong negative tau value. The pace of decrease is quantified by the Sen's slope, and the findings' dependability is further reinforced by the confidence interval. According to the data, there has been a noticeable decline in the prevalence of malaria, which can be linked to both improved malaria control measures and potentially shifting environmental factors. Planning for public health and allocating resources for malaria control initiatives depend heavily on this data.

Fascinating patterns emerged from the examination of the spatio-temporal distribution of malaria prevalence among children in Elgeyo-Marakwet West sub-County region. There may be reason for concern for the increase in malaria incidence in the years 2016, which suggested a larger malaria burden in the region. In this instance, variations in the area's temperature and precipitation patterns could have made the environment more conducive to mosquito reproduction and the spread of malaria. Furthermore, a lack of access to diagnostic tools and efficient treatment could lead to underreporting of malaria cases or a delay in treatment, which would raise the disease's prevalence.

The unavoidable reality of climate change is that it refers to changes in the seasons, wherein the frequency and intensity of weather events vary over several years to more extremes. According to the results of this study, Elgeyo-Marakwet West sub-County region is among the several areas that are seeing climatic changes while also having malaria endemicities. This is consistent with earlier research by Rahmani *et al.*, (2022) that found a positive and significant relationship between climate change and the parasite Plasmodium group and Anopheles mosquitoes, which carry malaria. According to the study, there was a statistically significant correlation between malaria incidences in different parts of Southeast Asia and variations in temperature, precipitation, humidity, and wind speed over a period of many years.

Further, research by Mafwele and Lee (2022) looked at the correlations between climatic variables and malaria transmission in Africa, examining temperature, precipitation, and malaria incidence data for 43 African nations from 1901 to 2015. The study-built networks to ascertain the connections between the elements of climate change, including temperature and rainfall, and the spread of malaria. The results showed that among the variables influencing the rise in malaria infections in various regions are weather and climate.

There is a nonlinear relationship between temperature and malaria transmission within a particular temperature range, according to the third objective study results. The results resonate with the findings by Murdock *et al.*, (2016). Study showed that minute changes in temperature could have a significant impact on the dynamics of malaria transmission; nevertheless, few empirical or modelling investigations take these effects into account. Furthermore, the study hypothesized that under high transmission settings now in place, warming in the present and the future could decrease transmission potential rather than increase risk. In particular, the effect of temperature on malaria transmission varies and is not constant for temperatures between 16 and 30°C. It is observed that a temperature of 25°C is optimal for malaria transmission. This indicates that the ideal temperature range for the growth and spread of malaria is within the stated range. The development of the malaria parasite within malaria vectors, such as mosquitoes, or their ability to survive and reproduce may be negatively impacted by temperatures that fall or rise over this ideal range.

There are multiple reasons for the nonlinear impact of temperature on malaria transmission. Different factors may have an impact on the development, reproduction, and frequency of bites of mosquitoes within the temperature range of 16–30°C. Variations in temperature thresholds can cause distinct physiological reactions in mosquitoes, leading to differences in the insects' sectorial capability—that is, their power to spread the malaria parasite. Additionally, temperature is essential to the growth of the Plasmodium malaria parasite. There may be ideal temperatures within the specified range for the parasite's effective growth and maturation inside the mosquitoes. Variations from these ideal temperatures, however, may interfere with the parasite's growth and hinder its capacity to spread to people.

Notably, rainfall plays a crucial role in creating suitable breeding habitats for Anopheles mosquitoes, the primary vectors of malaria. Increased rainfall can lead to the formation of stagnant water bodies, which provide ideal conditions for mosquito breeding. As noted by Kim et al. (2019), heavy precipitation can transform rivers into pools, enhancing mosquito populations and subsequently increasing malaria transmission rates. Conversely, excessive rainfall can wash away mosquito breeding sites, potentially reducing malaria incidence in certain areas. This dual effect highlights the importance of understanding local climatic patterns when assessing the risk of malaria outbreaks.

Research has shown that climatic variability, including rainfall patterns, directly impacts malaria transmission dynamics. For instance, Ayanlade et al. (2020) found that malaria cases in Colombia and Venezuela surged by more than one-third during dry El Niño conditions, indicating that fluctuations in rainfall can significantly affect malaria prevalence. Additionally, Hussien (2019) emphasizes that warm temperatures combined with sufficient rainfall are critical in inducing spikes in malaria incidences, particularly in East African highlands where ecological conditions favor mosquito proliferation. This study conducted in Elgeyo Marakwet West Sub-County corroborates these findings by demonstrating a strong correlation between climate variations, specifically rainfall and temperature, and the frequency of malaria cases among children. This underscores the necessity for integrated approaches that consider both climatic factors and ecological conditions in developing effective malaria control interventions.

CHAPTER FIVE: SUMMARY OF FINDINGS, CONCLUSIONS AND RECOMMENDATIONS

5.1 Summary

The study addressed the persistent public health problem of malaria prevalence among children in Elgeyo Marakwet West Sub-County, exacerbated by climate variability, particularly seasonal changes in temperature and rainfall. It employed a mixed-method approach using secondary time-series data from health facility records and meteorological sources spanning 2012-2022. Statistical techniques included descriptive statistics, Mann-Kendall trend tests, principal component analysis to identify key climate factors, logistic regression to assess their effects on malaria prevalence, and propensity score matching to evaluate the impact of malaria control interventions.

The primary objective of the study was to determine the effect of climate variability on malaria prevalence among children in Marakwet West Sub-County. The study's first objective was to analyze the spatio-temporal distribution of malaria prevalence among children in Marakwet West Sub-County. The malaria prevalence significantly decreased between 2012 and 2022, according to the Mann-Kendall test results. The comparison of malaria cases by season shows clear differences in the average number of cases across the various seasons. The seasonal study reveals large variations in the number of cases of malaria; the highest incidence was noted during the OND season, which was followed by MAM, and a considerable decline during JJA.

The second objective assessed the association of climate variables and malaria prevalence among children in Marakwet West Sub-County. The region experiences two distinct periods of rainfall namely, March-Aprill-May (wet periods) and October-November-December periods (wet period). Sen's slope analysis and the Mann-Kendall test results showed that there are no statistically significant trends in either yearly rainfall or maximum temperature during the course of the study. Although there are marginal signs of a decrease in yearly precipitation and stability in the highest temperature, the large confidence intervals and high p-values imply that these results might not represent significant shifts. Rainfall does not directly influence thriving of vectors, therefore, influences seasonal variation of disease vectors. On temperature component, the results revealed an existing positive strong significant relationship between temperature and the thriving of vectors.

The third objective analyzed the effect of climate variables on malaria prevalence among children in Marakwet West Sub- County. The results revealed that the climate variables were statistically significant ($p=0.051$) malaria prevalence. In this case, the effect of temperature on the transmission of malaria was nonlinear for the temperatures between 16-25°C with its peak being at 23°C. Similarly, the results showed a nonlinear relationship between malaria incidence and rainfall (Figure 4.2).

The fourth objective analyzed the impacts of malaria interventions on malaria prevalence. According to the data, there is a -0.39241 average drop in malaria cases in the control group when mosquito nets are used. The p-value of 0.22282 indicates that more research with a bigger sample size may be required to confirm the findings, even though the effect is statistically significant.

The study on climate variability's effect on malaria prevalence among children in Elgeyo Marakwet West Sub-County revealed key findings including a significant overall decline in malaria cases from 2012-2022 (Mann-Kendall Tau = -0.881, $p=0.0002$), with seasonal peaks in OND (mean 267 cases) and MAM seasons due to rainfall fostering mosquito breeding, and lowest incidence in JJA (mean 40 cases) from cooler, drier conditions; strong nonlinear temperature-malaria links peaking at 23°C; over 51% of children reporting recent infections linked to nearby stagnant water; and positive marginal effects of rainfall (0.000484 cases/mm) and maximum temperature (0.157 cases/°C) on prevalence, with a nonlinear temperature peak at ~23°C optimal for vectors; PCA confirmed strong associations among temperature range, rainfall patterns, and child age. Over 51-61% of children reported recent malaria, exacerbated by stagnant water (63.5%) and shrubs (68.3%) near homes as breeding sites, while interventions like mosquito nets reduced cases by -0.392. Hypothesis outcomes supported rejection of all nulls: H01 rejected as spatio-temporal distribution showed significant changes (e.g., declining annual trend); H02 rejected due to significant climate-malaria associations via PCA (four components explaining 58.9% variance); H03 rejected confirming climate variables significantly affect prevalence (logistic model $p<0.05$); and H04 rejected as control interventions like ITNs and IRS demonstrated substantial impact on reducing incidences.

5.2 Conclusion

The study on the effects of climatic variability on malaria prevalence among children in Elgeyo Marakwet West Sub-County has yielded significant findings that align with its specific objectives. Firstly, the analysis of the spatio-temporal distribution of malaria prevalence revealed a noteworthy decline in malaria cases from 2012 to 2022, indicating that despite ongoing challenges, there is potential for effective malaria control measures in the region. This decline was particularly associated with climate variables, demonstrating a strong correlation between temperature fluctuations and malaria incidence, especially within the critical temperature range of 16-25°C, with a peak at approximately 23°C. Furthermore, the study assessed the association and effect of climate variables on malaria prevalence, confirming that higher temperatures and moderate rainfall significantly influence malaria transmission dynamics. The results suggest that as climate change continues to evolve, the risk of malaria may increase, particularly among children who are most vulnerable to severe outcomes.

Lastly, the evaluation of malaria control interventions indicated that while interventions such as insecticide-treated nets (ITNs) and indoor residual spraying (IRS) are in place, over half of the surveyed children had contracted malaria in the months leading up to the study. This highlights the need for enhanced community engagement and education regarding these interventions and their proper use. In conclusion, this research underscores the importance of integrating climatic data into public health strategies for malaria control. It provides critical insights for policymakers to develop targeted interventions that consider both environmental factors and community needs, ultimately aiming to reduce the burden of malaria among children in Elgeyo Marakwet West Sub-County. By addressing these findings, stakeholders can better anticipate future trends in malaria prevalence and implement more effective strategies to protect vulnerable populations.

The research conducted on the effects of climatic variability on malaria prevalence among children in Elgeyo Marakwet West Sub-County has made significant contributions to malaria intervention strategies. One of the key additions is the establishment of a mathematical model that describes the relationship between climate variables and malaria prevalence. This model helps to quantify how temperature and precipitation influence malaria transmission, providing a scientific basis for predicting malaria outbreaks based on climatic conditions. By identifying the nonlinear relationship between temperature ranges and malaria incidence, particularly the peak transmission occurring around 23°C, the study offers valuable insights for tailoring interventions to specific climatic scenarios.

The findings indicate a strong correlation between climatic variations and malaria incidence, which suggests that existing control measures may need to be adjusted in response to changing climate patterns. The research highlights the necessity for policymakers to consider these climatic influences when developing and implementing malaria interventions. This could involve enhancing community awareness programs about the risks associated with climate change and its impact on malaria transmission, as well as reinforcing existing control measures such as insecticide-treated nets (ITNs) and indoor residual spraying (IRS) in areas identified as high-risk based on climatic predictions. Overall, the study provides a framework for improving malaria interventions by linking environmental factors with health outcomes, ultimately aiming to reduce the burden of malaria among children in this vulnerable region.

The research has significantly contributed to the understanding and development of malaria intervention strategies. In this case, the study highlights the importance of integrating climate data into public health strategies for malaria control. By demonstrating a strong correlation between climate variations and malaria prevalence, the research emphasizes that existing control measures must adapt to changing environmental conditions. This insight is vital for policymakers as it suggests that interventions should be tailored to specific climatic scenarios, enhancing their effectiveness in reducing malaria incidence among vulnerable populations, particularly children. The findings also underscore the need for community engagement and education regarding malaria prevention strategies. The study revealed that a significant percentage of children had contracted malaria in the months leading up to the survey, indicating gaps in awareness and preventive practices. By promoting community-based education programs focused on eliminating mosquito breeding sites and utilizing preventive measures such use of insecticide-treated mosquito nets (ITNs), public health officials can empower communities to take proactive steps in mitigating malaria risk.

5.3 Recommendation

Based on the study objectives regarding the effects of climatic variability on malaria prevalence among children in Elgeyo Marakwet West Sub-County, several recommendations can be drawn to enhance malaria control strategies and improve health outcomes for this vulnerable population.

The aspect on Surveillance should be strengthened. It is essential to establish a robust surveillance system that continuously monitors both climatic variables and malaria incidence among children. This system should utilize advanced technologies such as Geographic Information Systems (GIS) to map the spatio-temporal distribution of malaria cases in relation to climate data. By improving data collection methods, health authorities can identify trends and patterns more effectively, allowing for timely interventions during peak transmission periods.

Implementing community-based education programs focused on malaria prevention is crucial. These programs should aim to raise awareness about the importance of eliminating mosquito breeding sites, such as stagnant water bodies, and promote the use of preventive measures like insecticide-treated nets (ITNs) and indoor residual spraying (IRS). Engaging local communities in these initiatives will empower them to take proactive steps in reducing malaria transmission risks.

Policymakers should incorporate climate adaptation strategies into existing malaria control frameworks. This includes conducting research to understand how changing climate patterns affect mosquito populations and malaria transmission dynamics. By aligning public health strategies with environmental considerations, authorities can develop more effective interventions that address the dual challenges of climate change and malaria prevalence.

Regular assessments of existing malaria control interventions are necessary to determine their effectiveness in reducing incidence rates among children. This involves analyzing data on treatment outcomes, community engagement levels, and environmental factors influencing malaria transmission. By understanding what works and what does not, health officials can refine their strategies and allocate resources more efficiently.

5.4 Study limitations

This study was restricted by its small sample size and the fact that it was conducted in only one sub-county. Additional investigation is required to validate these results and evaluate the effect of climate change on malaria in other regions of Kenya.

5.5 Future Research Areas

Future study could focus on larger-scale investigations to confirm the link between climate variability and malaria prevalence. Additional research ought to look into the processes through which malaria transmission is impacted by climate change. Other possible research directions include analyzing the economic and social effects of malaria in the context of climate change, as well as developing and evaluating malaria control measures that are climate resilient.

REFERENCES

Amadi, M., & Erandi, K. H. (2024). Assessing the relationship between malaria incidence levels and meteorological factors using cluster-integrated regression. *BMC Infectious Diseases*, 24(1), 664.

Asale, A., Abro, Z., Enchalew, B., Teshager, A., Belay, A., Kassie, M., & Mutero, C. M. (2021). Community knowledge, perceptions, and practices regarding malaria and its control in Jabi Tehnan district, Amhara Region, Northwest Ethiopia. *Malaria Journal*, *20*(1), 459.

Ayanlade, A., Nwayor, I. J., Sergi, C., Ayanlade, O. S., Di Carlo, P., Jeje, O. D., &Jegede, M. O. (2020). Early warning climate indices for malaria and meningitis in tropical ecological zones. *Scientific Reports*, *10*(1), 1-13.

Baghbanzadeh, M., Kumar, D., Yavasoglu, S. I., Manning, S., Hanafi-Bojd, A. A., Ghasemzadeh, H., &Haque, U. (2020). Malaria epidemics in India: Role of climatic condition and control measures. *Science of the Total Environment*, *712*, 136368.

Briët, O. J., Vounatsou, P., Gunawardena, D. M., Galappaththy, G. N., & Amerasinghe, P. H. (2008). Temporal correlation between malaria and rainfall in Sri Lanka. *Malaria journal*, *7*, 1-14.

Carolina, D., Mukuma, L., Matoba, J., Sing'anga,C, C., Jennifer, S., Shields .T. & Clive J. S. (2022). Impact of aerial humidity on seasonal malaria: an ecological study in Zambia. *Malaria Journal*, 325 (2022). Retrieved from https://malariajournal.biomedcentral.com/articles/10.1186/s12936-022-04345-w

Caputo, A., & Garavelli, P. L. (2016). Climate, environment and transmission of malaria. *Infez Med*, *2*, 93-104.

Dabaro, D., Birhanu, Z., Negash, A., Hawaria, D., & Yewhalaw, D. (2021). Effects of rainfall, temperature and topography on malaria incidence in elimination targeted district of Ethiopia. *Malaria journal*, *20*, 1-10.

Fouque, F., & Reeder, J. C. (2019). Impact of past and on-going changes on climate and weather on vector-borne diseases transmission: a look at the evidence. *Infectious diseases of poverty*, *8*(03), 1-9.

Hussien, H. H. (2019). Malaria's association with climatic variables and an epidemic early warning system using historical data from Gezira State, Sudan. *Heliyon*, *5*(3), e01375.

Kigen, G., Muli, J., Mureithi, J., et al. (2021). *Ethnobotanical Study of Medicinal Plants Used to Treat Malarial Infections by the Marakwet Community in Kenya*. Africa Environmental Review Journal.

Kim, J. E., Choi, Y., & Lee, C. H. (2019). Effects of climate change on Plasmodium vivax malaria transmission dynamics: a mathematical modeling approach. *Applied Mathematics and Computation*, *347*, 616-630.

Kogan, F. (2020). *Remote sensing for malaria: Monitoring and predicting malaria from operational satellites*. Cham, Switzerland: Springer Nature Switzerland AG.

Macharia, P.M., Giorgi, E., Noor, A.M. (2018). *Spatio-temporal analysis of Plasmodium falciparum prevalence to understand the past and chart the future of malaria control in Kenya*. Malaria Journal.

Mafwele, B. J., & Lee, J. W. (2022). Relationships between transmission of malaria in Africa and climate factors. *Scientific Reports*, *12*(1), 14392.

McNeish, D. (2018). Thanks coefficient alpha, we'll take it from here. *Psychological methods*, *23*(3), 412.

Maniga, J. N., Mong'are, S., Masai ,R., Odda, J., Odoki, M., Ntulume, i., Pacifica Bwogo , I., Itundinda, j., & Adekunle, A. S. (2022). Trend of Malaria Burden Among Residents of Kisii County, Kenya After More Than a Decade Usage of Artemisinin Combined Therapies, 11–Year Laboratory Based Retrospective Study. doi:doi: 10.2147/IDR.S370218

Ministry of Health. (2020). *Malaria Indicator Survey 2020.* Nairobi: Ministry of Health. Retrieved 8 1, 2024, from https://dhsprogram.com/pubs/pdf/MIS36/MIS36.pdf

Ministry of Health. (2022). *Malaria Indicator Survey 2020.* Nairobi: Ministry of Health.

Nassiuma D. K. (2000). *Survey sampling: Theory and methods.*Njoro, Kenya: Egerton University Press.

Nkiruka, O., Prasad, R., & Clement, O. (2021). Prediction of malaria incidence using climate variability and machine learning. *Informatics in Medicine Unlocked*, *22*, 100508.

Nyawanda, B.O., Beloconi, A., Khagayi, S., et al. (2023). *The relative effect of climate variability on malaria incidence after scale-up of interventions in western Kenya: A time-series analysis of monthly incidence data from 2008 to 2019*. ScienceDirect.

Segun, O. E., Shohaimi, S., Nallapan, M., Lamidi-Sarumoh, A. A., &Salari, N. (2020). Statistical modelling of the effects of weather factors on malaria occurrence in Abuja, Nigeria. *International journal of environmental research and public health*, *17*(10), 3474.

Siedlecki, S. L. (2020). Understanding descriptive research designs and methods. *Clinical Nurse Specialist*, *34*(1), 8-12.

United Nation. (2019). *Climate Change and Malaria - A Complex Relationship.* Geneva: UN. Retrieved 8 1, 2024, from https://www.un.org/en/chronicle/article/climate-change-and-malaria-complex-relationship#:~:text=An%20increase%20in%20temperature%2C%20rainfall,it%20was%20not%20reported%20earlier.

United Nations. (2020). *Climate Change and Malaria - A Complex Relationship.* Geneva: United Nations . Retrieved 8 1, 2024, from https://www.un.org/en/chronicle/article/climate-change-and-malaria-complex-relationship#:~:text=An%20increase%20in%20temperature%2C%20rainfall,it%20was%20not%20reported%20earlier.

World Health Organization. (2019). *Compendium of WHO malaria guidance: prevention, diagnosis, treatment, surveillance and elimination* (No. WHO/CDS/GMP/2019.03). World Health Organization.

Yi, L., Xu, X., Ge, W., Xue, H., Li, J., Li, D., ...& Li, J. (2019). The impact of climate variability on infectious disease transmission in China: Current knowledge and further directions. *Environmental research*, *173*, 255-261.

Zhao, H., Lai, Z., Leung, H., & Zhang, X. (2020). *Feature learning and understanding: Algorithms and applications*. Cham: Springer.

APPENDICES

Appendix 1: Questionnaire

Dear Respondent,

My name is Pamela Muange Mbithi, a master's student taking environmental sustainability and climate change at Kenyatta University in Kenya. I am now conducting research on climate variability and the prevalence of malaria among children in Marakwet West Sub-County. As a result, I respectfully ask that you take a few minutes to complete this survey in its entirety. We will only use the information you give us for this study, and we take your privacy very seriously.

Instructions

Tick where appropriate

Before filling the questionnaire, the respondent has to confirm that they have a child and that the child has been within Marakwet County in the last three months or so.

Name of the sub-county________________

Section A: BIOGRAPHIC INFORMATION

1. Household members

	Name of the household member	Age of the household member	Gender of the household member	weight of the household head	Relation with the household head
1					
2					
3					
4					
5					
6					

2. What is the highest education level attained by the household head?
   - ☐ None
   - ☐ Primary Education
   - ☐ Secondary Education
   - ☐ Vocational Education
   - ☐ College Education
   - ☐ University Education
3. What is the main occupation of the household head?
   - ☐ Government Employed
   - ☐ Employed in a Private entity
   - ☐ Self-employed
   - ☐ Peasant farmer
   - ☐ None
4. What is your estimated household income in a month?
   - ☐ Below Ksh 20,000
   - ☐ Ksh 20,000 – Ksh 50,000
   - ☐ Above Ksh 50,000

SECTION B: INDOOR MALARIA TRANSMISSION

5. Does your house have mosquito net(s)?
   - ☐ Yes
   - ☐ No
6. How long ago did you acquire the mosquito net(s)?
   - ☐ Less than a month ago
   - ☐ Between one and three months ago
   - ☐ More than three months ago
7. From where did you obtain this mosquito net(s)?
   - ☐ Government donation
   - ☐ NGO donation
   - ☐ Religious donation

☐ Individually purchased

☐ Other

8. Does the sleeping area of your children have an actively used mosquito net?

   ☐ Yes

   ☐ No

9. Has any of your children contracted malaria in the last three months?

   ☐ Yes

   ☐ No

SECTION C: HOUSEHOLD ENVIRONMENT

10. Is there any pond(s) or any other form of stagnant water body(s) near your home?

    ☐ Yes

    ☐ No

11. Are there shrubs and thickets in the vicinity of your home?

    ☐ Yes

    ☐ No

SECTION D: OUTDOOR MALARIA TRANSMISSION

12. Has anyone from the household been sick of malaria in the past three months?

    ☐ Yes

    ☐ No

13. If yes, who was it?

    ☐ Adult

    ☐ Child

    ☐ Both

14. What time do you get home after the normal activities of the day?

    ☐ Early than 4 pm

    ☐ 4-5 pm

    ☐ 5-6 pm

    ☐ 6-7 pm

☐ Past 7pm

15. What time do you finally get into the house and shut all windows and the door?

    ☐ 5-6 pm

    ☐ 6-7 pm

    ☐ Past 7pm

16. What is the latest time that children are allowed to play outside in the evening?

    ☐ 4-5 pm

    ☐ 5-6 pm

    ☐ 6-7 pm

    ☐ 7-8 pm

17. Where are your meals cooked?

    ☐ Main house

    ☐ Kitchen house

    ☐ Open air

18. Do you know of any activities that are organized in the village in the evenings or at night?

    ☐ Yes

    ☐ No

19. Have you ever attended any of these activities?

    ☐ Yes

    ☐ No

20. When out at night, do you worry about being bitten by mosquitoes?

    ☐ Yes

    ☐ No

21. How do you protect yourself from being bitten by mosquitoes when out at night?

    ☐ Use sweater or coat

☐ Use a cloth cover/Kitambaa / Shuka

☐ Don't use anything

22. What time do you go to sleep at night?

☐ 7-8 pm

☐ 8-9 pm

☐ 9-10 pm

☐ 10-11 pm

☐ Past 11 pm

23. What time do you wake up in the morning?

☐ Earlier than 4 am

☐ 4-5 am

☐ 5-6 am

☐ 6-7 am

☐ 7-8 am

☐ Past 8 am

24. What activities do you do outside the house during the morning hours?

☐ Morning house chores

☐ Farming activities

☐ Go to work (employment)

SECTION E: The association of climate variables and malaria prevalence among children in Elgeyo-Marakwet West Sub-County

25. Temperature plays a key role in malaria transmission by influencing thriving of vector and parasite

Strongly agree [ ]

Agree [ ]

Neutral [ ]

Disagree [ ]

Strongly disagree [ ]

26. What range of temperatures causes high vector population turnover?

1 – 10 °C [ ]

11-20 °C [ ]

21-30 °C [ ]

31-40 °C [ ]

Over 41 °C [ ]

27. Rainfall influences malaria transmission in Elgeyo Marakwet West sub county

Strongly agree [ ]

Agree [ ]

Neutral [ ]

Disagree [ ]

Strongly disagree [ ]

28. The annual rainfall trend in the region and the general absence of permanent water bodies contribute to low but varying numbers of recorded malaria cases

Strongly agree [ ]

Agree [ ]

Neutral [ ]

Disagree [ ]

Strongly disagree [ ]

29. Are there other variables closely associated with climate variability and malaria which you feel are critical to consider? Explain.

………………………………………………………………………………………………..

………………………………………………………………………………………………..

30. Kindly explain the typical rainfall patterns during the MAM (March-April-May), OND (October-November-December), and JJA (June-July-August)? seasons in the region within the past one year.

………………………………………………………………………………………..

………………………………………………………………………………………..

31. Kindly indicate the seasonal variations in mean temperature within the region during the following periods MAM (March-April-May), OND (October-November- December), and JJA (June-July-August) in the past one year?

………………………………………………………………………………………….

………………………………………………………………………………………….

SECTION F: Effect of climate variables on malaria prevalence among children in Marakwet West Sub- County

32. The rate at which malaria spreads among children in the region is influenced by temperature and rainfall

Strongly agree	[ ]
Agree	[ ]
Neutral	[ ]
Disagree	[ ]
Strongly disagree	[ ]

33. Briefly indicate some of the negative and positive influence of rainfall on malaria Transmission in the region……………………………………………………………

……………………………………………………………………………………….

34. There is an association between mean monthly rainfall and malaria cases in the region

Strongly agree	[ ]

Agree [ ]

Neutral [ ]

Disagree [ ]

Strongly disagree [ ]

35. There is an association between mean maximum temperature and malaria cases amongst children in Elgeyo-Marakwet region

Strongly agree [ ]

Agree [ ]

Neutral [ ]

Disagree [ ]

Strongly disagree [ ]

36. The region records monthly malaria peaks amongst children

Strongly agree [ ]

Agree [ ]

Neutral [ ]

Disagree [ ]

Strongly disagree [ ]

37. The region experiences perennial malaria peaks amongst children

Strongly agree [ ]

Agree [ ]

Neutral [ ]

Disagree [ ]

Strongly disagree [ ]

THE END. THANK YOU FOR YOUR PARTICIPATION

Appendix II: Research Permit

REPUBLIC OF KENYA

NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

Ref No: 169468

Date of Issue: 17/September/2023

RESEARCH LICENSE

This is to Certify that Ms.. PAMELA KALONDU MUANGE of Kenyatta University, has been licensed to conduct research as per the provision of the Science, Technology and Innovation Act, 2013 (Rev.2014) in Elgeyo-Marakwet on the topic: EFFECT OF CLIMATE VARIABILITY ON MALARIA PREVALENCE AMONG CHILDREN MARAKWET COUNTY KENYA for the period ending : 17/September/2024.

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