

**CLIMATE VARIABILITY AND MALARIA TRANSMISSION TRENDS IN
DIFFERENT ALTITUDES OF LOWER LAKE VICTORIA BASIN,
KENYA**

BY

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DECLARATION

This thesis is my original work and has not been presented for a degree or any other award in any university. It has been complemented by referenced sources duly acknowledged where text, data (including spoken words), graphics, pictures or tables have been borrowed from other sources.

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DEDICATION

To my father, the late Joshua Olela Oboch and my mother, the late Turfosa Ojwang'
Olela.

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LIST OF ACRONYMS AND ABBREVIATIONS

ARIMA	- Auto Regressive Integration Moving Averages
CCA	- Climate Change Adaptation
ENSO	- El Nino Southern Oscillation
HSD	- Honest Significance Difference
ITN	- Insect Treated Nets
IRS	- Indoor Residual Spray
KU	- Kenyatta University
LLVB	- Lower Lake Victoria Basin
LVB	- Lake Victoria Basin
LVBC	- Lake Victoria Basin Commission
MAM	- March, April and May
MoH	- Ministry of Health
MSC	- Mumias Sugar Company
NAO	- North Atlantic Oscillation
NACOSTI	- National Commission for Science Technology and Innovation
OND	- October, November and December
PMI	- Presidential Malaria Initiative
RH	- Relative Humidity
SPSS	- Statistical Package for Social Sciences
SH	- Specific Humidity
WHO	- World Health Organization
SONY	- South Nyanza

OPERATIONAL DEFINITION OF TERMS AND CONCEPTS

- Climate Variability:** Short term fluctuations in weather characteristics in space and time within a given climatic period. In this case it will refer to three climate elements: temperature, rainfall and humidity.
- Climate Change:** Long term shifts from the normal climate patterns
- Health Facility:** A hospital, dispensary or clinic at any level together with the personnel employed to serve the patients.
- Lower Lake Victoria Basin:** The surroundings of Lake Victoria occurring between altitudes 1100m and 1600m above sea level.
- Prevalence rate:** The proportion of the population that suffers malaria at a given time.
- Malaria Transmission:** The spread of malaria morbidity as a result of being bitten by malaria infected mosquitoes.
- Malaria Morbidity:** Unhealthy or disease mood resulting from the number of sick Individuals infected by malaria per 1000 of the total population in an area over a given period.
- Malaria Transmission scenario:** The development in events of the spread of malaria morbidity.
- Study period:** The period 2001 – 2020.
- Real dry months:** Months registering absolutely no rainfall

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ABSTRACT

Consequences of global climate variability and change are some of the biggest environmental challenges the world is facing. Impacts include increased frequency of extreme weather events. The impacts vary, Africa being the most vulnerable due to her high dependence on natural resources. One of the issues most associated with the challenges is malaria prevalence. Half of the world's population, (3.4 billion people in 92 countries), is at risk, 1.1 billion at high risk. Malaria burden is greatest in the developing countries of the tropics such as Africa which has 91% of the related deaths, 60% being children under five years. Climate extremes have increased in East Africa, which is predicted to add 75.9 million people to the risk bracket. In Kenya, malaria is blamed on high rainfall, temperature and relative humidity. This study evaluated climate variability and malaria transmission trends in different altitudes of Lower Lake Victoria Basin (LLVB), Kenya where malaria prevalence rate was 27% despite varying between 4% - 8% in other parts of the country. Descriptive and correlational designs with quantitative methods were used to analyze spatiotemporal variability of selected climate elements and malaria transmission trends. Target population was flooded malaria morbidity cases recorded at Sub – County Hospitals. Meteorological data was obtained per sampled county and sub - county i.e. Migori - SONY Central Meteorological Station, Kisumu - Kisumu Airport Meteorological Station and Kakamega -MSC Meteorological Station. Data for the selected climate parameters were collected for twenty years except Relative Humidity from Kisumu Airport which was only available for 12 years (2009-2020). Health data was obtained from the Kenya Health Information System (KHIS) for ten years (2011 to 2020) through sampled Sub-County Level 4 Hospitals. ANOVA was used to analyze variability among climate and malaria transmission variables, Pearson's Correlation Coefficient tested relationships while Descriptive Time Series and "ARIMA regression models" were respectively used to give trends and to predict future climate and malaria scenarios. Results revealed that Malaria transmission and climatic variables significantly varied in space and time. Mean annual malaria transmission in Kisumu was 3902.87, Kakamega 3385.53 and Migori 2130.33. Mean annual temperature was 23.77⁰C in Kisumu, 22.61⁰C in Kakamega and 22.52⁰C in Migori. The two had insignificant monthly and annual correlations. However, climate elements insignificantly defined transmission differently at different altitudes. In a further analysis, stepwise linear regression dropped all climatic variables and left only altitude as the significant determinant of malaria transmission variability in the LLVB. This made the study use altitude and transmission levels to zone LLVB as follows: 1001m to 1200m – high transmission; 1201 to 1400 - medium transmission; 1401 to 1600 – low transmission. The study predicted that malaria transmission would increase in high and medium transmission zones while decreasing in low transmission zones. This meant that malaria prevalence would still vary depending on altitude. The revelations were used to inform experts in policy decision making on reduction of malaria transmission. This was to enhance malaria eradication processes in the LLVB, Kenya, and hence promote the realization of Kenya's vision 2030.

CHAPTER ONE: INTRODUCTION

1.1 Background to the Study Problem

Consequences of global climate variability and change are some of the biggest environmental threats and challenges the world is currently facing. Impacts include heightened temperatures which according to Lake Victoria Basin Commission (LVBC), (2018-2023) are proposed to increase by 3⁰C by the year 2100, rainfall anomalies and increased frequency of other extreme weather events. The impacts vary or are determined by where a person lives and how sensitive the people are to the resulting impacts (WHO, 2014). LVBC (2018-2023) identified Africa as the most vulnerable due to her high dependence on natural environmental resources.

Alonso & Noor, (2017), claimed that one of the consequences of the impacts is malaria, a threatening disease caused by parasites transmitted to people through bites of infected female *Anopheles* mosquitoes. Distribution of mosquitoes is influenced by altitude, temperature, relative humidity and rainfall. From that report, half of the world's population (3.4 billion people) in 92 countries was at risk, 1.1 billion being at high risk. That means more than one malaria morbidity case occurred per 1000 members of the population per year. Hope is that malaria transmission is preventable and the disease is curable (WHO, 2021).

Teboh *et al.* (2020) claimed that 228 million cases and 405 000 deaths of which 67% (272 000) were children under 5 years of age occurred in the world in 2018. WHO (2021) talked of 229 million morbidity cases and 409 000 deaths in 2019, an increase of 1 million in morbidity, and 4 000 deaths respectively. Older adults, pregnant women, infants, children 5 years and below, HIV/AIDs patients and non-

immune migrants were at higher risk. WHO (2021) report indicated a further increase (241 million) in 2020, a positive deviation of 12 million according to Ewnetu *et al.* (2022).

Malaria is a threatening disease caused by parasites transmitted to people through bites of infected mosquitoes whose distribution is influenced by altitude, temperature, relative humidity and rainfall. However, success history of the Roll Back Malaria initiative in 2015 increased interest in eliminating the burden. From that time, Global malaria elimination strategy (2015–2030) was endorsed to create a malaria-free world. In this effort, World Health Organization (WHO) has a vision to reduce malaria morbidity by at least 40% in 2020, 75% by 2025, and 90% by 2030 through step by step elimination from at least 10 countries in 2020 and 20 countries in 2025 before the final 35 countries in 2030 (Ewnetu *et al.*, 2022).

Most malaria transmission vulnerabilities occur in the third world countries (Kapesa *et al.*, 2018). Though previously wide spread, malaria is now mainly confined to Africa (where 91% of the malaria related deaths occur, 60% of them being children under five years), Asia and Latin America (Hemingway *et al.*, 2018). Teboh *et al.* (2020) added that of the 228 million morbidity cases in the world, 93% were found in the WHO African region, 3.4% in South East Asia and 2.1% in Eastern Mediterranean Region.

In Africa malaria morbidity is most associated with climate change (Alonso & Noor, 2017). Teboh *et al.* (2020) claimed that WHO African region accounted for 94% of the world's malaria morbidity cases and deaths (WHO 2021). According to Ryan *et al.* (2020), many countries in Africa South of the Sahara now have weak

surveillance systems and are not well positioned to assess disease distribution and trends making it difficult to optimize responses.

About 51% of all global cases reported in the year 2019 were: Nigeria (27%); Democratic Republic of Congo (12%); Uganda (5%); Mozambique (4%); Niger (3%). African countries must therefore be active on the track of elimination if the world is to realize pre-elimination targets otherwise malaria will not be history from Africa and the rest of the world (Ewnetu *et al.*, 2022).

Occurrences of climate extremes have increased in East Africa. The worst case regional scenario of climate change predicted an additional 75.9 million people at risk from endemic (10 – 12 months) exposure to malaria in Eastern and Southern Africa by 2080. The greatest population at risk was in Eastern Africa (Ryan *et al.*, 2020). According to Ryan *et al.* (2020), hot spots of endemic suitability include Lake Victoria region. Recurrence patterns of droughts and floods have been associated with El Niño - La Niña episodes and Indian Ocean Dipoles escalating malaria transmission in many parts of this region (Kapesa *et al.*, 2018).

Githure, *et al.* (2022) claimed that approximately 75% of the Kenya's population was at risk of malaria transmission in 2019. Transmission accounted for 18% of out – patient consultations and 10% of hospital admissions (Oxborough 2016). Githure, *et al.* (2022) further claimed that Kenya has five epidemiological zones with the LLVB being the most endemic. Davies *et al.* (2020) put it that 29% (14.4 million) of the Kenya's population live in malaria endemic areas with 9.8 million living in the eight counties of the Lower Lake Victoria Basin (LLVB), Kenya.

According to Githure *et al.* (2022), there were increasing uses of many interventions, i.e. PMI provided ITNs, IRS and promoted Case Management Drug Based preventions like in pregnancy. Kapesa *et al.*, (2018) had however observed that many areas in Western Kenya were still experiencing malaria transmission dynamics. It was a threat with a prevalence rate of 27%, while varying between 4% and 8% in the rest of Kenya (Hemingway *et al.*, 2018), with malaria morbidity case incidence of 70.1 per 1000 being at risk.

Oxborough (2016) identified the LLVB, Kenya comprising of eight counties, with a total population of more than 8.7 million to bear the highest brunt of malaria morbidity in the country. From the 2016 report, the eight counties combined had 38/1000 morbidity cases compared to 6/1000 in the other counties of Kenya. The LLVB counties showed 26.7% parasitemia compared to 8.2% in the other counties of Kenya.

Malaria transmission in Kenya is largely determined by altitude, rainfall, and temperature. Kenya's altitude is naturally varied even at micro levels. Such variations create contrasts in the country's climate which ranges from tropical at the coast, temperate in the interior to very dry in the north and north east (Davies *et al.*, 2020).

Kipruto *et al.* (2017) established that changes in malaria prevalence corresponded to variations in rainfall and maximum temperatures differently due to small variations in altitude. Since Lake Victoria Basin (LVB) has typical equatorial climate, the varying altitudes in the region were expected to modify spatio - temporal – climates leading to variation in malaria transmission. This study determined the patterns

taken by climatic and malaria transmission variability in the LLVB, Kenya. Conducted at different altitudes of the LLVB, it helped to fill a gap by relating malaria transmission with varying altitudes, temperature, relative humidity and rainfall. This helped to identify malaria transmission areas which needed more surveillance than others and hence promoted the expectations of Kenya's vision 2030 on health issues.

1.2 Statement of the Problem

Malaria in Kenya had witnessed a significant decrease in transmission over the past few years due to intensified intervention measures put in place by the Kenya government supported by the international communities such as Roll Back Malaria initiative of 2015, the recent US Presidential Initiative which sponsored the IRS and ITN in many parts of Western Kenya among others. These had taken place alongside the government's efforts to ensure provision of effective medication and awareness creation. The progress led to profound hope in attaining pre – elimination limits despite a number of challenges, one being heterogeneity in distribution where prevalence rate was much higher in places like the LLVB than in other parts of the country hence slowing the progress. The said hope made the Kenya National Malaria Control Strategy aim at reaching pre – elimination levels for most parts of the country. To achieve sustainable control and elimination, clear understanding of transmission characteristics was needed to identify more threat factors. This availed an opportunity for appropriate direction of interventions.

LLVB, exists with a number of plains, valleys, hills hence a variety of different altitudes. Given that transmission is a factor of climatic conditions defined by altitudinal differences, variation in relief obviously affected mosquito population,

distribution and survival hence varied climate – malaria relationships. Transmission reduction strategies however remained uniform despite such variations. Assessment of climate variability over different altitudes in relation to malaria transmission trends was critical in the LLVB so as to enhance integrated approaches with emphasis on reducing transmission in various parts. Pre – elimination interventions had not yet targeted this as a challenge.

Further still, LLVB housed more than 8 million people, about 18% of the country's population whose health issues could not be ignored especially given that while malaria transmission rates in Kenya had gone very low (4% - 8%), it was still a threat to the LLVB, where the prevalence rate remained at 27%.

This study therefore investigated issues of heterogeneity in malaria transmission distribution in relation to climatic conditions defined by varying altitudes of The LLVB, Kenya. It provided clear understanding of transmission characteristics which helped in identifying malaria morbidity hot spots. The findings provided important information for planning the present and future intervention strategies in the Lower Lake Victoria Basin, Kenya.

1.3 Justification of the Study

Since climate variability is taking place triggering climate change, consistent and systematic spatiotemporal analysis was needed to understand the new levels of the malaria transmission scenario at the LLVB, Kenya. As Mordecai *et al* (2013) put it, although there had been enormous global malaria burden for more than a century, research had not yielded adequate understanding of the mechanistic link between the environmental variables such as climatic elements and malaria transmission. Long

term incremental changes meant that people everywhere, including LLVB, Kenya, had to adapt to the new weather patterns and their outcomes (Parry *et al.*, 2012).

Mordecai *et al* (2013) also argued that the effects of increasing temperature in warmer regions where conditions supported endemic malaria transmission were often ignored. Under such circumstances, it became difficult to know exactly what went on in such areas. LLVB, Kenya was an example of such areas. It had always been assumed under the umbrella studies of the entire LVB of East Africa. However, Mwangiru (1986) and Kerandi *et al.* (2017) defined LLVB as an area with varied altitudes meaning it has to experience varied climatic conditions that influenced malaria transmission differently. Lake Victoria Basin Commission (LVBC) (2018-2023) confirmed this when it established considerable variations in rainfall in the LVB yet effects of such variations had not been investigated.

LVBC (2018-2023) projected warmer and wetter conditions that were adequate to both vector- borne and diarrheal diseases. However small a geographical unit may be, factors influencing climate variability are so heterogeneous and dynamic that a situation in one place might not be similar to the other considering spatiotemporal environmental variations. According to Akech *et al.* (2019), malaria transmission in Kenya was determined largely by altitude, temperature, humidity and rainfall. Variations in these, although generalized could be detected at micro scales influencing malaria transmission variability at such levels. For that reason, it was necessary to study malaria transmission at different altitudes of the LLVB, Kenya.

LVBC (2018-2023) predicted wide variability in both incident and prevalent malaria in the Kenya's LVB which would see 5.8 million people being affected annually

while mortality would increase to 15, 700 people annually. These were expected to stretch the available health facilities and escalate the cost of treatment to 86 million dollars annually. The eastern section of the LVB which is mostly Kenya was projected to bear the highest brunt. Given that LLVB was in the Eastern side of the LVB and had not received any significant attention despite being categorized as malaria endemic, it was found to be worth the study.

WHO (2017) noted that, “each region has its own intervention package - we cannot do the same things everywhere”. Knowledge of the effect of climate variability on malaria transmission helped define parasite distribution at different altitudes. Such information was found to be vital in the formulation of policies concerning contemporary and future malaria transmission reduction strategies in the LLVB, Kenya.

As Wickremasinghe (2012) put it, complex relationship between climate and malaria still created knowledge gaps in the mechanisms of the linkage. This scholar claimed that under dry conditions, heavy rainfall provided good breeding grounds for mosquitoes while in some areas heavy rains were found to wash out breeding sites hence reducing malaria incidences. With multiple transmission reduction strategies, which one to apply; when, where and how were found to be determined by how environmental factors were systematically understood. These called for local level-research interventions in the LLVB, Kenya.

According to Alegana *et al.* (2021), LLVB, Kenya was home to over 9.4 million people representing more than 18% of the country’s population. The health issues of such a huge population could not be ignored. On the other hand, Oxborough (2016)

and Hemingway *et al.* (2018) had established that malaria transmission rate in Kenya had gone very low yet it was still a threat to the LLVB, Kenya where the prevalence rate was at 27% despite varying between 4% - 8% in most parts of the country. Based on such observations, it was necessary that this study be conducted in the LLVB, Kenya.

1.4 Objectives of the Study

1.4.1 General Objective

The general objective of the study was to establish the influence of climate variability on malaria transmission trends in different altitudes of lower Lake Victoria Basin, Kenya.

1.4.2 Specific Objectives

The study focused on the following specific objectives:

- i. To analyze spatiotemporal variability of temperature, relative humidity and rainfall in different altitudes of lower Lake Victoria Basin.
- ii. To analyze spatiotemporal variation of malaria transmission in different altitudes of lower Lake Victoria Basin.
- iii. To establish the spatiotemporal relationship between variability in climate parameters (temperature, relative humidity and rainfall) and malaria transmission (morbidity) in different altitudes of lower Lake Victoria Basin.
- iv. To predict the future relationship between climate variability and malaria transmission in different altitudes of lower Lake Victoria Basin.

1.5 Research Questions

The study addressed the following research questions:

- i. How do temperature, relative humidity and rainfall vary in different altitudes of lower Lake Victoria Basin?
- ii. How does malaria morbidity vary in different altitudes of lower Lake Victoria Basin?
- iii. What is the relationship between variability in climate parameters (temperature, rainfall and relative humidity) and malaria transmission (morbidity) in different altitudes of lower Lake Victoria Basin?
- iv. What would be the future malaria transmission trends typical to different altitudes of Lower Lake Victoria Basin?

1.6 Hypotheses

- i. There is no significant spatiotemporal variation in the temperature means, relative humidity and rainfall, and malaria transmission in lower Lake Victoria Basin.
- ii. There is no significant relationship between variability in climate parameters (temperature, rainfall and relative humidity) and malaria transmission (morbidity) in different altitudes of lower Lake Victoria Basin.

1.7 Significance of the Study

This study was important as it was expected to boost:

- i. “WHO” Global Technical Strategy for malaria 2016 – 2030 whose set targets were: Reducing malaria case - incidences by at least 90% by 2030; Reducing malaria mortality rates by at least 90% by 2030;

Eliminating malaria in at least 35 countries by 2030 (Kenya inclusive);

Preventing resurgence of malaria in all malaria free countries.

- ii. The PMI's 2005 goal to eradicate world-wide malaria by 2040-2050.
- iii. The efforts of the United Nations Development Program (UNDP) among other development partners in promoting the development agenda.
- iv. The efforts of Kenya's vision 2030 development blue print which prioritized preventive health care at community levels through decentralized national health care system.

The study was expected to benefit the communities of the Lower Lake Victoria Basin by expanding their knowledge on the role of climate variability on malaria transmission in different altitudes of the area.

For a community to understand climate risk issues, effectively use available information, develop the necessary institutions and networks, plan and build appropriate Climate Change Adaptation (CCA), and to evaluate and monitor these, it is important to use local experiences.

The study availed the latest information on Climate - Malaria relationships. The information was very important to the vulnerable communities of the Kenya's Lower Lake Victoria Basin in accelerating reduction in vulnerabilities while building resilience and safety measures at the local levels and beyond.

The study organized a data base upon which interested scholars could make references. It was again expected to enrich the malaria/climate literature for the Lower Lake Basin of Kenya.

1.8 Scope and Limitation of the Study

This study analyzed climate (Temperature, Rainfall and RH) variability and malaria transmission (Morbidity) trends in different altitudes of lower Lake Victoria Basin, Kenya. The altitudes varied from 1550m in Migori County down to 1100m at its lowest in Siaya County, and then rose again to 1535m in Kakamega and 1559m in Vihiga making up the eight counties. Out of the eight, only three were sampled as follows: Kisumu (1001m – 1200m), Kakamega (1201m – 1400m), Migori (1401m – 1600m).

The area hosted a population of over 9.4 million people (Alegana *et al.*, 2021). Climate data collected covered 20 years (2001 - 2020) while malaria transmission data covered 10 years (2011 - 2020). Temporal variability of climate elements and that of malaria transmission were analyzed on monthly and annual basis covering the same period over which data was collected. Spatial variability on the other hand was based on altitudes. Malaria and climate were correlated and regressed for 10 years. Only three climate parameters that had been identified by the previous scholars as the major determinants of malaria transmission were used in the study (temperature, relative humidity and rainfall).

The study was limited by the fact that malaria transmission data from KHIS could be obtained for only 10 years. At the same time, there was a lot of clinical malaria transmission data which the researcher ignored in favor of microscopic ones. Another limiting factor was time since census approach would have delayed the process leading to dilution of results. This issue of time was thus overcome by sampling only three counties among eight. Results were then inferred on the entire study area. Missing climate and malaria transmission data were minimal. Where

they occurred, they were interpolated using estimation and comparison for effective harmonization and fair representation.

CHAPTER TWO: LITERATURE REVIEW

2.1 Introduction

This section was an overview of trends of climate variability, malaria transmission and how climate variability and malaria transmission related under different environments. Based on the study objectives, each stage of the review was punctuated by a clear statement of the identified gaps for the study. The section concluded by giving a theory, a model and a conceptual framework that guided the study.

2.2 Variability of Climate Parameters in Different Regions

Perkins (2017) put it forward that, “Climate variations normally occur naturally without human influence”. Examples included: NAO (North Atlantic Oscillation), an anomalous change that occurs near Iceland and the Azores High; El Nino Southern Oscillation (ENSO) which takes place between a warming Phase (La Nina) and a cooling phase (El Nino) with a natural phase in between; Madden – Julian Oscillation, a wave which traverses the planet along the tropics, among others.

Crimmins *et al.* (2022) observed that average global temperatures had risen faster since the late 1970s (0.32 to 0.55°F per decade since 1979). Of the top 10 warmest years on record, nine had occurred since 1998 with 2012 and 2016 being the warmest on record. The 2012–2021 decade was the warmest since the beginning of thermometer-based observations. Global temperature had risen at the rate of 0.17°F per decade on average since 1901. United States had warmed faster than the global rate with some parts experiencing more warming than others.

Lindsey and Dahlman (2020) claimed that temperature variations experienced locally and in short periods may occur significantly due to predictable, cyclic events like night and day, summer and winter, and also due to hard-to-predict wind and precipitation patterns. Global temperatures depend on how much energy the planet receives from the Sun and how much is radiated back into space. The scholars also argued that Temperatures may drop 2 degrees in one region while rising 5 degrees in another. Exceptionally cold winters in one place might be balanced by extremely warm winters in another. Onyutha (2021) characterized the African continent with the warming over periods starting 1901-1940 and 1979-2015. The continent however experienced cooling beginning 1941 to mid-1970s. Warming of the continent observed from 1979 to 2015 appeared stronger than from 1901-1940. Areas with high variability included Western Sahara, Mozambique, Egypt, Mauritania, and Lake Victoria region. Iyakaremye *et al.* (2021) projected that the magnitude of the highest temperature in Africa will increase by approximately 1.6/2.2°C in 1.5/2.0°C. The lowest temperature would increase by approximately 1.9/2.5°C in 1.5/2.0°C in the future climates where Eastern and Western African regions would be among the high intensity regions. The frequency of cold days was expected to decrease with the globe warming in many parts. However, impacts would differ among sub-regions.

Hanson (2019) observed that the topography of Kenya is defined by many different landscapes, ranging from coastal plains washed by warm waters of the Indian Ocean to the arid savannas and snow-capped mountains. Each of these varied regions has its unique climate, making it difficult to generalize the Kenyan weather. At the coast, the climate is tropical experiencing warm temperatures with the lowlands

being generally hot and dry. The highlands on the other hand are temperate and therefore cool.

According to Shin *et al.* (2021), it had become widely accepted that global warming alters the proportion of the water vapour available in the air. Some works reported that global warming increases Specific Humidity (SH) while RH remains constant at the global and regional scales. Water vapour is one of the critical variables that shapes hydrologic cycle and the Earth's energy balance. Long-term changes in these variables vary regionally as well as locally. Significant trends had been detected for RH in some regions, while they were not considered so in terms of global averages. Duane *et al.* (2008) claimed that on average, both relative humidity and absolute vapor pressure decreased with elevation in the East African region. Seasonal and diurnal variability in relative humidity (RH) is however enhanced toward the mountain summit. Strong diurnal cycle in humidity is a result of strong upslope moisture transport during the day counterbalanced by the reverse at night. Cooling on the lower slopes during the months of June and July weakens the lapse rates, consequently the convective activity.

Scott *et al.* (2017) posited that in Kenya, Temperature, humidity and heat index differ in several informal settlements including in Kibera – Nairobi which is the largest slum neighborhood in Africa. Temperature and thermal comfort index known colloquially as the heat index often exceed measurements observed at the Dagoretti station by several degrees celsius. On average, May is the most humid month, at 78.0%. February is the least humid at 62.0%. The average annual percentage is 72%. From Kerubo *et al's.* (2021) point of view, climate of Kenya is essentially defined by three major factors: temperature, rainfall and humidity. These three factors are

controlled by altitude such that the higher you go the cooler it is. This makes altitude another factor responsible for climate variation.

Evans *et al.* (2020) established that Lake Victoria Basin is wet throughout the year with two rainy seasons of March, April and May (MAM), and, October, November and December (OND). These could be due to influences of ITCZ, Congo Airstream, Westerlies and Monsoons. The scholars further determined that normal wetness had declined giving way to both extremely dry and wet conditions. Arid conditions are dominant around the lake where thermal stability prevails. The entire LVB experiences a range of climates with modified equatorial type on the highlands while semi-arid closer to the lake. Due to the varied terrain, a study of the rainfall dynamics was still necessary. Lake Victoria Basin Commission (LVBC) (2018-2023) postulated that in the recent past, LVB had been characterized by frequent episodes of either deficient or excessive rainfall. Annual rainfall of 6% - 50% across the basin counties for the period 1981-2010 was observed.

Dinse *et al.* (2009) argued that climate variations might bring extreme weather events subsequently affecting micro-environmental conditions hence influencing other occurrences. Herero *et al.* (2010) posited that climate change influenced climate variability hence extreme events leading to humans becoming vulnerable to suffering.

The above scholars observed the varying patterns of global and local weather events. Such major variations affect the local micro - climates differently calling for micro-climatic studies. These effects were felt differently at different altitudes within the

LLVB, Kenya where such studies had never been conducted. It was thus necessary that climate variability scenario was analyzed and established at different periods within different altitudes at local scales. This was necessary for understanding the differing effects of such variations in different places of the study area. That was the reason why this study sought to analyze spatiotemporal variability of temperature, relative humidity and rainfall in different altitudes of lower Lake Victoria Basin, Kenya.

2.3 Spatial and Temporal Variation of Malaria Transmission

Roser *et al.* (2020) observed that just a few generations ago, malaria was a common issue in many parts of the world but over the course of the 20th century, it had been eliminated in many populous regions saving lives of millions of people. Roser *et al.* (2020) posited that malaria was not only a disease of the tropics but a disease that had been eliminated elsewhere including East Asia and Australia, parts of the Caribbean, South America and Africa except some parts of the tropics. This is an indication that by identifying the hot spots and related right intervention and emphasis for different transmission regimes, it was possible to further reduce and subsequently eradicate malaria transmission in the remaining pockets of the world.

Bhattacharya *et al.* (2006) developed a set of transmission windows typical to India in terms of different temperature ranges for particular ranges of relative humidity. Using that criterion, the studies were able to establish the most endemic areas. This enabled the identification of the present while predicting the future malaria distribution such as where it would persist, shift to or from, or clear up all together or where it would just widen.

WHO (2017) recognized that malaria transmission in Western Kenya which is home to LLVB dropped from 38% in 2010 to 27% in 2015. This kind of drop ought to have been given systematically within years and over the years at different altitudes within the study area for better association with climatic factors. While this drop of 11% was being observed in the Lake Victoria Basin, an increase of 4% was registered at the coast, an indication that variations in trends were not uniform in all the areas at the same time.

Matsushita *et al.* (2019) observed that geographical differences can influence varied climate – Malaria relationships. According to Ewnetu *et al.* (2022) altitude and temperature are two very closely linked geographical variables. Increase in altitude obviously triggers a corresponding decline in temperature. It had been observed that for every 100 m increase in altitude, there is a corresponding 0.5 °C fall in temperature. Such temperature responses define the sporogonic cycles of malaria parasites in vectors. In relatively hotter villages, *Anopheles arabiensis*, *Anopheles pharonensis* and *Anopheles funestus*, often play a big role in malaria transmission. In very high altitude (relatively low temperature), beyond the distribution range of *Anopheles arabiensis*, less efficient vectors (*Anopheles cinereus* and different *Myzomia* species) do serve to transmit malaria at lower rates. Using altitude range, it is possible to estimate the rate of malaria transmission at differing altitudes. An example is where the scholars compared malaria transmission between 2601–2800 m and 1800–2000 m altitude ranges. It was established that the occurrence at 1800–2000 m was higher by 24.5%.

WHO (2017), further observed that malaria transmitting mosquitoes had started developing resistance to pyrethroid insecticides used in two biggest malaria

preventive tools (ITN and IRS) in western Kenya. This challenged the possibility of maintaining the progressive advances experienced in the area in the recent past, hence the need to keep abreast with the trends in order to understand the fluctuations due to such resistances and deal with them.

Omondi *et al.* (2017) studying Perennial transmission of malaria in the low altitude areas of Baringo County, Kenya learnt that the riverine zone had highest malaria case transmissions (23.2%). It was followed by the lowlands (0.9%). Midlands detected no malaria cases. The highland zones recorded few cases during the third follow up. Up to 10.7% cases were reported during the dry period while 2.9% during the long rains and 5.7% during short rains. The study revealed that malaria prevalence in Baringo County was mainly confined to the riverine zones where transmission was perennial. Higher cases were recorded during dry seasons compared to the wet seasons. This is not always the case as it is a belief that high rainfall is always responsible for escalated malaria transmission.

Emrouznejad & Yang (2018) identified myriad altitudes in the LLVB, Kenya and since Malaria transmission is primarily associated with altitude, temperature humidity and rainfall, diverse malaria ecologies are possible at different sites resulting in significant variations in malaria prevalence and incidences. Siya *et al.* (2020) put it that malaria control interventions should be strengthened and designed to strategically eliminate malaria cases across all the altitudinal zones. Integration of climate and altitude information within malaria interventions is necessary and is only possible when there is adequate information on the same. This would obviously strengthen eradication strategies.

Kapesa *et al.* (2018) established that clinical presentations of severely ill malaria patients varied from site to site. The same was witnessed with case fatalities; the highest being experienced in low transmission areas. It was observed that different sites responded to similar interventions differently with some areas witnessing reduction while others did not. Such variations in responses could be due to variations underlying hidden climatic elements that determine malaria transmission in an area. It should be noted that where one or two elements are at their minimum or maximum transmission thresholds, they either negatively or positively determine the transmission behaviours. Surveillance under such circumstances becomes a problem calling for knowledge of climate-malaria relationships.

LVBC (2018-2023) recognized malaria among the most common killer diseases in the region alongside cholera and respiratory tract infections. It predicted that wide variability would occur in both incident and transmission trends. The projections provided evidence of seasonality, cyclical patterns, and strong but temporally varying trends in malaria cases whose nature and details varied at different sites.

The above kinds of study were necessary for the LLVB, Kenya where they had never been conducted to help in establishing the nature of variability in malaria transmission. This was to be useful in determining the kinds of intervention strategies that would be effective for an area instead of a generalized approach. Besides, prediction is a key to “prevention” which is said to be better than “cure”. To identify the nature and factors influencing malaria transmission in different places of the LLVB, this study was vital for identifying the right intervention and emphasis at different places and at different times.

2.4 Relationship between Variability in Climate Parameters and Malaria

Transmission

Malaria is one of the few climate – sensitive health outcomes that has been subjected to thorough global and regional assessments using a range of malaria impact models and climate scenarios with varying results (Caminade *et al.*, 2014). Caminade *et al.* (2014) posited that to facilitate comparison of impacts under a range of climate scenarios and malaria models, a structure was needed that would differentiate variability originating from different inputs in the impact estimates.

While studying the impact of climate change and variability on wild life resources in Southern Africa, Descamps *et al.* (2017) observed the importance of understanding climate factors in adaptive, management and protection strategies. According to WHO (2019) malaria transmission depends on climatic conditions such as temperature, rainfall and humidity which influence the number and survival of mosquitoes. The study emphasized that seasonal malaria transmission in many places peak during and just after the rains.

Bhattacharya *et al.* (2006) argued that for most *anopheles* vector species that transmit malaria, the optimal temperature range is within 20⁰C to 30⁰C which should extend over a period for completion of the sporogony. Bhattacharya *et al.* (2006) said that transmission also depends on season with a rainy period being preferred for vector multiplication. Relative humidity should neither be below 55% nor above 80% otherwise the life span of the mosquito would be so shortened that transmission diminishes. These are the major climatic determinants of malaria transmission. Differing altitudes in a study area would influence their variability and hence the variability of malaria transmission.

M'Bra *et al.* (2018) studied the influence of change in temperature and precipitation on transmission of malaria in Korhogo-West Africa had established that transmission rate mostly depended on rainfall. Malaria incidences showed negative association with temperature while it indicated positively with rainfall.

In Baringo County, Kenya, Kipruto *et al.* (2017) found out that changes in malaria prevalence corresponded with variations in rainfall and maximum temperatures. It was observed that rainfall affected the entire study area while temperature only affected the riverine zones positively. Two malaria peak seasons were identified in the lowland zones while the other areas indicated three peak seasons largely following climate trends. The highland areas recorded statistically significant differences in the monthly malaria peaks (epidictic) while the reverse was true in the lowlands and riverine zones where malaria was present throughout the year (endemic). The implication here is that malaria may be present throughout the year but could experience peak periods depending on the controlling climate parameter.

As had been said, in some places, all the three identified climate parameters might simultaneously present an enabling transmission environment while elsewhere, two or three may collaborate in providing such environments. Unless such factors are determined, surveillance process may face challenges in determining the relevant mitigation, management or adaptive strategies.

County (2013) observed that human health had already been compromised by a range of factors including climate variability. Vectors, pathogens, and hosts reproduce within certain optimal climatic conditions whose changes could greatly modify the properties of disease transmission such as for malaria in the East African

highlands. It appeared that climate change had altered the ecology of some disease vectors in the region and subsequently the spatiotemporal transmission of these diseases. The study also projected impacts like prolonged periods of elevated malaria transmission interchanging with periods of low transmission making the disease highly cyclic.

Platt *et al.* (2018) defined malaria hotspots as areas where transmission intensity exceeded the average level and became more pronounced as transmission declined. In the study it was argued that targeting hotspots might have accelerated reductions in transmission and could be pivotal for malaria eradication. The study temporally based over six months but did not give specific spatial distribution of the study sites. However, it turned out that weather temporal or spatial, hotspots remained dynamic.

These studies observed variations in the relationship between climate variability and malaria transmission at different sites. They observed that different climatic parameters influence malaria occurrence differently. Specification of the hotspots was to be key factors in determining which adaptive strategy to apply when and where in the LLVB, Kenya. Such variations were studied in different specific altitudes of the lower Lake Victoria Basin to help explain transmission in different areas. This was a gap this research sought to fill. The study defined malaria hot spots by correlating climate variability parameters with malaria epidemiology trends within different specific regions separated by altitudinal differences in the LLVB, Kenya. This was vital in attempting to explain the influence of climate variability parameters on malaria transmission.

2.5 Predicting the Future Malaria Transmission Trends

Parihar *et al.* (2022) established that change in temperature and rainfall in future might influence the potential changes in the malaria transmission in Odisha. The model used projected future increases in temperature and rainfall over most parts and it was found that the future changes in increasing temperature and rainfall could potentially decrease mosquito density by the end of the century. Findings by Parihar *et al.* (2022) suggested that spatiotemporal distribution of malaria transmission during both summer and winter were to decrease with an increase in temperature of 3⁰C–4⁰C and increase in rainfall of 20% to 40% by end of the century with respect to the then climate scenario. Similar results were seen for the future changes in warm night verses cold night temperatures by 4.4 °C to 4.3 °C where malaria transmission was likely to reduce by 12.07% to 8.92% by end of the century. In particular, the decreasing trend in malaria transmission during the post monsoon season (OND) was statistically significant.

Diouf *et al.* (2022) observed that malaria prevalence was expected to diminish over West Africa in the near and far future with the magnitude of the decrease being higher in the far future. Such a decrease over the far future seemed to be associated with climate change. This study however highlighted that malaria prevalence was expected to increase in the southern part of the study region. It was expected that over the 2080s, climate would become very unsuitable in the northern part of the Sahel, with no more additional people at risk. Diouf *et al.* (2022) claimed that warm temperatures could impact on the adult mosquito survival scheme starting to kill a lot of adult mosquitoes implying decrease in malaria transmission. The change in malaria risk as simulated must be interpreted within the framework of local

conditions and developments, such as the health services, the parasite reservoir, and mosquito densities. In the context of climate change, these results were expected to be useful for decision-makers who planned public health measures in affected countries in West Africa and elsewhere. These results could be useful for stakeholders in order to develop mitigation and vector control strategies.

Bhattacharia *et al.* (2006) established a set of transmission windows typical to India in terms of different temperature ranges for a particular range of relative humidity by analyzing the then climate trends and corresponding malaria incidences. Using that criterion, the highest malaria transmission regions emerged and this enabled them to predict the future malaria distributions, that is, where it would persist, shift to or clear up altogether, or just widen the scope. According to them, climate signals in the last 100 years showed an increasing trend in surface temperature by 0.3⁰C, a change in the spatial rainfall patterns with respect to normal and occurrence of more intense and frequent extreme temperature, rainfall and cyclone events.

According to Tonnnang *et al.* (2010), vector – borne diseases were climate sensitive and this had raised concern over the implication of climate change on future disease risk. Tonnnang *et al.* (2010) posited that the problem of malaria vectors shifting from their traditional locations to invade new zones was an important concern. The study established that in Africa, shifts would occur in species boundaries towards the south and the east. Such predictions were very crucial in understanding the possible future geographical ranges of malaria transmission. They could facilitate planning for various transmission reduction options. Working knowledge of where malaria would potentially occur was very essential for malaria control policy makers and managers. Tonnnang *et al.* (2010) asserted that understanding the role of climate

and environment on the potential for future transmission was highly valuable for efficient planning.

Cella *et al.* (2019) observed that Climate Change or Climate Variability in different climatic scenarios do affect human health by increasing morbidity and disabilities through the emergence of diseases in previously non-endemic regions. According to the study, Climate Change may bring negative or positive impacts on infectious disease transmission, specifically diseases transmitted by vectors such as malaria. Climate Variability and Change may include alterations in one or more climate variables i.e. temperature, precipitation or humidity, and these changes may impact on the distribution of pathogens and vectors mainly by altering survival and reproduction patterns. Climate Variability and Change could cause higher frequency of infectious disease epidemics following floods and storms and those were anticipated to have mixed effects on the spread of malaria transmission based on vector biology in regions that are currently extremely cold for survival.

Cella *et al.* (2019) posited that climate/malaria models depict an increase in the geographic distribution of the disease as global environmental temperatures and conditions worsen. Based on the current Climate Variability and Change, it is predicted that in 2050, malaria may threaten some previously unexposed regions of the sub-Saharan Africa, causing a 50% higher probability of malaria. Studies that associated malaria cases and climatic factors in 25 African countries that were observed over a period of 11 years found that the number of malaria cases per 1,000 people was significantly influenced by climatic factors with incidences of malaria generally increasing under Climate Variability and Change.

As Cella *et al.* (2019) put it, incidences of malaria are sensitive to short-term fluctuations in temperature and rainfall patterns, and with extreme precipitation, washing anopheline mosquito larvae from the breeding sites may lead to decreased incidences of malaria. It was noticed that the mean temperature and precipitation did not change significantly over the past century in the highlands of East Africa, but malaria incidences have significantly increased. It was established that temperature in East Africa increased by 0.5°C between 1950 and 2002 and this led to significant increase in the number of cases of malaria.

Like Bhattacharia *et al.* (2006) did, this study intended to determine the present and future malaria transmission windows based on the selected climate elements and altitudes. Although LLVB is a small endemic area in Kenya, there was need to establish areas that could be more malaria prone in terms of climate variability and if possible, predict the situation was to be under the future climate scenarios. This kind of study was very necessary for determining the then and future malaria situation for the disease to be effectively controlled and subsequently eradicated in the LLVB and the entire country. This was the gap the study sought to fill.

2.6 Theoretical Framework

The study was based on, the systems “complexity theory” by Berreby (1996) and the “ARIMA” Model by “George Box and Gwilym Jenkins” of 1970. The systems “complexity theory” by Berreby (1996) operates on the basic premise that there is a hidden order to the behaviour of complex systems.

2.6.1 The Systems “Complexity Theory”

According to this theory, climate, drainage, vegetation and relief interact with malaria vectors as the major players influencing spatiotemporal variation of malaria transmission. Each of the mentioned parameters is in itself a system. When they interact, they constitute a complex system. According to Dhiman *et al* (2008), three climate elements: temperature; rainfall; humidity are the main players determining variations in malaria transmission. They are part of the complex system. The three interact to provide conducive environments for malaria transmitting vectors to breed, thrive to maturity and transmit the disease. In that context, climate on its own was a system whose influence needed to be critically studied.

Dhiman *et al.* (2008) asserts that the said climate elements are also influenced by external factors such as diversity in altitude and other environmental factors. This study thus adopted the complexity systems approach by identifying differing altitudes, studying how the altitudes interacted with climate to produce environments which became conducive for reproduction and breeding of mosquitoes to maturity before acting to bite human beings and transmit malaria. These parameters acted dependently governed by laws of nature some of which humans may or may not control. In adopting the complexity approach, each of these was studied as units of the complex system with the aim of getting either single or multiple outcomes.

Interdependencies may influence occurrences at various levels differently, for example, micro scale cannot be generalized with regional and global scales since any minor changes in the climate system may yield varied significant results at micro levels different from the mega scales. This may lead to differentiation in aerial

malaria transmission and subsequently different transmission reduction strategies as may be governed by the society's culture, academic exposure, economic endowment and the prevailing level of transmission. To understand such complexities and be able to explain and adapt to the outcome, in this case malaria transmission, it was necessary that researchers carry out effective investigations on the behaviour of each system within the complexity system, and it was through this approach that this study sought to evaluate climate variability and malaria transmission trends in the LLVB, Kenya.

2.6.2 “ARIMA” Model

The “ARIMA” model popularly known as “Box – Jenkins model” was first popularized by two scholars, “George Box and Gwilym Jenkins” both of whom it is named after, in 1970, (Stellwagen & Tashman 2013). It is a mathematical expression describing the probability structure of a time series (Agrawal & Adhikari, 2013). The main aim of a time series modeling is to carefully collect and rigorously study the past observations of the time series to develop an appropriate model which describes the inherent structure of the time series (Agrawal & Adhikari, 2013). Careful and rigorous approaches were used in collecting and studying malaria and climate data in the LLVB, Kenya. The “ARIMA” according to Brownlee (2017) is a model that is used for organizing and forecasting time series data. This study used the model to study and forecast the future influence of climate on malaria transmission in the study area.

Stellwagen & Tashman (2013) argued that for superior outcome of the model, data to be used must conform to the necessary assumptions. It is a class of models that

explains a given time series based on its past values i.e. its own lags and the lagged forecast errors (Prabhakaran, 2019). It provides a simple but powerful method for making skillful time series focus. It is a simpler generation of Autoregressive Moving average and adds the notion of integration. The components of “ARIMA” according to Stellwagen & Tashman (2013) include:

- i. AR – Auto regression – this uses dependent relationship between an observation and some number of lagged observation.
- ii. I - Integration – the use of differing raw observation in order to make moving averages stationery.
- iii. MA – Moving averages – a model that uses dependency between an observation and residual error from a moving average model applied to lagged observation.

This model was suitable for this study as Stellwagen & Tashman (2013) posit that:

- i. It can account for trend and reasonable patterns. These were some of the key concerns of objective 4 of this study.
- ii. It can be automated. This meant that data could easily be handled using the “STATA” software.
- iii. It is adaptive and can adjust to new information. This made autocorrelation possible i.e. malaria transmission could be auto-correlated with climate variability data. Autocorrelation shows how the model works hence eases the explanation of the outcome.

According to Agrawal and Adhikari (2013), the popularity of the model is based on its flexibility to represent several varieties of time series with simplicity. It also offers opportunities for model building. The “ARIMA” time series model greatly

suited the study since the study area did not have adequate knowledge on the statistical patterns displayed by malaria transmission against climate variability parameters at different altitudes.

2.7 Conceptual Framework

From the foregoing literature, systems “complexity” theory and the “ARIMA” time series model, a conceptual framework was developed (Figure 2.1). It gave the relationship among altitude, time, climate (temperature, relative humidity and rainfall) variability and malaria transmission (morbidity). Altitude and time formed the first set of independent variables. Climatic parameter took both dependent and independent roles being dependent to time and altitude while independent to mosquito population and subsequently malaria transmission. The three climate elements had to be optimal for effective malaria transmission to occur. However, the three elements might have varied due to various other reasons. This study looked at variations influenced by extreme weather events and altitude over time. The three climatic elements might have occurred normally or extremely but either way, they influenced malaria transmission differently by negating or propagating it depending on varying altitudes. This called for varied malaria management styles at different transmission sites.

Figure 2.1 illustrates the relationship where altitude and time defined climatic conditions which provided suitable breeding environment for mosquitoes to multiply. High population of mosquitoes meant increased biting rates and subsequently increased malaria transmission rates. In the process, treatment and prevention measures intervened and influenced the transmission outcome either

positively or negatively depending on how the intervention processes were administered and how they were perceived by the vulnerable communities. This study thus found out the level of malaria transmission in relation to climate variability at different altitudes in the LLVB, Kenya.

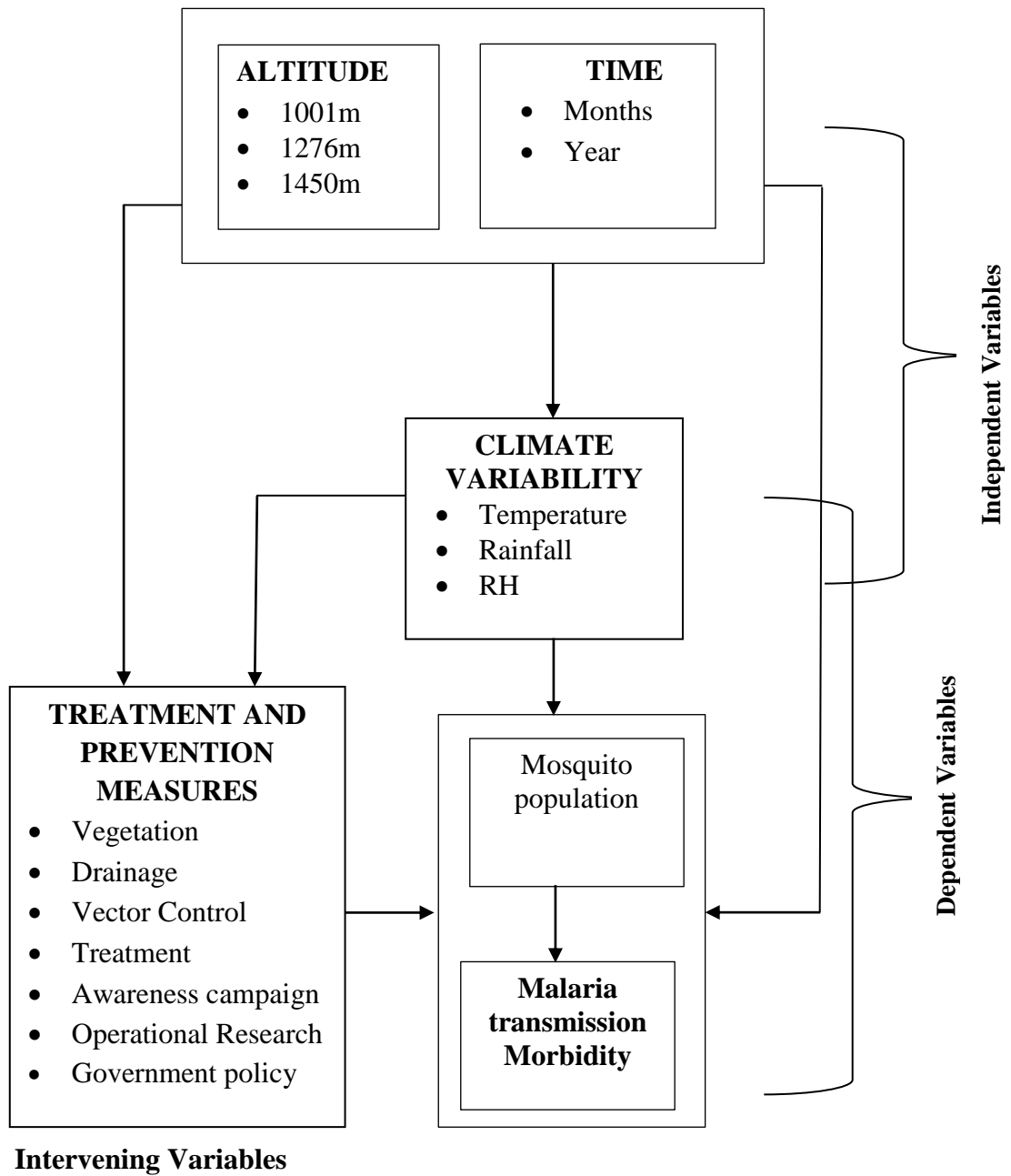


Figure 2.1: Climate Variability and Malaria Transmission Trends

Source: Modified from Berreby (1996) and Borak S et al., (2013)

CHAPTER THREE: RESEARCH METHODOLOGY

3.1 Introduction

Chapter three describes the study area and explains the methodology of the thesis. It is the part where the study strategies were outlined i.e. research design, target population, sample and sampling procedures, approaches to data collection and data characteristics. This section also explained validity and reliability of the instruments used for data collected and analysed including the tools that were used. Data management and ethical considerations were all explained.

3.2 Study Area

The study was carried out in the Lower Lake Victoria Basin, Kenya which is made up of the following eight counties: Migori, Homabay, Kisumu, Vihiga, Siaya, Kakamega, Bungoma and Busia. From the eight, three (Migori, Kisumu and Kakamega) were sampled for the study (Figure 3.1). The LLVB counties are located between latitudes 1.15°N and 1.75°S , and longitudes 33.95°E and 35.05°E (Emrouznejad & Yang, 2018). The Basin covers an area of about $42,724\text{km}^2$ making about 22% of the entire LVB. The shore line is 550Km, about 16% of the entire shore line and a lake surface of $4,128\text{km}^2$, making 6% of the entire surface (Mafuta *et al.*, 2017). The land covering this area slopes from an altitude of 1550m in Migori County down to 1100m at its lowest in Siaya County, and then rises again to 1535m in Kakamega and 1559m in Vihiga Counties (Mwagiru, 1986; Kerandi *et al.*, 2017).

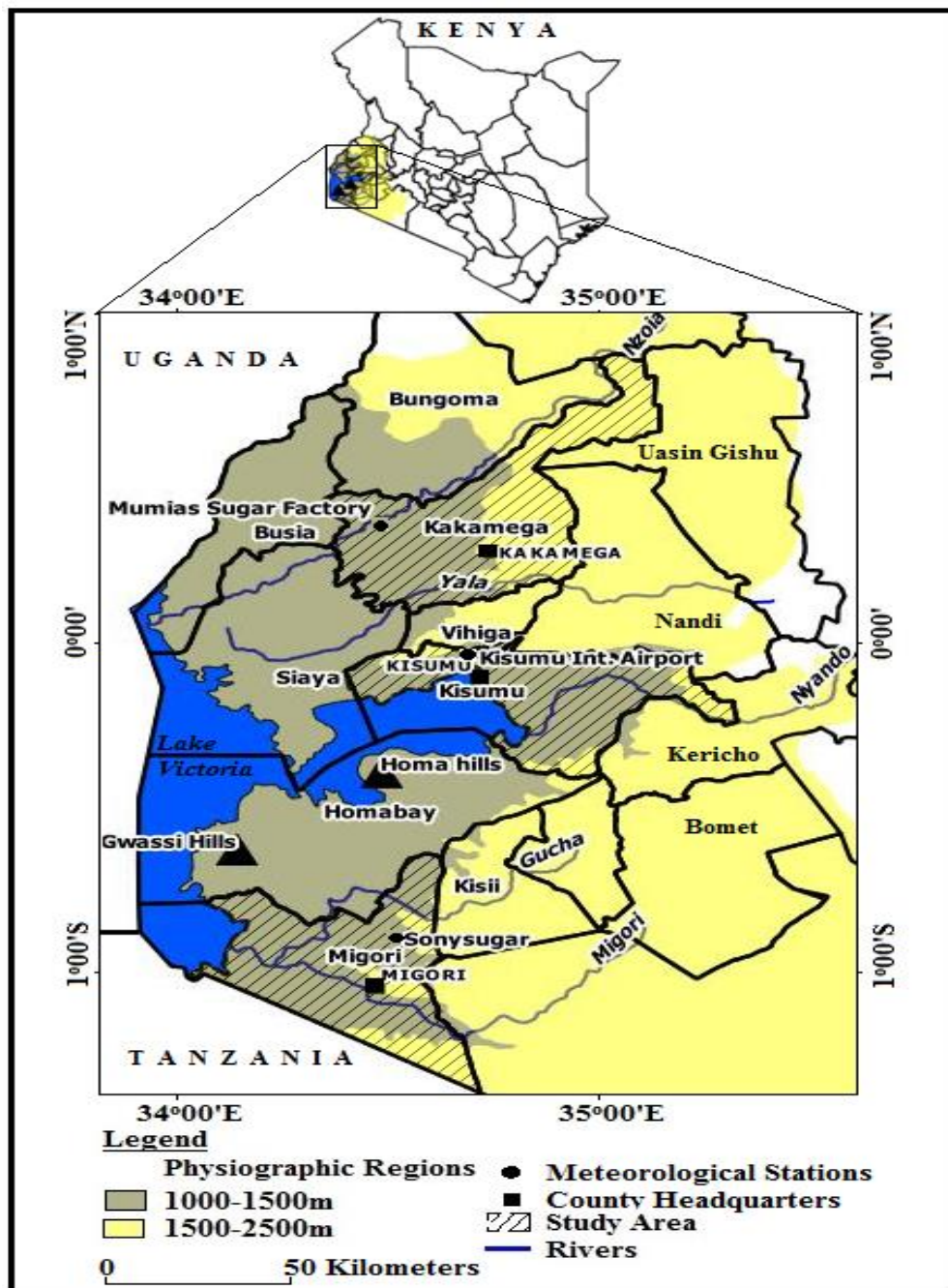


Figure 3.1: Map of the study area

Source: Modified from Kenya government (1970) *National Atlas of Kenya*.

The lowlands are traversed by rivers Kuja, Migori, Sondu, Nyando, Yala and Nzoia.

The southern end of the lowlands is dotted with hills such as Homa (1,751m), Ruri (1,705m), Gwasi (2,271m) and there is Kanyamwa Escarpment overlooking

Lambwe Valley to the South East. The climate of the area is Equatorial modified by the presence of the lake and the surrounding highlands. Rainfall ranges from 1100mm in Homabay County to 1971mm in Kakamega County, an average of 1556.5mm annually (De Alban *et al.*, 2018). Temperatures range from 20.0°C in Vihiga County to 22.5°C in Homabay County, an average of 21°C (De Alban *et al.*, 2018, Okuneye *et al.*, 2018). There are two rainfall regimes with no real dry season, rainfall being highest between March to May and between October to December.

Vegetation cover includes swampy grasslands and swampy forests, dry grasslands and dry woodlands, savannah forests and tropical forests depending on altitude. Much of the vegetation has since been cleared to give way for other activities like agriculture, settlement, urbanization, various construction works like roads, industries among others (Mafuta *et al.*, 2017). Major economic activities are fishing, tourism, mining, service industry, power generation, agriculture with crops grown being maize, sugarcane, rice, beans, potatoes, vegetables among others (Mafuta *et al.*, 2017).

County health facilities are Migori, Homabay, Kisumu, Kakamega, Busia, Mbale, Bungoma and Siaya. All are level 4 hospitals. The LLVB meteorological stations are Kisumu International Airport, Kibos Cotton Station, Busia Cotton Station, Ahero Irrigation Scheme, Koru Coffee Research Station, Mumias Sugar Company and SONY SUGAR. The inhabitants include Suba-Luos, Luos, Kurians, Nandis, Luhyas, Somalis, and small pockets of Indians, Arabs and Nubians (Hamel *et al.*, 2011).

The LLVB, Kenya was preferred for this study because from the literature review, the area was malaria endemic and despite the malaria transmission reduction in most

parts of Kenya, at LLVB, the prevalence rate remained high. On the other hand, most of the studies carried out in this area had hardly considered the influence of the existing altitude variations on climate variability, vector distribution, and hence variation of malaria transmission.

3.3 Research Design

This study adopted descriptive and correlation study designs to evaluate the effect of climate variability on malaria transmission trends in different altitudes of lower Lake Victoria Basin (LLVB), Kenya. Climate data (temperature, relative humidity and rainfall) were obtained from the meteorological stations within the three sampled counties (Migori, Kisumu and Kakamega). Malaria data were also obtained from the health facilities in the said three counties. The designs used quantitative technique as the key approach in this research. The techniques were used in establishing the descriptive and inferential characteristics of temperature, relative humidity, rainfall and malaria transmission.

The designs had the following advantages: they answered the “what and how” questions which were the questions this research sought to answer; they were accurate and systematic; Correlation design was suitable in giving the relationship between climatic characteristics and malaria transmission without the influence of extraneous variables; they were quick, reliable and cost effective. The specific variables and categories of analysis are presented in Table 3.1.

3.4 Target Population

LLVB, Kenya was home to over 9.4 million people representing more than 18% of the country’s population according to Alegana *et al.* (2021). The target population for this study was all malaria transmission cases reported to all the health facilities in

the LLVB, Kenya. Elnour *et al.* (2023) placed the transmission rate in this region at 27% which represented a flooded sample of over 2.54 million. The study therefore had a target population of over 2.5 million people. The target population data would be obtained from Sub – County Health Facilities which received records from all other facilities within each Sub – County. In another level, the study targeted all the Counties within the study area which formed the sample frame for the counties that would be sampled. The sampled counties subsequently formed sampling frames from which the study Sub - Counties were sampled for both malaria transmission and meteorological data.

3.5 Sampling Procedure and Size

The study used “mixed sampling technique” which involved different parallel sampling schemes or sampling schemes at different levels (multi-stage sampling) (Onwuegbuzie and Collins, 2007). The study started by using “area sampling”, a type of cluster sampling applied where the total area of interest happens to be big and involving geographic divisions, (Kothari, 1990). The sampling frame was made up of eight counties of the LLVB, Kenya from which the researcher chose three based on altitude as follows: 1000 – 1200 m, Kisumu; 1201 – 1400 m, Kakamega; 1401 – 1600 m, Migori. The sampled counties formed the sampling frames for one sub – county each. The Sub – Counties were each purposively sampled on the basis of proximity to a meteorological station and a health facility both of which had to depict desired relevant altitudinal characteristics. The health facilities provided “monthly” flooded malaria morbidity records covering a period of ten years at specified altitudes as follows: Kombewa Level 4 (1100m) for Kisumu; Mumias West Level 4 (1276m) for Kakamega; Awendo Level 4 (1450m) for Migori

(County, 2013). This approach was expected to increase the level of accuracy on the relationship between malaria transmission and climate elements. Twenty –year “daily” Meteorological (Temperature, Rainfall and RH) records were obtained from Mumias Sugar Meteorological station for Kakamega, Kisumu International Airport Meteorological station for Kisumu and Sonysugar Meteorological station for Migori.

3.6 Validity and Reliability of the Instruments

Validity

Daniel (2007) defines validity as a fundamental rule to ensure that information collected for research must be accurate. To ascertain the said accuracy, what is used to obtain the information, the procedure and the source of that information must also be accurate. This ensures that the study obtains the intended result. In a nutshell, Daniel (2007) posits that validity in research imply accuracy of research instrument. Sethi *et al.* (2017) define it as the extent to which the requirement of a scientific research method has been followed during the process of generating research findings.

To ensure validity in this study, a proposal was made and approved by the KU Graduate School on the 1st of March 2021 (Ref C82/27290/14). The Graduate School then issued a research authorization letter on the 1st of March 2021 (Ref C82/27290/14). The same research authorization letter was used to introduce the researcher to NACOSTI for research permit (License No NACOSTI/P/21/9466). All the said documents supported the study in obtaining further permission i.e. from County Governments, County Commissioners, County Public Health Officers and County Education Officers (Appendices XII - XX). The documents were used to introduce the researcher to relevant administrators of the targeted facilities whom

subsequently introduced the researcher to the relevant experts authorized to handle the targeted valid data.

Before issuing the data, the experts and the researcher ensured that the information was valid. It was then signed and official stamp appended. Data for climate parameters were thus obtained from registered meteorological stations as follows: South Nyanza (SONY) Central Meteorological Station (Code 9034145) for Migori County; Kisumu International Airport Meteorological Station (Code 637080-9999) for Kisumu County; Mumias Sugar Company (MSC) Meteorological Station (Code 8934-133) for Kakamega County. Malaria Morbidity records were obtained from the MOH -recognized Sub - County health facilities as follows: Kakamega County, Mumias West Sub-County (Level 4 Hospital), Kisumu County, Seme Sub-County (Level 4 Hospital) and Migori County, Awendo Sub-County (Level 4 Hospital). As had been said earlier, missing data were minimal and in cases where they occurred, they were interpolated using estimation and comparison for effective harmonization and fair representation. Data was then summarized and confidently used to give content valid results.

Reliability

This study used secondary data. According to Olabode *et al.* (2019), reliability of secondary data depends on quality and accuracy of the primary sources they were drawn from. Olabode *et al.* (2019) emphasizes that reliability of secondary data also depends on clear specification of data collection and analysis procedures. A study which precisely presents a whole research process is considered to display a high level of reliability. In the case at hand, secondary data was collected from recognized government agencies i.e. Government Hospitals and recognized State

Corporations where there were experts employed to skillfully collect, record and archive data.

This study used all the necessary logistics in acquiring the data from experts. It has consistently presented the procedures used for collecting, analyzing, presenting and finally reporting the outcome implying that the data collected and used for this study was conformable and can be replicated in another study having similar intentions. Reliability reflects how consistent research procedures or instruments are. It refers to the degree of consistency demonstrated in a study. The implication is therefore stability or dependability of the instruments used (Daniel 2007). This study having clearly stated the procedures, and given the relevant dates for each activity was considered to have attained significant level of reliability.

3.7 Data Collection and Data Characteristics

Monthly secondary data were obtained from routine malaria case transmission records archived by the Kenya Health Information System (KHIS), and climate data from selected Meteorological Centres. Malaria case transmission records for Kakamega County, Mumias West Sub-County (Level 4 Hospital), Kisumu County, Seme Sub-County (Level 4 Hospital) and Migori County, Awendo Sub-County (Level 4 Hospital) were all obtained from the Kenya Health Information System (KHIS) through Sub-County Hospital records offices. The health records were available for ten years (2011 - 2020) and were not categorized according to gender. The records included suspected (clinical) and confirmed (laboratory tested) cases for the < 5 years in age, the > 5 years in age, and malaria in pregnancy.

Meteorological records on the other hand were obtained from South Nyanza (SONY) Central Meteorological Station (Code 9034145) for Migori County, Kisumu Airport Meteorological Station (Code 637080-9999) for Kisumu County and Mumias Sugar Company (MSC) Meteorological Station (Code 8934-133) for Kakamega County. Daily records for three selected climate parameters: temperature in degrees centigrade, percentage relative humidity and rainfall in millimeters were collected for twenty years (2001 - 2020) except Kisumu Airport Relative Humidity which was only available for twelve years (2009-2020).

3.8 Data Analysis

To analyze the collected data, the researcher used Shapiro Wilk W test, ANOVA, Tukey's Honest Significance Difference, Descriptive Time Series, Pearson's Product Moment Correlation Coefficient and ARIMA Regression model.

Shapiro Wilk W test

This is a "goodness – of – fit test" which examines how close a sample data is to a normal distribution by ordering and standardizing the sample (van den Berg., 2019). In this research, the test was done to establish whether the climate and malaria data collected and used were fit for this research. It involved a computation process using the following formula.

$$W = \frac{\left(\sum_{i=1}^n a_i x_{(i)}\right)^2}{\sum_{i=1}^n (x_i - \bar{x})^2} \dots\dots\dots \text{Equation}$$

3.1

Where:

- i. α_i - tabulated coefficients,

- ii. n - the number of observations,
- iii. x^i - the i th order statistic,
- iv. x_i - the original observations and
- v. \bar{x} - the sample mean

ANOVA

This is a statistical test which tells you if there are any statistical differences among the means of three or more independent groups and whether the differences are significant or not (Sawyer, 2009). In this case, one - way ANOVA was used in testing the variability of climate elements and that of malaria transmission at different altitudes. It was used at 95% confidence interval (CI). Computation used the following formula:

$$F = \frac{\sum n_j (\bar{X}_j - \bar{X})^2 / (k-1)}{\sum \sum (X - \bar{X}_j)^2 / (N-k)} \dots\dots\dots \text{Equation}$$

3.2

Where:

- i. x - values of the ordered samples
- ii. k - the groups error
- iii. N - total number of observations throughout the groups
- iv. \sum - sum of values

Tukeys Honest Significance Difference (HSD) test

This test is used after ANOVA to find out which specific group means (compared with each other) are significantly different. It compares all possible pairs of the means (Chmiel *et al.*, 2022). In this research Tukeys Honest Significance Difference (HSD) test was used for testing the significance in the distribution of malaria

transmission and climate elements. The means were separated at $P \leq 0.05$. It was computed as follows:

$$q = \frac{\overline{x_1} - \overline{x_j}}{\sqrt{S_w^2 / n}} \dots\dots\dots \text{Equation}$$

3.3

Where:

- i. q – the distribution
- ii. S – variance
- iii. n – number of observations
- iv. \bar{x} – the sample mean

Pearson's Correlation Coefficient

This measures the statistical relationship between two continuous variables. It gives information about the magnitude of association and the direction of the relationship (Schober *et al.*, 2018). Pearson's Product Moment Correlation Coefficient was used in this study to correlate the suspected and confirmed malaria transmission cases. It was also used to establish the strength of the relationship between malaria transmission and selected climate elements. Computation was done using the following formula:

$$r = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n\sum x^2 - (\sum x)^2][n\sum y^2 - (\sum y)^2]}} \dots\dots\dots \text{Equation}$$

3.4

Where:

- i. r – correlation coefficient
- ii. x - values of the x variables
- iii. \bar{x} – mean of values of the x variables
- iv. y - values of the y variables

ARIMA Regression Models

ARIMA is a statistical model which uses time series data to inherently predict future trends based on the past values Agrawal & Adhikari, (2013). It is suitable for short term forecasting like in the case at hand and only needs historical none – stationary data (Prabhakaran., 2019). In this research, Descriptive time Series and “ARIMA regression models” were used to predict future malaria transmission trends. ARIMA was used to develop a model for predicting the inherent malaria transmission trends in different altitudes of the LLVB, Kenya. It was defined by the following formula:

$$Y_t = \beta_1 + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \dots + \phi_p Y_{t-p} \dots \dots \dots \text{Equation 3.5}$$

Where:

- i. Y – Predicted variable
- ii. Y_t – total of predicted variables
- iii. β – beta coefficient
- iv. β_1 – beta coefficient of lag1
- v. ϕ – moving average parameters
- vi. Y_{t-1} – lag 1 of the series

Trends

According to Cheuseva (2019) a trend line indicates a linear relationship using the equation that follows:

$y = mx + b$ Equation
3.6

Where:

- i. y – trend line of dependent variable
- ii. m – slope
- iii. x – independent variable
- iv. b – y intercept

Table 3.1: Summary of Statistical Tools

Objective	Variables		Statistical Tools
	Independent	Dependent	
To analyse spatio temporal variability in temperature, rainfall and relative humidity in different altitudes of lower Lake Victoria Basin.	Time in years Time in months Altitude	Climate Variability - Rainfall - Temperature - Humidity	- ANOVA - Descriptive Time series - Pearson's Product Moment Correlation Coefficient. - Tukey's HSD. - Shapiro Wilk W Test
To examine spatial and temporal variation of malaria morbidity in different altitudes of lower Lake Victoria Basin.	Time in years Time in months Altitude	Malaria Transmission -Morbidity	- ANOVA - Descriptive Time series - ARIMA - Pearson's Product Moment Correlation Coefficient. - Tukey's HSD.
To establish the spatiotemporal relationship between variability in climate parameters (temperature, rainfall and relative humidity) and malaria transmission (morbidity) in different altitudes of lower Lake Victoria Basin.	Climate Variability - Rainfall - Temperature - Humidity - Altitude	Malaria Transmission - Morbidity	- Pearson's product moment correlation coefficient. - Regression
To predict the future transmission trends typical to the different altitudes of lower Lake Victoria Basin?	Climate Variability - Rainfall - Temperature - Humidity - Altitude	Malaria Transmission - Morbidity	-ARIMA - Descriptive Time series

3.9 Data Management, Ethical and Logistical Considerations

3.9.1 Data Management

The researcher ensured to acquire original data from the correct sources. Data were then safely filed and stored for only relevant and timely referencing. Confidentiality of data was taken into account and data was made to be secure until the results of the analysis were ready for publication by the researcher. Confidentiality here was meant to protect the acquired data from theft and misuse since secondary data is very costly.

3.9.2 Ethical and Logistical Considerations

The study proposal was reviewed and approved by Kenyatta University and the National Council for Science and Technology. Clearance was then sought from various local administrators who allowed research activities to go on within their areas of jurisdiction. In ethical considerations, the researcher ensured to explain to the relevant persons i.e. the meteorological officers in charge of records and the records officers at the health facilities that the study was purely for study purposes, for the benefit of the participants, and for the benefit of the population of the LLVB and beyond. The officers were appropriately informed of the purpose of conducting the research so as to win their confidence in provision of the required data. The researcher assured the officers that the findings, proposed policies and recommendations would be communicated once the study was completed.

CHAPTER FOUR: RESULTS AND DISCUSSION

4.1 Introduction

This is the chapter in which results of the study findings are presented, interpreted and discussed. It is divided into four parts: spatiotemporal variability of selected climate parameters which as Bhattacharya *et al.* (2006) put it are believed to be the major environmental determinants of malaria transmission (temperature, relative humidity and rainfall) ; spatiotemporal variability of malaria transmission; spatiotemporal relationship between variability in climate parameters and malaria transmission, and predicting spatial relationship between climate variability and malaria transmission in different altitudes of the LLVB, Kenya.

4.2 Spatiotemporal Variability of Selected Climate Parameters

This study determined spatiotemporal variation of the three selected climate parameters within the sampled counties of the study area. It looked at varying “means” and “trends” of: temperature, relative humidity and rainfall and established spatiotemporal occurrences the variables at different altitudes of the study area.

4.2.1 Temperature

Mean temperature distribution in the three regions was tested using Shapiro Wilk W test of Normality. The findings indicated that, average temperatures in Kakamega, Kisumu and Migori Counties over the period (2001 – 2020) normally varied with Shapiro Wilk W values of 0.98, 0.97 and 0.98 respectively, meaning the data used were normally distributed and were confidently subjected to further analysis (Prob > z of 0.00, 0.00 and 0.00 respectively), (Table 4.1).

Table 4.1: Normality test result of the mean temperature in the three areas over the period 2001 – 2020

Variable	Obs	W	V	Z	Prob > z
Kakamega County	240	0.97550	4.286	3.379	0.00036
Kisumu County	240	0.97682	4.056	3.251	0.00058
Migori County	240	0.96972	5.299	3.872	0.00005

Source: Field data

4.2.1.1 Temperature variation (ANOVA)

Temperature variability in the period, 2001 – 2020 in Kisumu, Migori and Kakamega Counties were compared using Analysis of Variance (ANOVA) at 95% confidence interval (CI). The findings indicated that there was significantly higher temperature mean in Kisumu County (23.77⁰C) during the period compared to Kakamega County (22.61⁰C) and Migori County (22.52⁰C) (F = 120.87, P = 0.00). The means were separated by Tukeys Honest Significance Difference (HSD) at P ≤ 0.05. When correlated with the altitudes of these areas, the result was negative (r - 0.896). Kisumu County which is at the lowest altitude registered the highest temperature followed by Kakamega County then Migori County in that order. This confirmed the postulation by Evans *et al.* (2020) that thermal stability dominantly prevailed around the lake. According to Evans *et al.* (2020) the entire LVB experienced a range of climates with modified equatorial type on the highlands while hot and semi-arid closer to the lake as was the case in Kisumu County. Kakamega and Migori County temperatures however did not significantly differ (Table 4.2). Given altitudinal differences of the selected sites, the findings reflected

evidence of normal lapse rate and confirmed natural spatiotemporal variation of temperature in the study area as was observed by (Perkins 2017).

Table 4.2: Average temperatures (in 0C) in Kakamega, Kisumu and Migori Counties during the period 2001-2020

Region	Mean \pm SE	Minimum	Maximum
Kisumu County	23.77 \pm 0.05b	22.25	26.25
Kakamega County	22.61 \pm 0.062a	20.75	25.65
Migori County	22.52 \pm 0.08a	20.1	26.65
F –value	120.87		
P –value	0.0001		

Mean values in the same column denoted by similar letters are not significantly different. Mean separated using Tukey’s Honest Significance Difference (HSD) at $P \leq 0.05$.

4.2.1.2 Monthly Temperature Trends

During the period of study (2001 – 2020) the highest monthly mean temperature in Kisumu County was recorded in the month of February (24.81⁰C). The lowest was in June (22.08⁰C). In Kakamega County, the temperature was highest in March (23.31⁰C) and lowest in July (21.83⁰C). Temperature in Migori County was highest in March (23.38⁰C) and lowest in June (21.78⁰C) otherwise in all the cases, temperatures were highest between February and March, lowest between June and August then rose again to December. In all the cases, temperature tended to divide a year into three “temperature seasons” by being “High – Low – High” (Figure 4.1). Temperature generally indicated decreasing trends from the beginning of the year towards the end in the sampled counties (Figure 4.1). These occurrences happened as had been observed by Perkins (2017) that climate variations do occur naturally without human influence, and as LVBC (2018-2023) claimed, these effects were felt differently at different altitudes within the basin.

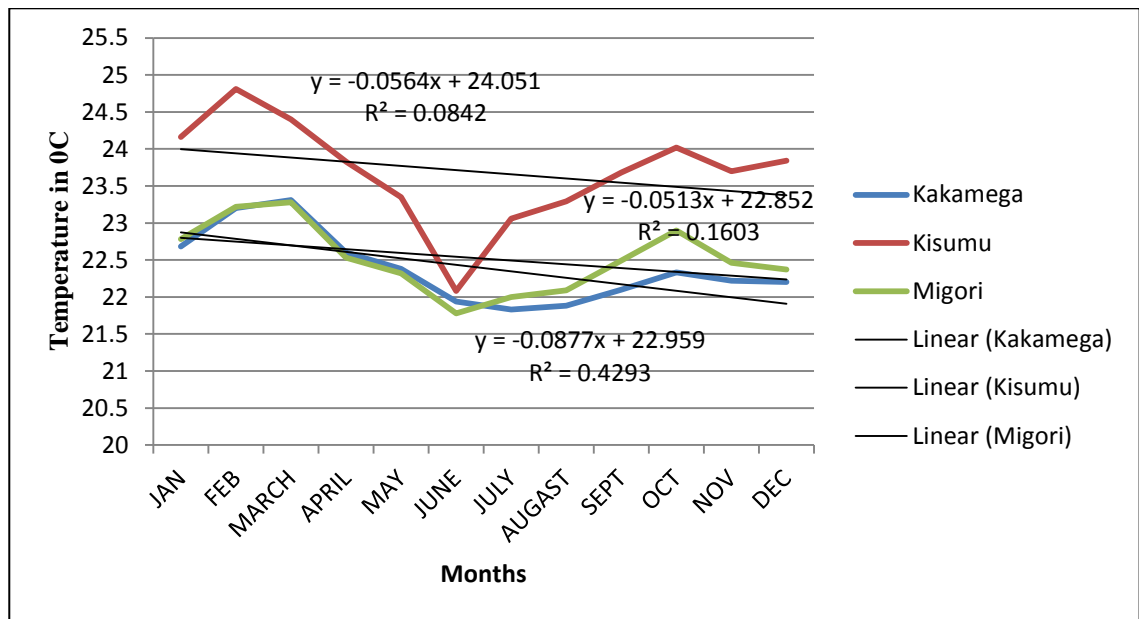


Figure 4.1: Monthly Temperatures in Kakamega, Kisumu and Migori Counties (2001 – 2020)

4.2.1.3 Annual Temperature Trends

Temperature trends during the study period revealed that mean annual temperature was highest in Kakamega County (23.58⁰C) in the year 2004 and lowest in the year 2020 (21.69⁰C). It was highest in Migori County in the year 2020 (24.12⁰C) and lowest in 2001 (21.04⁰C). In Kisumu County, mean annual temperature was highest in the year 2010 at 24.33⁰C and lowest in 2001 (23.21⁰C) (Figure 4.2). As was posited by Perkins (2017) and LVBC (2018-2023) that major variations affect local micro – climates differently, highest and lowest temperature events occurred at different times in different areas. This confirmed spatiotemporal variation of temperature occurrence in the LLVB.

The trend during the study period further revealed that temperature decreased in Kakamega County while it increased in Kisumu and Migori Counties. In Kakamega County, the decrease was at an R^2 value of 23.6%. In Kisumu County, the increase was at an R^2 value of 3.8% while in Migori County it was at an R^2 value = 66.64% (Figure 4.2). Of particular interest was the fact that the highest and lowest events occurred at different times in different areas and these again confirmed spatiotemporal variations of temperature in the study area during the study period. The reduction in Kakamega County undermined the argument by LVBC (2018-2023) that temperature will rise by 3°C by the year 2100. Although climate change is real, such micro occurrences like in Kakamega should not be ignored in climate change studies.

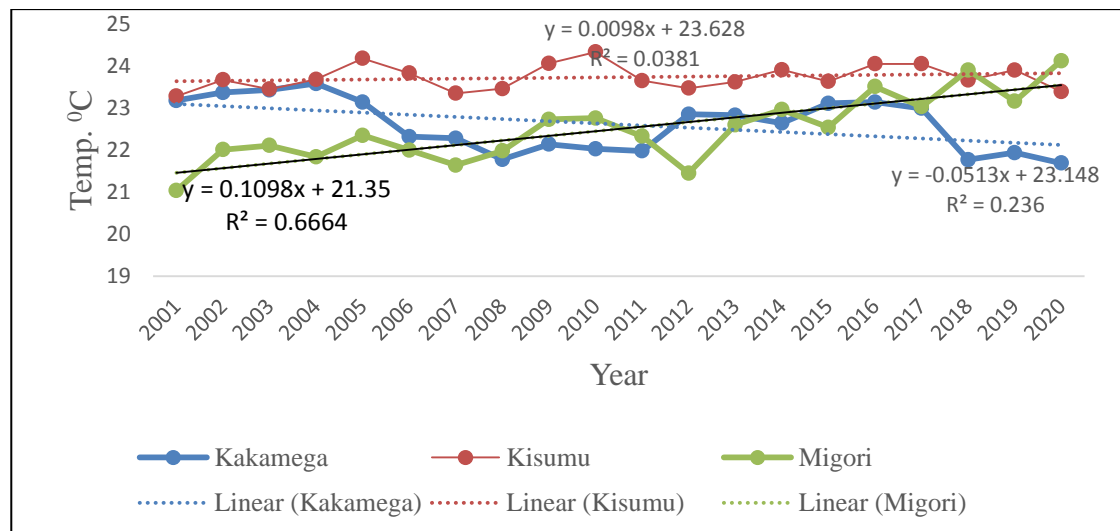


Figure 4.2: Annual Temperature Trends in Kakamega, Kisumu and Migori Counties (2001 – 2020)

The significantly higher temperature in Kisumu compared to Kakamega and Migori Counties were a clear indication that temperature significantly varied in space and time during the study period. The negative correlation ($r = -0.896$) among the means and the altitudes, revealed a positive lapse rate in the area. The increasing trends in

Migori and Kisumu Counties with a decrease in Kakamega County were a further evidence of variation. Monthly trends cyclically peaking in February and March, low in June and July then peaking again in October were evidence of the monthly cycles predicted by LVBC, (2018-2023).

LVBC, (2018-2023) proposed that temperature would increase by 3°C by the year 2100. If this proposal was something to go by, then Kisumu County mean temperature by the year 2100 would be 26.77°C , Kakamega may continue reducing, become stable or reverse direction and increase, while Migori would be 25.52°C . Such changes were to be observed differently all over LLVB, Kenya as was seen in the sampled counties whose altitudes varied between 1069m in Siaya County and 2248m in Migori County (Mwagiru, 1986; Kerandi *et al.*, 2017). Though they are within malaria transmission thresholds, the changes were predicted to have significant implications on the entire social and physical environments of the study area (LVBC 2018-2023). Of particular concern would be human vulnerability especially to diseases like malaria, and food production.

4.2.2 Rainfall (in mm)

Annual rainfall data in the three areas was tested using Normality test (Shapiro Wilk W test). The result indicated that, annual rainfall in Migori County varied significantly over the study period (W value of 0.87, Prob > z of 0.00). Rainfall data for Kakamega and Kisumu Counties did not significantly vary over the study period (Prob > z greater than 0.05). This confirmed that rainfall in Kakamega and Kisumu Counties was normally distributed (Table 4.3). The researcher therefore worked out the means and used them to conduct the analysis.

Table 4.3: Normality test result of the annual rainfall in the three regions over the period 2001 – 2020

Variable	Obs	W	V	Z	Prob>z
Kakamega County	20	0.96533	0.821	-0.398	0.65474
Kisumu County	20	0.95398	1.089	0.172	0.43162
Migori County	20	0.87455	2.970	2.193	0.01414

4.2.2.1 Rainfall Variation (ANOVA)

Mean total annual rainfall in the three areas during the study period (Kisumu, Migori and Kakamega Counties) was compared using One-way ANOVA. The means were separated by Tukeys HSD at $P \leq 0.05$ and were found to be significantly different ($F = 26.79$, $P = 0.00$). Mean annual rainfall in Kisumu County ($1455.3 \pm 59\text{mm}$) was significantly lower compared to Migori County ($1885.8 \pm 77\text{mm}$) and Kakamega County ($2192.6 \pm 76\text{mm}$) (Table 4.4). This was typical of Kisumu given her proximity to the lake as had been observed by Evans *et al.* (2020) that regions bordering the lake normally have very low rainfall.

Comparing the mean total annual rainfall during the study period by altitude, Kisumu County whose altitude is lowest also experienced the lowest rainfall followed by Migori County which though higher than Kakamega County, received a lower mean. Kakamega County experienced the highest mean ($2192.6 \pm 76\text{mm}$) among the three sampled stations during the study period (Table 4.4). From this observation, there was rainfall variation which never indicated a clear relationship with altitude.

Table 4.4: Mean Total annual rainfall (in mm) in Kakamega, Kisumu and Migori Counties during the study period

Region	Mean \pm SE	Minimum	Maximum
Kakamega County	2192.6 \pm 76.3c	1674.4	2823.7
Migori County	1885.8 \pm 77.4b	1424.3	2906.2
Kisumu County	1455.3 \pm 59.6a	981.0	2125.9
F -value		26.79	
P -value		0.0001	

Mean values in the same column denoted by similar letters are not significantly different. Mean separated using Tukey's Honest Significance Difference (HSD) at $P \leq 0.05$.

4.2.2.2 Monthly Rainfall Trends

In the study period (2001 – 2020) the mean monthly rainfall generally revealed increasing trends i.e. in Kisumu County, the increase was at an R^2 value = 1.1%, Migori County, R^2 value = 3.58% and Kakamega County, R^2 value = 0.8%. The R^2 values however indicated that the increases were not significant (Figure 4.3). Rainfall was high in Kakamega, Kisumu and Migori Counties in the month of April. Lower rainfall levels were recorded in the months of February and July in the three stations. The months of January and February were drier than the rest of the year. There was a gradual increase from February to a peak in April before descending to its lowest in July then rising again to double maxima in September and November for Kisumu County. In Kakamega County, the peak occurred between September and October while for Kisumu County, it was in November. As had been observed earlier, quantity varied but did not obey the altitudinal variations. It was highest in Kakamega County most of the times followed by Migori and Kisumu Counties in that order. The differences were typical indicators that rainfall occurrences spatiotemporally varied in the study area.

Another major observation made was that despite high rainfall in all the stations in the months of March-May and September–December, and low rains in the months of June and July (double maxima regime), a characteristic that had been observed by LVBC (2018-2023) in the study of the LLVB, East Africa, wet periods were longer while dry periods were shorter than had been observed by LVBC (2018-2023). Quantities both temporally and spatially varied. It is only in the Months of December and January that all the stations registered almost similarly insignificant quantities of rainfall. The study areas were wet throughout the year with literally no real dry month and fairly two well defined seasons separated by two low rainy periods occurring in the months of January – February and June – July (Figure 4.3). Again, these were typical indicators of spatiotemporal varying rainfall patterns in the study area.

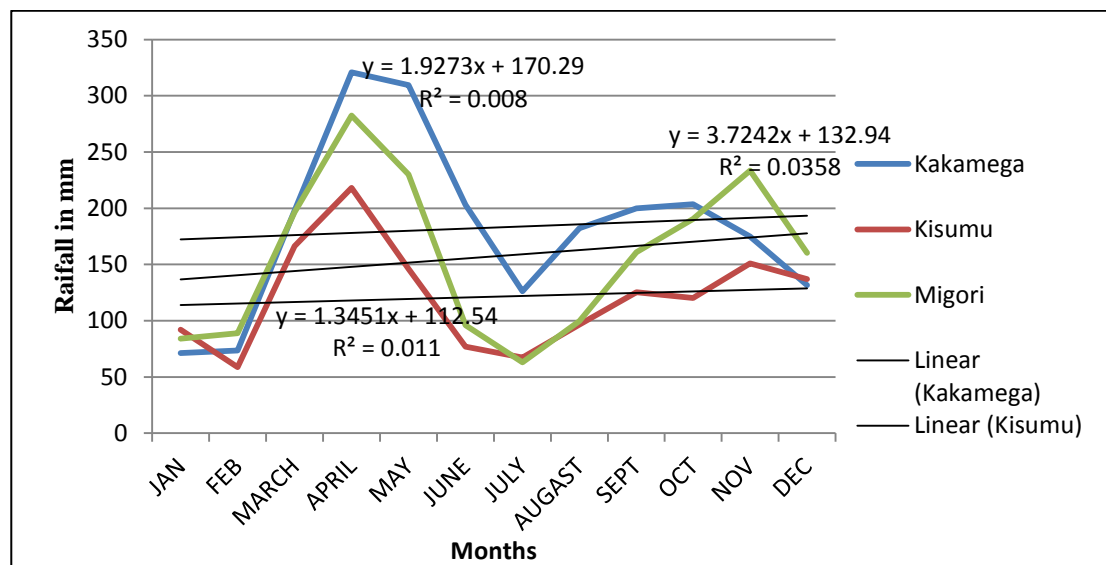


Figure 4.3: Monthly rainfall in Kakamega, Kisumu and Migori Counties (2001 – 2020)

4.2.2.3 Annual Rainfall Trends

To get a good impression of Figure 4.4, total annual rainfall figures were scaled down by 12 (Appendix II). They should not be confused for monthly rainfall totals. The trends in the three regions increased during the study period: Kisumu County rainfall increased at an R^2 value = 7.74%; Kakamega County, R^2 value = 7.23%; Migori, R^2 value = 11.15% (Figure 4.4). From the R^2 values, the increase in rainfall during the period was not significant.

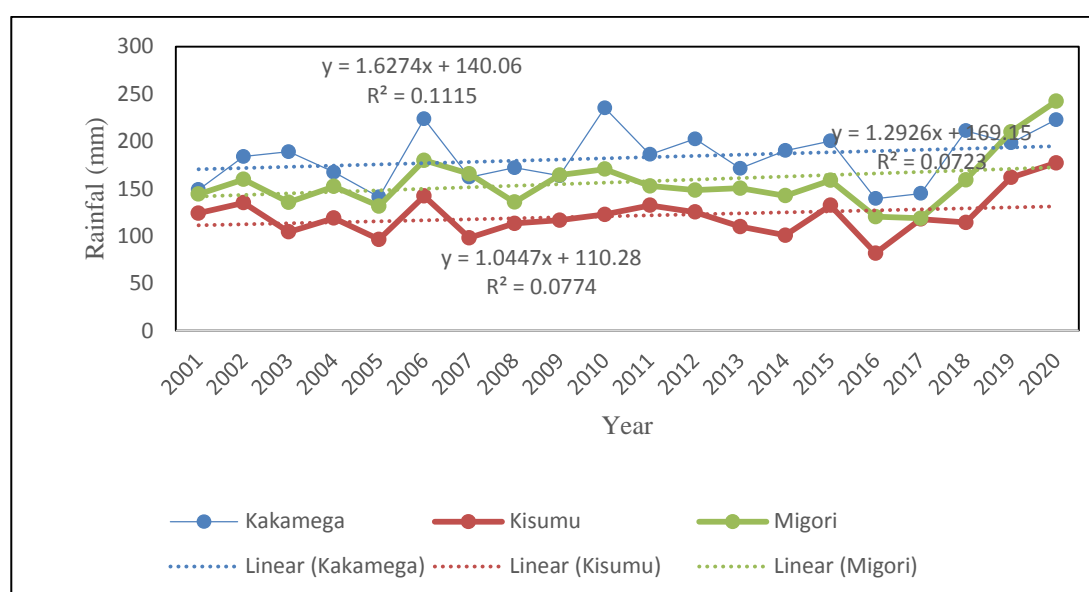


Figure 4.4: Total annual rainfall (in mm) (scaled down by 12) trends during the study period in the three regions

Migori County recorded the highest (2906.2 mm) annual rainfall in the year 2020 and the lowest (1424.3mm) in 2017. In Kakamega County, the highest rainfall was recorded in the year 2010 (2823.7 mm) and lowest (1674.4mm) in the year 2016. Kisumu County had the highest (2125.9 mm) in the year 2020 and the lowest (981.0mm) in 2016 (Appendix III).

As Dinse *et al.* (2009) had earlier argued that climate variations might bring extreme weather occurrences, extreme events of rainfall were observed during this study i.e. extremely high rainfall in the year 2006 for all the stations, the year 2010 for Kakamega, and the year 2020 for all the stations. On the other hand, extremely lows for all the stations were observed in the year 2016 proceeding to 2017 for Kakamega and Migori Counties. Kisumu County registered the lowest in the year 2016. The extreme rainfall occurrences were also evidence to the postulations by LVBC (2018-2023) that in the recent past, LVB had been characterized by frequent episodes of either deficient or excessive rainfall. As had earlier been proposed by the LVBC 2018 - 2023, such effects were felt differently at different altitudes within the basin. Dinse *et al.* (2009) also argued that climate variations which occurred at mega scales do have impacts at micro scales. This might have been the case for the extreme rainfall occurrences in the study area.

The study of rainfall revealed spatiotemporal variability among the three sampled areas during the study period as was established by ANOVA and the means separated using Tukeys Honest Significance Difference (HSD) at $P \leq 0.05$. The trends during the study period indicated variability. Monthly trends tended to divide a year into two high rainy seasons of March to May and September to November separated by two low rainy periods occurring between January to February and between June to July. There were no real dry months during the study period. The fact that rainfall did not pattern up with altitude by being higher in Kakamega County than it was in Migori County made it difficult to pre-empt what might have happened in areas that had not been investigated. The findings further confirmed, as

had been observed by Evans *et al.*, (2020) that rainfall in East Africa spatiotemporally varied.

4.2.3 Relative Humidity

Relative humidity data in the three areas was tested using Shapiro Wilk W test of Normality. The result showed that, Relative Humidity significantly varied in Migori County while it was normal in Kakamega and Kisumu Counties over the period with Shapiro wilk W values of 0.87, 0.94, 0.95 respectively and a Prob > z of less than 0.05 (Table 4.5). The study thus worked out the means and used them to conduct the analysis.

Table 4.5: Normality test result of the mean RH in the three areas over the period 2001 – 2020

Variable	Obs	W	V	Z	Prob>z
Kakamega County	20	0.93527	1.532	0.860	0.19495
Kisumu County	12	0.94097	0.986	-0.027	0.51071
Migori County	20	0.86703	3.147	2.311	0.01042

4.2.3.1 Relative Humidity Variability (ANOVA)

Mean Relative Humidity (RH) data for (2001 – 2020) compared using ANOVA at 95% confidence interval (CI) revealed significant differences i.e. in Kisumu County the mean was 58.77%, Kakamega County 67.74% and Migori County 66.88% (F = 30.37, P = 0.00). The means were separated using Tukeys HSD at $P \leq 0.0$. Like in the case of rainfall, RH was highest in Kakamega County followed by Migori and lastly Kisumu hence not consistent with altitude. There were no extreme events. Annual trends were increasing. The observed variations confirmed the findings

made by Perkins (2017) that the global variations occurring naturally affected local micro – climates differently. (Table 4.6).

Table 4.6: Average RH in % in Kakamega, Kisumu and Migori Counties in the study period 2001-2020

Region	Mean \pm SE	Minimum	Maximum
Kisumu County	58.77 \pm 0.58a	35.0	74.0
Kakamega County	67.74 \pm 0.471b	41.0	79.5
Migori County	66.876 \pm 0.907b	51.5	82.5
F -value		30.37	
P -value		0.0001	

Mean values in the same column denoted by similar letters are not significantly different. Mean separated using Tukeys HSD at $P \leq 0.0$

4.2.3.2 Monthly Relative Humidity Trends

Monthly, RH in Kakamega County was found to be relatively low (57.51%) and (56.59%) in January and February respectively. It begun to rise in March and stabilized between April and July then fell from August to December. In Kisumu County, RH was observed from the year 2009 to 2020 and the lowest case occurred in February after which it rose sharply to the month of April. There was some stability between April and June. From June, RH slightly ascended from a mean of 62.42% to a mean of 63.46% in July, again fairly stabilizing between July and December. In Migori County, RH was lowest in the month of June (63.98%) and august (63.85%). It was highest in October (68.98%) then descended to December (66.85%). Humidity in Migori County thus divided a year into two seasons of March – April and September – October. There were relatively no extreme cases observed

during a mean study year. In the three areas, Relative Humidity generally increased during a mean study year over the study period as is shown in the “figure 4.5” below such that, in Kakamega County, the increase was at R^2 value = 14.89%, Kisumu County, R^2 value = 9.29%, and Migori County, R^2 value = 0.22%, (Figure 4.5). The observed occurrences confirmed the observations made by Scott *et al.* (2017) that in Kenya, humidity differs in several informal areas.

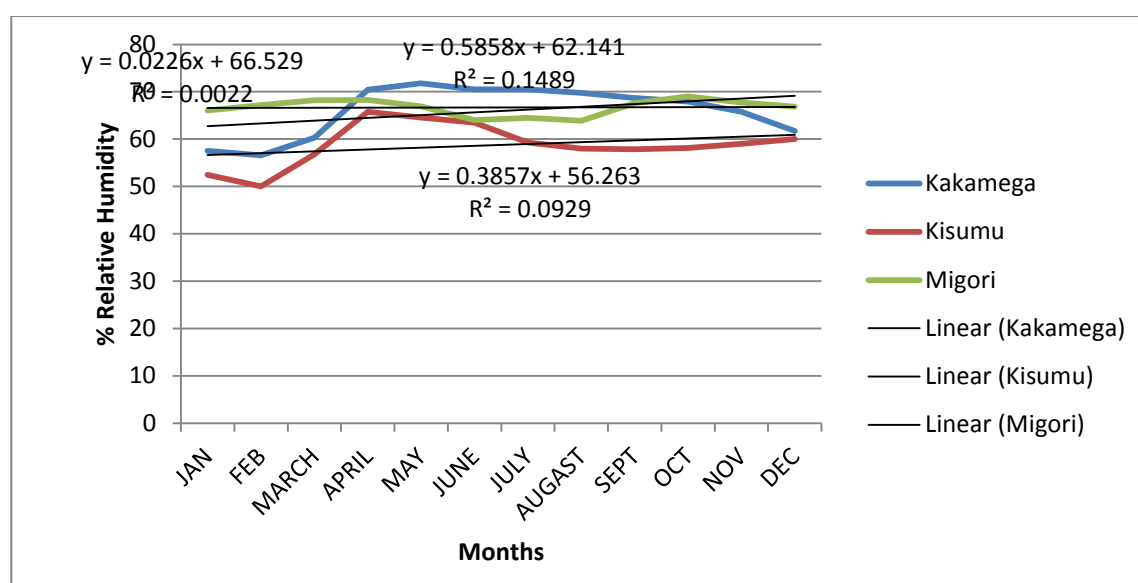


Figure 4.5: Monthly % Relative humidity in Kakamega, Kisumu and Migori Counties

4.2.3.3 Annual Variability of Relative Humidity (RH) Trends

In the three areas, relative humidity generally increased over the period. However, it also fluctuated during the same period. The highest case in Kakamega County occurred in 2019 (68.96%) and the lowest in 2005 (62.42%). Between 2009 and 2020, Kisumu County RH was highest in the year 2020 (62.96%) and lowest in the year 2009 (56.33%). In Migori County RH was highest in the year 2018 (74.22%)

and lowest in the year 2002 (62.17%). Generally, all the trends were observed to vary during the study period (Figure 4.6).

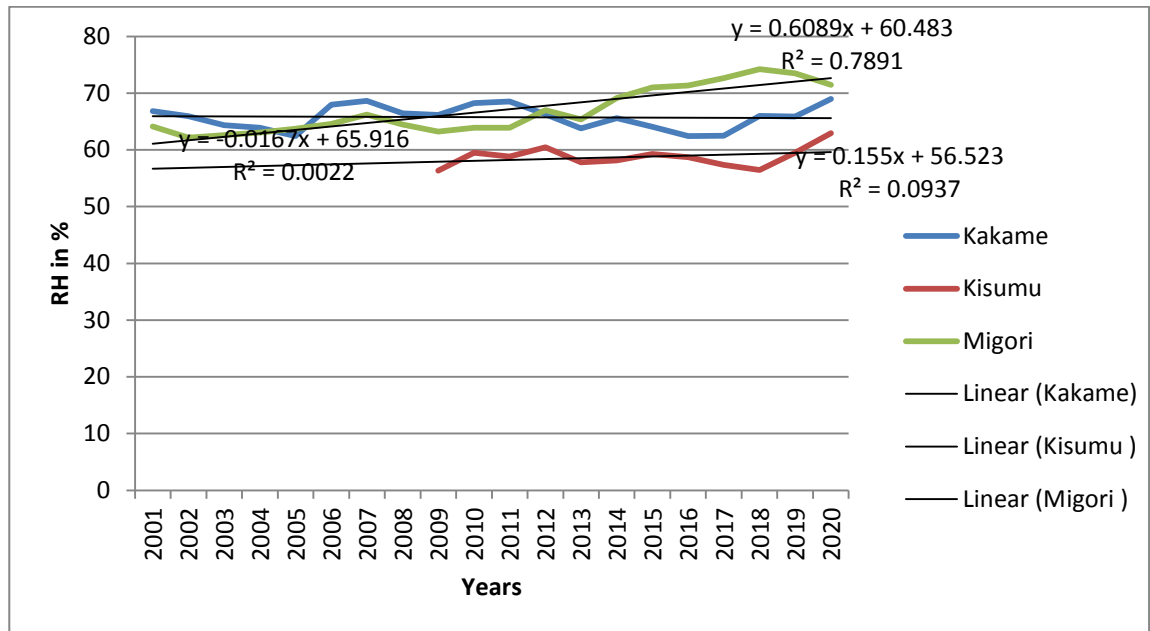


Figure 4.6: Annual % Relative humidity in Kakamega, Kisumu and Migori Counties

From the overall outlook, this study observed that all the selected climate elements significantly varied in space and time during the study period. Nicholson, S. E. (2017) recognized extreme events as evidence of climate change responsible for negative health and food production issues hence an argent need for mitigation and adaptation strategies at specific areas. Deviations in temperature and Relative Humidity were not significant i.e. the lowest temperature in Kisumu was 23.28⁰C and the highest 24.33⁰C from a mean of 23.77⁰C, Kakamega lowest was 21.69⁰C and the highest 23.58⁰C from a mean of 22.61⁰C while Migori lowest was 21.04⁰C and highest 24.12⁰C from a mean of 22.52⁰C. Highest and lowest events of Relative Humidity occurred at different times during the study period and there were no extreme cases. Of particular interest was the fact that all the selected climate parameters had

annually increasing trends over the 20 - year period except annual temperature in Kakamega County. Though the changes were not significant as were indicated by low R^2 values, when combined with variability and the observed rainfall extremes, there was evidence that climate change is with us and will make humans become vulnerable to sufferings (Herrero *et al.*, 2010).

4.3 Spatiotemporal Variability of Malaria Transmission

This section covered the period between the years 2011 and 2020 in three sampled counties of the LLVB, Kenya –Kakamega, Kisumu and Migori. The study compared the suspected cases with the confirmed ones in order to establish the kind of implication the suspected had on the confirmed. He then analyzed the varying malaria case transmissions monthly and annually. The section was finalized by discussing the findings.

4.3.1 Kakamega County

4.3.1.1 Suspected and Confirmed Malaria Transmission Cases

To determine the relationship between suspected and confirmed malaria transmission cases in Kakamega County among the < 5, Pearson's moment correlation analysis was carried out at 95% confidence interval (CI). The finding indicated that there was a negative relationship between the number of suspected and the number of confirmed cases among the < 5 populations ($r = - 0.043$, $P = 0.907$) (Table 4.7). It was observed that over the years, there were more suspected cases than confirmed. The suspected appeared to have been too high. Some of the years registering the highest suspected cases happened to register the lowest confirmed cases.

Table 4.7: Correlations for Kakamega County (< 5 Year)

		Suspected	Confirmed
Suspected	Pearson Correlation	1	-.043
	Sig. (2-tailed)		.907
	N	10	10
Confirmed	Pearson Correlation	-.043	1
	Sig. (2-tailed)	.907	
	N	10	10

Pearson's moment correlation analysis was again carried out at 95% confidence interval (CI). Again, there was a negative relationship between the number of suspected and the number of confirmed among the > 5, population ($r = -0.297$, $P = 0.405$) (Table 4.8). There were more suspected cases than confirmed, hence the suspected must have been too high.

After, correlating the suspected and confirmed > 5 and the < 5, the suspected were found to have been too high and could have an undefined affect the outcome. The researcher thus decided to ignore the suspected and only worked with the confirmed cases for further analysis.

Table 4.8: Correlations for Kakamega County (> 5years)

		Suspected	Confirmed
Suspected	Pearson Correlation	1	-.297
	Sig. (2-tailed)		.405
	N	10	10
Confirmed	Pearson Correlation	-.297	1
	Sig. (2-tailed)	.405	
	N	10	10

From the above correlation results, the researcher decided to use only the confirmed cases for analysis.

4.3.1.2 Monthly Trends of Malaria Transmission Cases in Kakamega County

Monthly trends of confirmed cases of malaria transmission in Kakamega County among those < 5 years and those > 5 years during the period (2011 – 2021) were highest in the month of May after which both declined towards September. From September, both cases slightly increased with the > 5 being highest in October and the < 5 in November. For the two populations, malaria was highest in May and lowest in December, otherwise both the < 5 and the > 5 indicated decreasing trends towards the end of the year, an indication that malaria was higher early in the year and reduced towards the end of the year (Figure 4.7). The similarity in occurrence meant that there was a common driving factor.

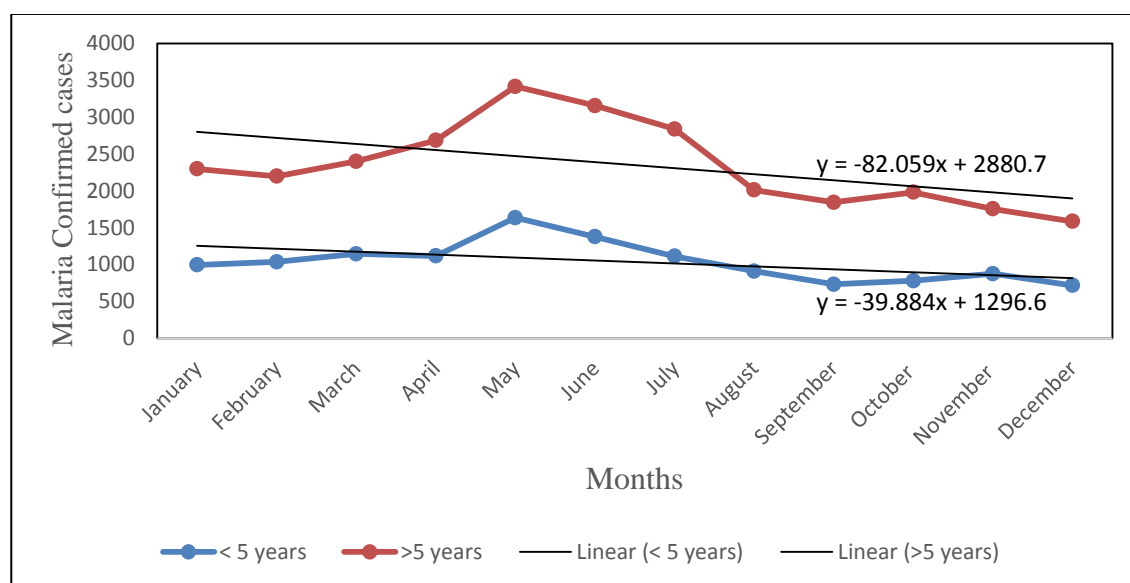


Figure 4.7: Mean Monthly Confirmed (< 5 and > 5) malaria case transmission in Kakamega County (2011 – 2021)

During the study period, total confirmed monthly mean malaria transmission in Kakamega County indicated a decreasing trend from the beginning of the year towards the end at R^2 value = 28.24%. An ascent was observed from February and rose to a peak in May (5053.3) after which the trend descended to its lowest in December (2305.4). The general trend revealed that malaria transmission was higher early in the year than later (Figure 4.8). The Kakamega County outcomes were evidence of seasonality, cyclical patterns, and strong but temporally varying trends in malaria cases whose nature and details varied (LVBC, 2018-2023). While Bhattacharya *et al.* (2006) developed a set of spatial transmission windows typical to India in terms of different temperature ranges, this study established temporal transmission windows occurring between April and May - a period when transmission was maximum. These were the periods when the rains were at their peaks and as Kapesa *et al.* (2018) put it, “Where one or two elements are at their minimum or maximum transmission thresholds, they will either negatively or positively determine the transmission behaviors”. The April – May Period was therefore a malaria transmission window that required surveillance in Kakamega County.

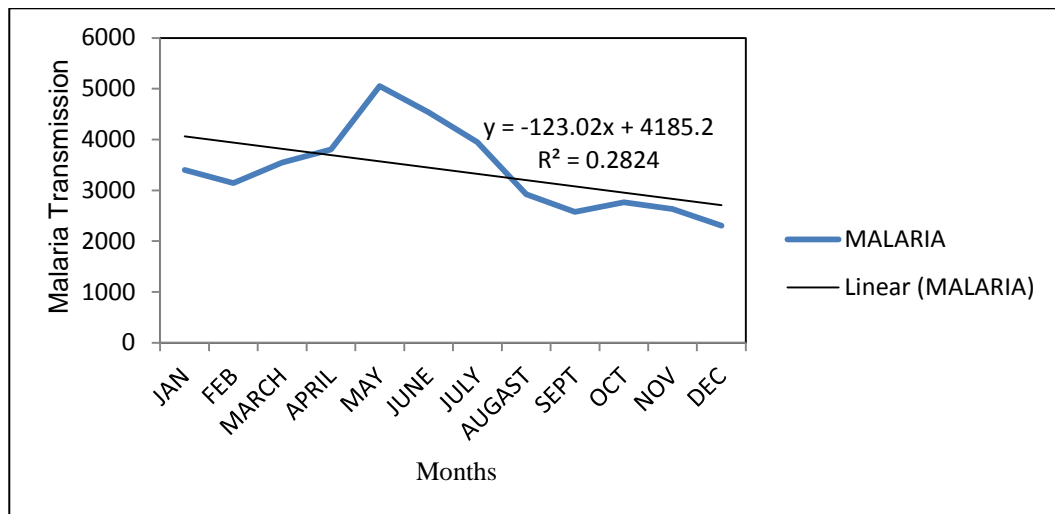


Figure 4.8: Mean Monthly Total Confirmed Malaria Case transmission trends in Kakamega County

4.3.1.3 Annual Trends of Malaria Transmission Cases in Kakamega County

From Descriptive Time Series, annual confirmed cases among the > 5 year olds were highest in the year 2019 with a mean of 3904 ± 491 and lowest in the year 2012 with a mean of 873.8 ± 43.6 . Among the < 5 year olds, malaria transmissions were highest in the year 2015 at a mean of 1670 ± 188 and lowest in the year 2012 at a mean of 514.9 ± 46.6 . Among the pregnant women it was highest in the year 2020 at a mean of 105.0 ± 28.9 and lowest in the year 2014 which had a mean of 34 ± 5.27 . From the available records, malaria transmission among the pregnant had only confirmed cases. The foregoing observations confirmed the aspect of temporal variation of malaria case transmission in the county (Figure 4.9). Figure 4.9 showed increasing trends among the > 5, < 5 and the pregnant populations. Bhattacharya *et al.* (2006) identified malaria transmission windows in India in terms of temperature ranges. Considering the trending values as at Figure 4.9, the > 5 rated highest compared to the < 5 and the pregnant mothers. This was an indication that the > 5

accounted for the greatest percentage of the malaria transmissions. From these findings, the study identified the highest rating of the > 5 compared to the < 5 as another window of opportunity for fighting malaria transmission in Kakamega County.

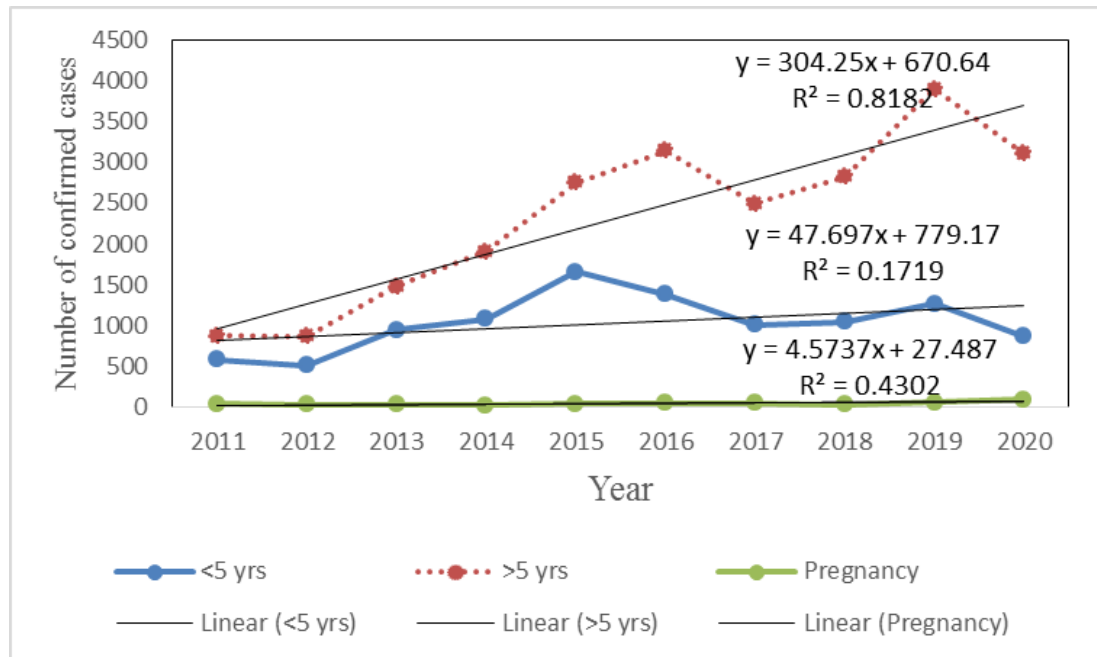


Figure 4.9: Mean Annual Confirmed (< 5, > 5 and pregnant mothers) malaria case transmission in Kakamega County (2011 – 2021))

“ARIMA” Model Analysis of time series for confirmed cases of malaria in Kakamega County showed that there were significant positive changes in malaria case transmissions among the people who were > 5 years of age with a z value of 5.60 and a P value of 0.00. Pregnant mothers had positive changes which were not significant at z value of 0.39 and P of 0.694. On the other hand, malaria transmission among the < 5 indicated negative changes that were not significant at a z value of -1.75 and p value of 0.081 (Table 4.9). This outcome indicates variations in the malaria transmission cases by age. As was seen in the Descriptive Time Series, age

factor should thus be a very important target in the war against malaria transmission. Again, the > 5 in Kakamega County should be targeted in the war against malaria transmission.

Table 4.9: ARIMA Regression for Kakamega County

```
. arima Year Mumiasless Mumiasmore Mumiaspregn
(setting optimization to BHHH)
Iteration 0: log likelihood = -11.820827
Iteration 1: log likelihood = -11.820827

ARIMA regression

Sample: 1 - 10                                Number of obs   =      10
Log likelihood = -11.82083                    wald chi2(3)    =     128.07
                                                Prob > chi2     =      0.0000
```

Year	Coef.	OPG Std. Err.	z	P> z	[95% Conf. Interval]	
Year						
Mumiasless	-.0036795	.0021076	-1.75	0.081	-.0078102	.0004512
Mumiasmore	.0035024	.0006253	5.60	0.000	.0022768	.0047281
Mumiaspregn	.0075206	.019086	0.39	0.694	-.0298873	.0449285
_cons	.7264946	1.599001	0.45	0.650	-2.407491	3.86048
/sigma	.7891051	.4383031	1.80	0.072	-.0699532	1.648163

Considering the entire study period and working only with the mean total confirmed malaria transmission cases, a rising trend was established ($Y = 351.9x + 1450$, R^2 value= 68.3%). It showed that cases of malaria transmissions were highest in the year 2019, mean 5176 ± 628 and lowest in the year 2012, mean 1388.75 ± 82.4 . The trend was thus rising significantly considering the R^2 value of 68.3% (Figure 4.10). The rising trends was either a confirmation of the observations made by WHO (2017) that in Western Kenya, the malaria transmitting vectors were developing resistance to preventive tools i.e. the pyrethroid insecticides used in ITN and IRS or, they were evidence of little or no preventive approaches during the study period. On the other hand, Roser *et al.* (2020) recognized malaria as a disease that had been eradicated elsewhere and that eradication would be possible in other parts of the

world. However, with resistance to the identified preventive tools, reduction or eradication would be a challenge in Kakamega County. The rising trend also undermined the observations made by WHO (2017) recognizing malaria transmission in Western Kenya to be dropping.

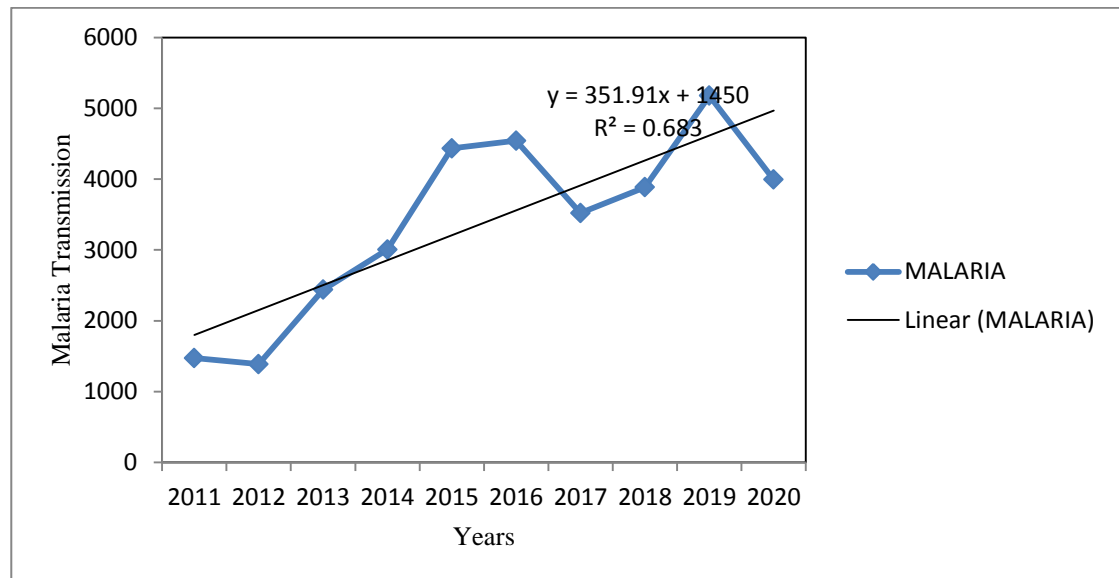


Figure 4.10: Mean Annual Total Confirmed Malaria transmission trends in Kakamega County

4.3.2. Kisumu County

4.3.2.1 Suspected and Confirmed Malaria Transmission Cases

To determine the relationship between suspected and confirmed malaria transmission cases in Kisumu County among the < 5, Pearson's moment correlation analysis was carried out at 95% confidence interval (CI). The finding showed that the number of suspected and confirmed cases both correlated positively ($r = 0.211$, $P = 0.559$) (Table 4.10). This indicated that, the suspicion parameters used had substantive components for predicting malaria transmission.

Table 4.10: Correlations for Kisumu County (< 5 years)

		Suspected	Confirmed
Suspected	Pearson Correlation	1	.211
	Sig. (2-tailed)		.559
	N	10	10
Confirmed	Pearson Correlation	.211	1
	Sig. (2-tailed)	.559	
	N	10	10

For the > 5, the finding showed that the number of suspected and confirmed cases were again correlated positively ($r = 0.370$, $P = 0.292$) (Table 4.11). This was a further indication that the suspicion parameters used in Kisumu had substantive components for predicting malaria transmission.

Table 4.11: Correlations for Kisumu County (> 5 years)

		Suspected	Confirmed
Suspected	Pearson Correlation	1	.370
	Sig. (2-tailed)		.292
	N	10	10
Confirmed	Pearson Correlation	.370	1
	Sig. (2-tailed)	.292	
	N	10	10

The suspicion parameters used in Kisumu were substantive but for uniformity, the study opted only for the confirmed malaria case transmissions for further analysis.

4.3.2.2 Monthly Trends of Malaria Transmission Cases in Kisumu County

Monthly trends of mean malaria transmission cases for the < 5 and the > 5 in Kisumu County, during the period 2011 – 2021 were generally declining – being high early in the year and low towards the end. High cases were observed between the months of May to July. Highest cases were observed in the month of July and

lowest in December (Figure 4.11). The similarity displayed by the two populations meant that there was a common influencing factor.

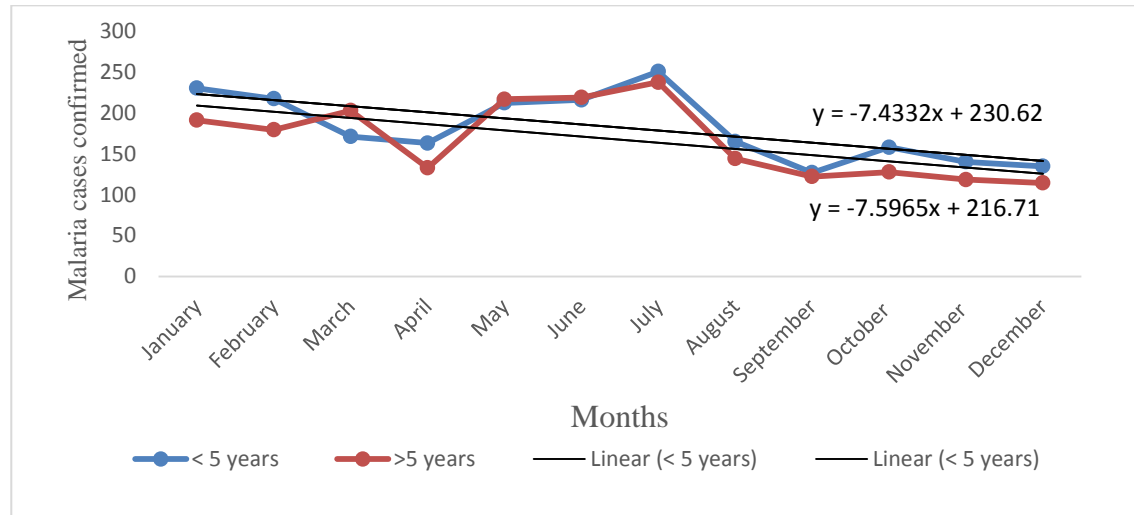


Figure 4.11: Mean Monthly Confirmed (< 5 and > 5) malaria case transmission in Kisumu County (2011 – 2021) (values scaled down by 12)

Mean total confirmed malaria case transmissions in Kisumu County, fell from January (5107.8) to April (3430.8) then rose again from April to July (5936.4). From July, the trend significantly fell to October (2473.9) after which it stabilized towards December. Mean total case transmission was highest in the month of July (5936.4) and lowest in the month of October (2473.5) (Figure 4.12). This differed from the Kakamega occurrences where the rise was experienced from February straight to a maximum in May. The fluctuations observed were again true as was projected by LVBC (2018-2023) that future malaria transmissions would display seasonality, cyclical patterns, and strong but temporally varying trends.

The implication must have been that the environmental conditions in Kisumu were more conducive for malaria transmission in January than April. The situation

improved from April to a climax in July. Dekens *et al.* (2013) claimed that rainfall increases vector population by creating new breeding grounds. This could explain the escalation between April and July. Dekens *et al.* (2013) however argued that too much rainfall washes away the breeding grounds which may lower the malaria transmission till a later date when i.e. soon after the said breeding grounds re – establish and prepare ways for increased vector population. This should explain the Kisumu case of malaria transmission falling between May and June then rising again to July. The Kisumu Transmission climaxed almost at the middle of the year. All these observations among others confirmed the spatiotemporal varying nature of malaria transmission in the LLVB, Kenya. Malaria transmission in Kisumu was however diminishing as the year advanced.

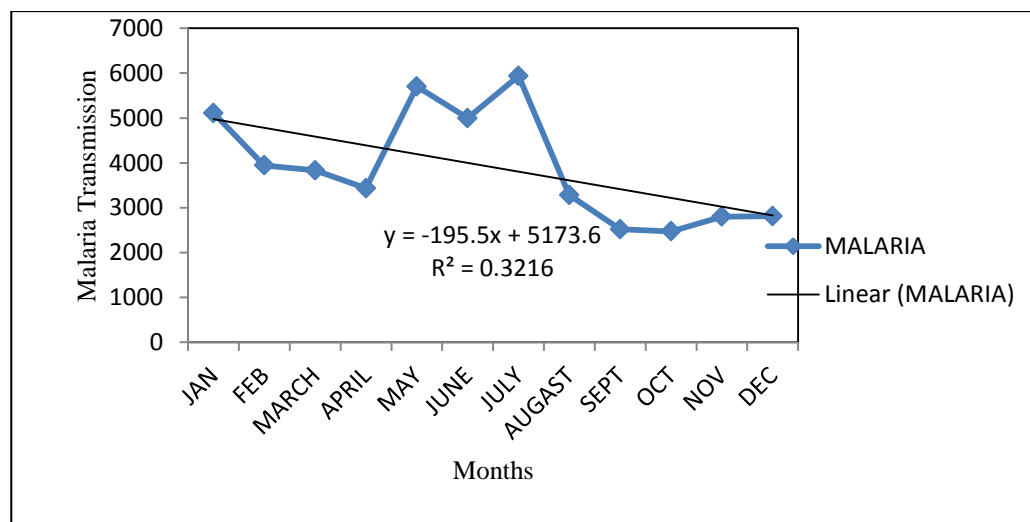


Figure 4.12: Mean Monthly Total Confirmed Malaria transmission trends in Kisumu County

4.3.2.3 Annual Trends of Malaria Transmission Cases in Kisumu County

Using descriptive time series over the study period, confirmed malaria transmission cases among the < 5, > 5 and the pregnant mothers all indicated increasing trends at

R^2 Value = 17.2%, R^2 Value = 68%, R^2 value = 2.5% respectively. The > 5 depicted significant increment at an R^2 value of 68% implying that the population that most accounted for the Kisumu escalating figures was the > 5. Like Bhattacharya *et al.* (2006) established a transmission window in India based on temperature, the higher > 5 malaria transmission values were a window of opportunity in the war against malaria transmission in Kisumu County. The < 5 appeared to have received greater surveillance services than the adults. The lowest cases for all were observed in the years 2012; the highest were in 2019 for the > 5 and, 2014 for the < 5 and the pregnant mothers. All were increasing (Figure 4.13). The almost similar trends among the two populations implied that there was a common influencing factor.

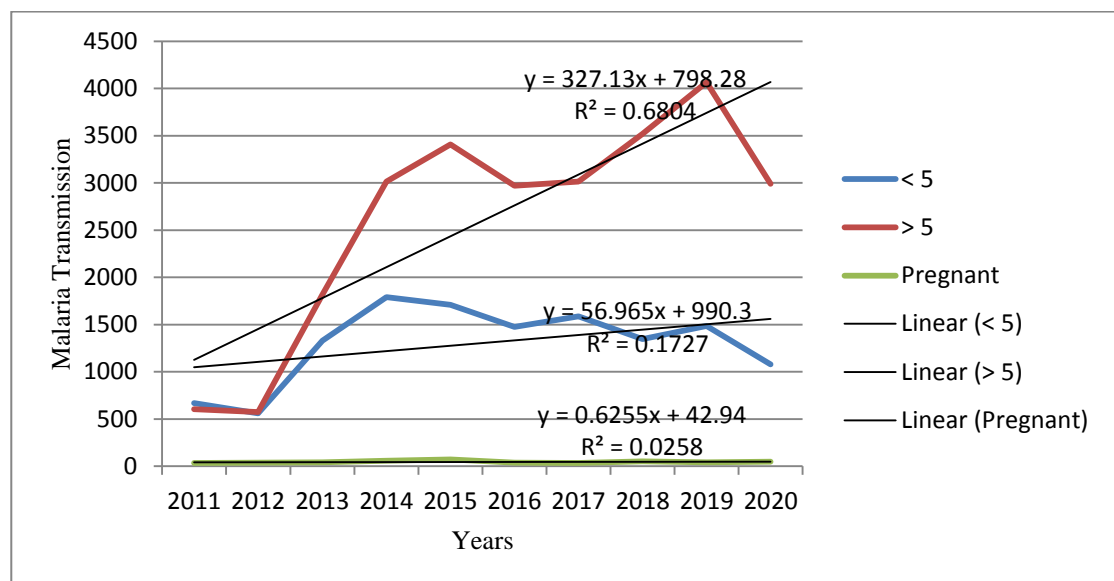


Figure 4.13: Mean Annual Confirmed (< 5, > 5 and Pregnant mothers) malaria case transmission in Kisumu County (2011 – 2021)

In Kisumu County, malaria case transmission had negative significant changes over the years among the < 5 year olds with a z value of -5.15 and a P Value of 0.00. However, there were significant positive changes in the cases among those > 5 years with a z value of 2.61 and a P Value of 0.01 (Table 4.12).

Table 4.12: ARIMA Regression for Kisumu County

```
. arima Year kombless kombmore kombpregnancy
(setting optimization to BHHH)
Iteration 0: log likelihood = -13.35297
Iteration 1: log likelihood = -13.35297

ARIMA regression

Sample: 1 - 10                Number of obs   =    10
                             Wald chi2(3)         =   36.07
Log likelihood = -13.35297    Prob > chi2      =   0.0000
```

Year	Coef.	OPG Std. Err.	z	P> z	[95% Conf. Interval]	
Year						
kombless	-.0360646	.0070063	-5.15	0.000	-.0497966	-.0223325
kombmore	.0301954	.0115534	2.61	0.009	.007551	.0528397
kombpregna~y	-.0152506	.2754825	-0.06	0.956	-.5551864	.5246851
_cons	7.132843	3.01057	2.37	0.018	1.232234	13.03345
/sigma	.9197609	.3511897	2.62	0.009	.2314416	1.60808

Considering the entire study period and working only with the total confirmed malaria transmission cases, an increasing trend was established at R^2 value = 55.6%. It indicated that case transmissions were highest in the year 2019 (5553 ± 1156) and lowest in the year 2012 (1135.7 ± 99.1) (Figure 4.14). From this outcome, it was concluded that the > 5 must have outweighed the < 5 when the two populations were combined. As was the case in Kakamega County, the rising trends in Kisumu County once more undermined the observation by WHO (2017) that malaria transmission in Western Kenya which was home to LLVB dropped from 38% in 2010 to 27% in 2015. It however confirmed the fact that, as was proposed by the current study, malaria transmission trends might not have been uniform. However, the rising trends confirmed the observation by WHO (2017) that malaria transmitting mosquitoes had started developing resistance to pyrethroid insecticides used in the two biggest malaria preventive tools (ITN and IRS) in western Kenya.

These negative observations established challenges that faced Kisumu County in her war against malaria transmission.

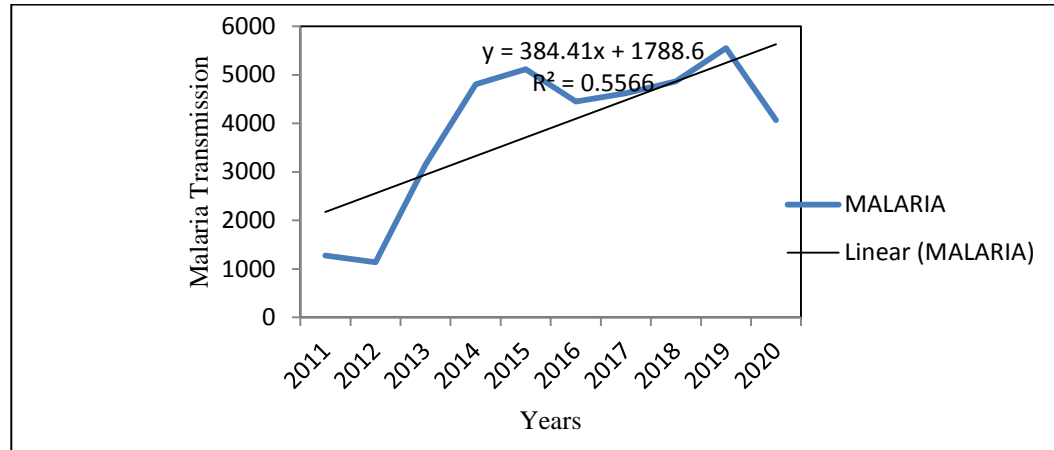


Figure 4.14: Mean Annual Total Confirmed Malaria transmission trends in Kisumu County

4.3.3 Migori County

4.3.3.1 Suspected and Confirmed Malaria Transmission Cases

A comparison of suspected malaria cases with the confirmed cases of the < 5 in Migori County was done and the results showed that more cases of malaria were suspected than confirmed, hence a negative correlation ($r = -0.239$, $P = 0.506$) (Table 4.13). The suspected cases in Migori County must have been too high.

Table 4.13: Correlations for Migori County (< 5 years)

		Suspected	Confirmed
Suspected	Pearson Correlation	1	-.239
	Sig. (2-tailed)		.506
	N	10	10
Confirmed	Pearson Correlation	-.239	1
	Sig. (2-tailed)	.506	

		Suspected	Confirmed
Suspected	Pearson Correlation	1	-.239
	Sig. (2-tailed)		.506
	N	10	10
Confirmed	Pearson Correlation	-.239	1
	Sig. (2-tailed)	.506	
	N	10	10

A negative relationship was again found between the suspected and confirmed malaria transmission cases in those > 5 years ($r = -0.070$, $P = 0.847$) (Table 4.14). As was the case with the < 5, the suspected cases among the > 5 must have been too high in Migori County.

Table 4.14: Correlations for Migori County (> 5 years)

		Suspected	Confirmed
Suspected	Pearson Correlation	1	-.070
	Sig. (2-tailed)		.847
	N	10	10
Confirmed	Pearson Correlation	-.070	1
	Sig. (2-tailed)	.847	
	N	10	10

Due to the over statement, the study ignored the suspected and worked with the confirmed.

4.3.3.2 Monthly Trends of Malaria Transmission Cases in Migori County

Monthly trends of confirmed cases of malaria transmission in Migori County among those < 5 years, > 5 years and the pregnant mothers during the period of 2011 – 2021 showed a general decrease with a lot of fluctuations from the beginning of the year towards the end. Peak periods occurred in the months of February and March

after which both declined towards December. The < 5, the > 5 and the pregnant mothers all indicated negatively (Figure 4.15), an indication that malaria was higher early in the year and cyclically reduced towards the end of the year. The high malaria transmission in Migori County early in the year was yet another window of opportunity but this time for Migori County. As was in the cases of Kakamega and Kisumu, the > 5 trended higher and this was another temporal hot spot and window of opportunity that could be utilized in the war against malaria transmission in Migori County according to Sarkar *et al.* (2019).

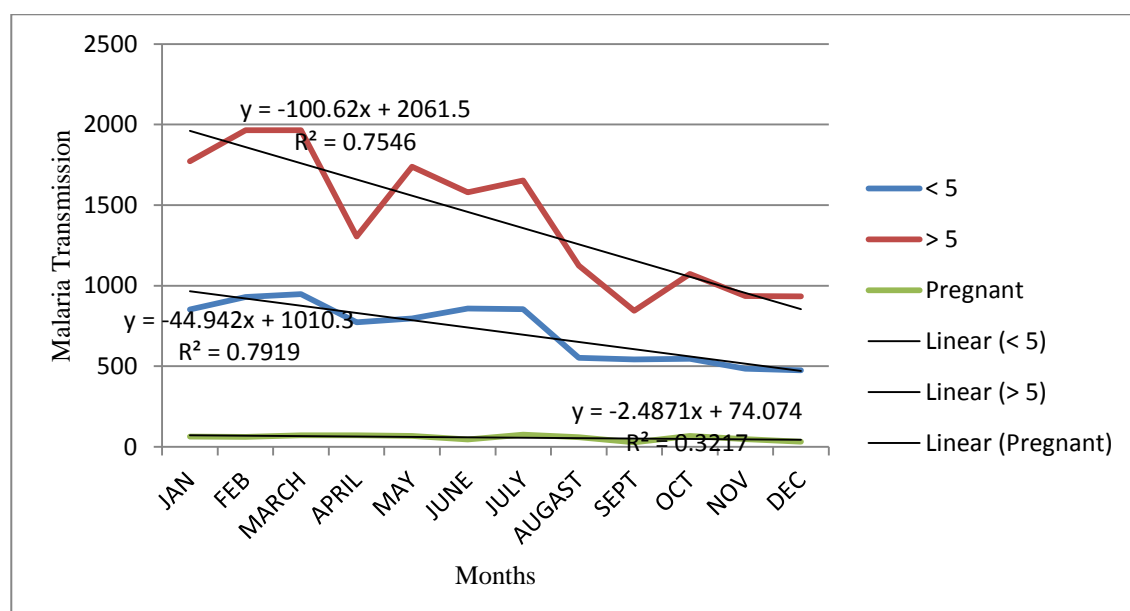


Figure 4.15: Mean Monthly Confirmed (< 5, > 5 and Pregnant mothers) malaria case transmission in Migori County (2011 – 2021)

Total monthly Confirmed malaria transmission cases in Migori County during the study period (2011 – 2021) generally declined. The highest mean for total malaria case transmission was realized in the month of February (2916.6) and lowest in September (1387.6) (Figure 4.16). This once more was a fulfillment to the projection made by LVBC (2018-2023) concerning the seasonality, cyclical

patterns, and strong but temporally varying trends of malaria transmission in Western Kenya. Identifying that malaria transmission peaks early in the year ensured possibility of right intervention and emphasis for different temporal transmission regimes. It was therefore possible to further reduce and subsequently eradicate malaria transmission in Migori County by putting emphasis on eradication strategies.

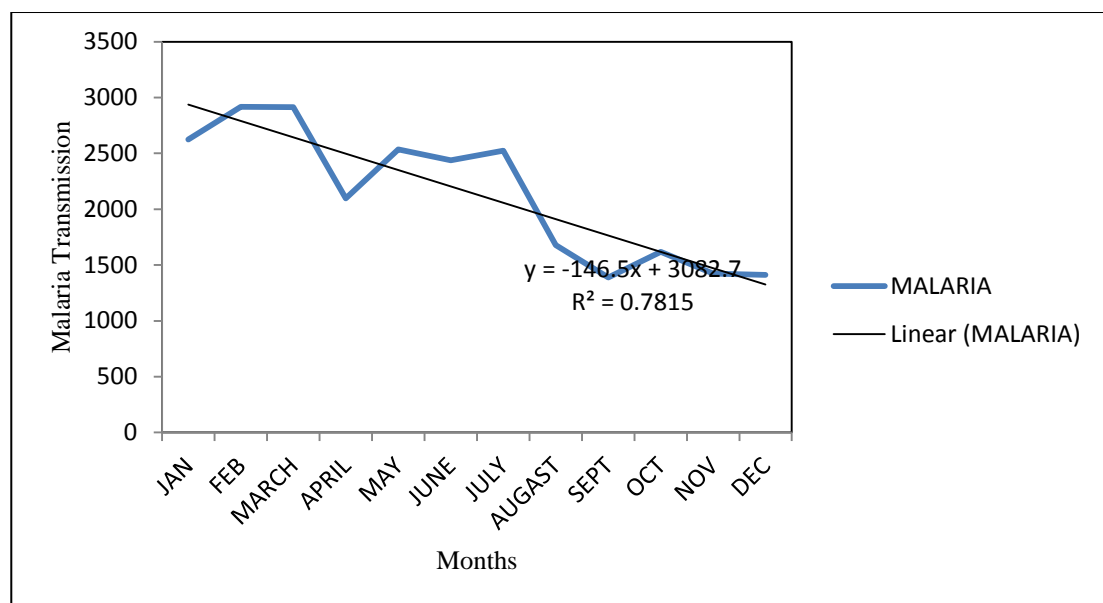


Figure 4.16: Mean Monthly Total Confirmed Malaria transmission trends in Migori County

4.3.3.3 Annual Trends of Malaria Transmission Cases in Migori County

During the study period, the highest confirmed case transmission was observed in the year 2014 (1660 ± 138) for both the < 5 (1660 ± 138) and the > 5 (2736 ± 259) followed by the year 2016 (2675 ± 414) for the > 5 only. The lowest was in the year 2020 for the < 5 (243.3 ± 29.3), for the > 5 , 2012 (453 ± 26.2) and for the pregnant mothers 2018 (23.5 ± 4.23). A very sharp rise was observed between the year 2012 and the year 2014 followed by diminishing trends from the year 2014 to the year

2020. All the cases indicated general diminishing trends towards the end of the study period (Figure 4.17). Like in the cases of Kisumu and Kakamega, the > 5 trended higher than the < 5, meaning it was the > 5 that accounted for the heightened transmission trend. This again opened a window of opportunity for the war against malaria transmission since the medics could now tell when malaria would strike and thus prepare for timely and targeted appropriate interventions.

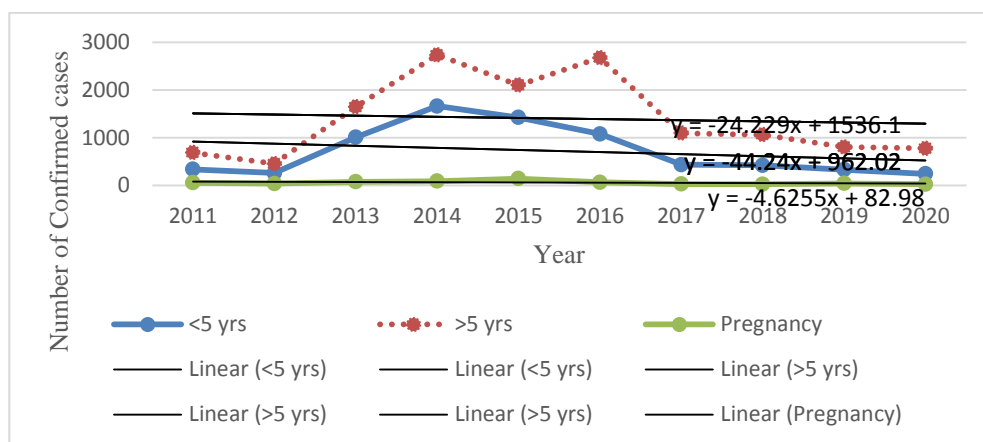


Figure 4.17: Mean Annual Confirmed (< 5, > 5 and Pregnant mothers) malaria case transmission in Migori County (2011 – 2021)

Among the persons < 5 years, > 5 years and the pregnant mothers in Migori County, there were no significant variations in malaria trends over the study period. This was confirmed by the ARIMA model (Table 4.15).

Table 4.15: ARIMA Regression for Migori County

```
. arima Year Awendoleless Awendomore Awendopregn
```

```
(setting optimization to BHHH)
```

```
Iteration 0: log likelihood = -23.360072
```

```
Iteration 1: log likelihood = -23.360072
```

```
ARIMA regression
```

```
Sample: 1 - 10
```

```
Number of obs = 10
```

```
Wald chi2(3) = 2.11
```

```
Log likelihood = -23.36007
```

```
Prob > chi2 = 0.5493
```

Year	Coef.	OPG Std. Err.	z	P> z	[95% Conf. Interval]	
Year						
Awendoleless	-.0056879	.0152058	-0.37	0.708	-.0354906	.0241149
Awendomore	.003488	.0054465	0.64	0.522	-.0071869	.0141628
Awendopregn	-.0160254	.1034095	-0.15	0.877	-.2187043	.1866534
_cons	5.616726	3.077053	1.83	0.068	-.4141877	11.64764
/sigma	2.501946	1.15535	2.17	0.030	.2375016	4.766389

Total Annual Confirmed malaria transmissions during the study period (2011-2020) were observed to be generally decreasing in Migori County, R^2 value = 2.76%. Compared to the increasing trends in Kakamega and Kisumu counties, this was evidence to the observation made by Kapesa *et al.* (2018) that different sites responded differently such that while some areas were witnessing reduction, others experienced increase. The reducing trend also supported the observation made by Roser *et al.* (2020) that by identifying the hot spots and related right intervention and emphasis for different malaria transmission regimes, it was possible to further reduce and subsequently eradicate the disease. The findings also conformed to that of WHO (2017) where they recognized that malaria transmission in Western Kenya which was home to LLVB dropped in 2015. Malaria transmission reduction and subsequent eradication are thus possible in Migori County. The very low R^2 value means the reduction was not significant over the years. Transmission was lowest in the year 2012 at a mean of 712.1 ± 28.6 and highest in the year 2014 at a mean of 4397 ± 329 (Figure 4.18). The fluctuations again conformed to the projections made

by LVBC (2018-2023) which provided evidence of seasonality, cyclical patterns, and strong, temporally varying trends in malaria transmission cases whose nature and details varied.

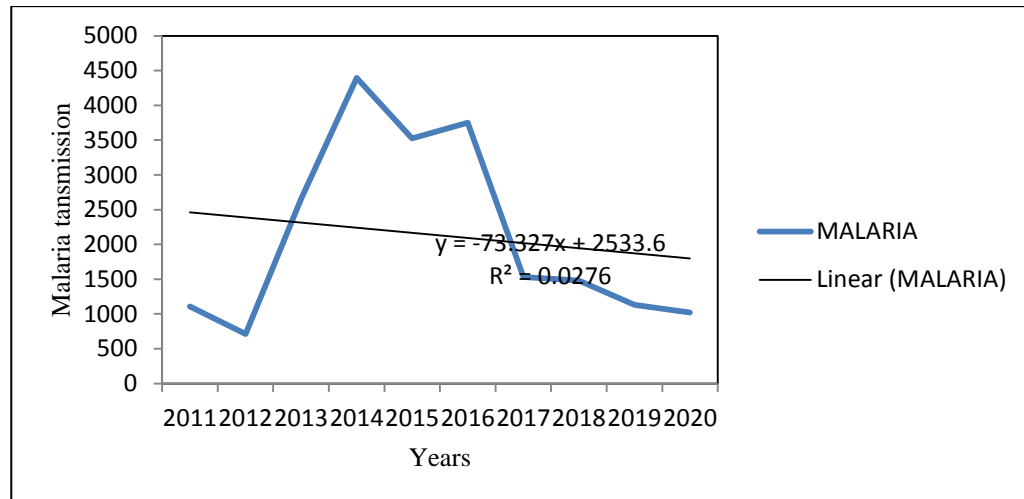


Figure 4.18: Mean Annual Total Confirmed Malaria transmission trends in Migori County

4.4 Total Confirmed Malaria Transmission in the Study Area

4.4.1 Analysis of Variance (ANOVA) for Malaria Transmission Variability

Spatiotemporal variability of total malaria transmission over the period, 2011 – 2020 in Kisumu, Migori and Kakamega Counties were compared using ANOVA at 95% confidence interval (CI) and the means were separated using Tukey's range test at $P \leq 0.05$. The findings showed there was a significantly higher malaria transmission in Kisumu County (3902.87 ± 493.3) followed by Kakamega County (3385.53 ± 407.7) then Migori County (2130.330 ± 422.3) ($F = 4.240$, $P = 0.025$), (Table 4.16). This as Kapesa *et al.* (2018) observed was evidence of spatial variation and as Sarkar *et al.* (2019) noticed malaria transmission windows in India, Kisumu was identified as a hot spot in the endemic LLVB, Kenya calling for special intervention measures.

Table 4.16: ANOVA table for malaria in the study area

Malaria cases Total confirmed	Mean SE	Minimum	Maximum
Kisumu County	3902.87 ±493.3	1135.67	5552.75
Kakamega County	3385.53 ± 407.7	1388.75	5175.50
Migori County	2130.330 ± 422.3	712.08	4397.08
F value	4.240		
P Value	0.025		

Mean separated using Tukeys Honest Significance Difference (HSD) at $P \leq 0.05$.

4.4.1.1 Mean Monthly Total Malaria Transmission Trends in the Study Area

During the study period (2011 – 2020) the mean monthly malaria transmission revealed decreasing trends in all the Counties. Migori County decreased at $Y = -146.5x + 3082$, Kisumu County, $Y = -123.0x + 4185$ and Kakamega County, $Y = -195.5x + 5173$. Elevated and suppressed malaria transmissions varied from one place to another. In all the counties, malaria transmission peaked between May and July. It was then low between September and December (Figure 4.19). This again confirms the cyclic nature of malaria transmission as was observed by County (2013).

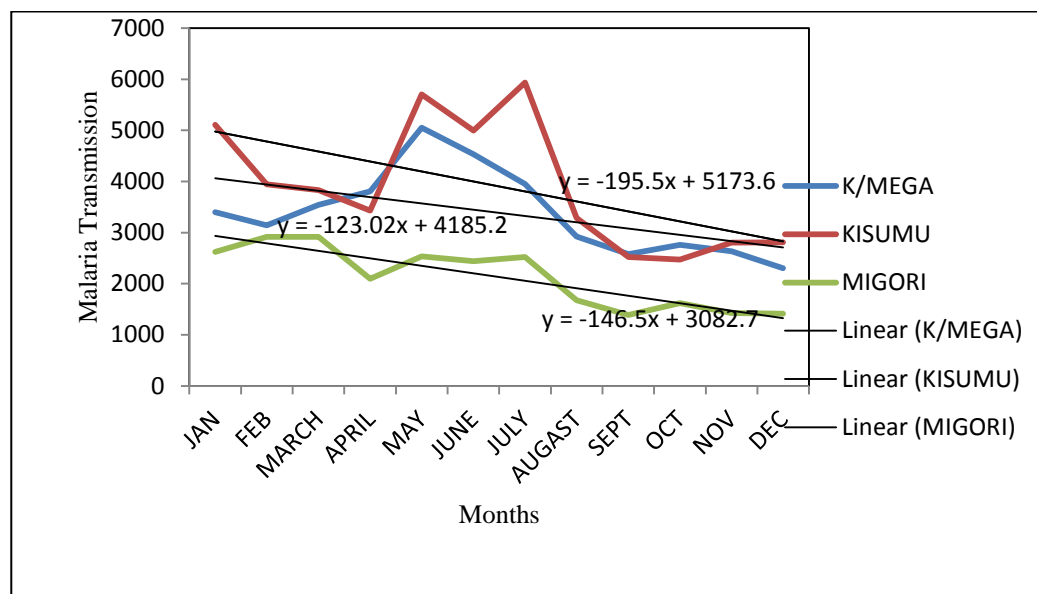


Figure 4.19: Mean monthly Total Malaria Transmission Trends in the Study Areas

4.4.1.2 Mean Annual Total Malaria Transmission Trends Analysis

Total malaria transmission trends during the study period revealed that mean annual malaria transmission was highest in Kakamega County (5176 ± 628) in the year 2019 and lowest in the year 2012 (1388.8 ± 82.4). It was highest in Migori County in the year 2014 (4397 ± 329) and lowest in 2012 (712.1 ± 28.6). In Kisumu County, mean annual malaria transmission was highest in the year 2019 at a mean of 5553 ± 1156 and lowest in 2012 (1135.7 ± 99.1).

The trend during the study period further revealed that transmission increased in Kakamega and Kisumu Counties while it decreased in Migori County. In Kakamega County the increase was at R^2 value = 68.3%. In Kisumu County, the increase was at R^2 value = 55.6% while in Migori County the decrease was at R^2 value = 2.7%. Interestingly the lowest events occurred in the same year (2012). It should also be observed that the highest events for Kakamega and Kisumu Counties occurred in

2019 while Migori County's highest was in 2014 after which transmission took a decreasing trend to the year 2020 (Figure 4.20).

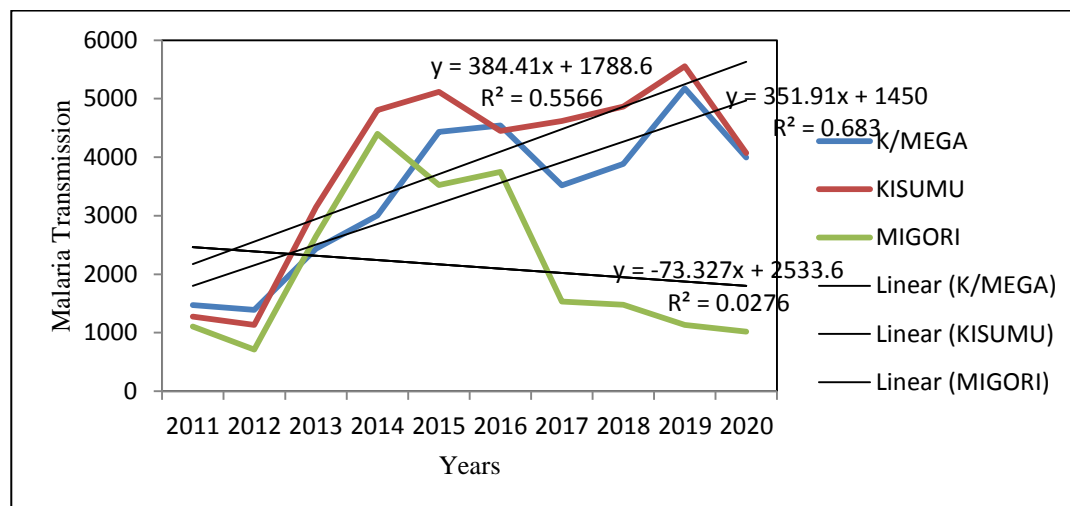


Figure 4.20: Mean Annual Total Malaria Transmission Trends in the Study Areas

4.4.1.3 ARIMA Model for Malaria Cases in the Study Area

This model (ARIMA) established significant variations in total confirmed malaria cases in Migori County ($P = 0.014$) over the study period (2011 – 2020). The model was; $Y = 0.1930 + 0.0011X_1 + 0.0011X_2 - 0.0012X_3$. Where $Y = \text{Year}$, $X_1 = \text{Malaria cases in Kakamega}$, $X_2 = \text{Malaria cases in Kisumu}$, $X_3 = \text{Malaria cases in Migori}$. In Kakamega and Kisumu, malaria cases were not significantly changing as the year progressed towards the end. This further confirmed the spatiotemporal nature of malaria transmission variability (Table 4.17).

Table 4.17: ARIMA table showing change in malaria cases in Kakamega, Kisumu and Migori Counties over the 10-year period (2011 – 2020)

ARIMA regression

Sample: 1 - 10
 Log likelihood = -14.45572

Number of obs = 10
 Wald chi2(3) = 41.73
 Prob > chi2 = 0.0000

Year	Coef.	OPG Std. Err.	z	P> z	[95% Conf. Interval]	
Year						
MaKakamega	.0010756	.0014455	0.74	0.457	-.0017574	.0039087
MaKisumu	.0010621	.0013026	0.82	0.415	-.0014909	.0036151
MaMigori	-.001164	.0004745	-2.45	0.014	-.0020941	-.000234
_cons	.1930146	1.987756	0.10	0.923	-3.702916	4.088945
/sigma	1.026992	.3172334	3.24	0.001	.4052257	1.648758

Considering monthly confirmed malaria cases, the model similarly showed significant variations in confirmed malaria cases in Migori County ($P = 0.001$) during the period (2011 – 2020). The model was; $Y = 17.7715 - 0.00023X_1 + 0.00069X_2 - 0.00617X_3$ where $Y = \text{Year}$, $X_1 = \text{Malaria cases in Kakamega}$, $X_2 = \text{Malaria cases in Kisumu}$, $X_3 = \text{Malaria cases in Migori}$ (Table 4.18). The changes were significant in Migori County while in Kakamega and Kisumu Counties, the numbers of malaria cases were not significantly changing in a year during the study period.

areas were witnessing reduction, others did not. This could explain the increasing trends in Kisumu and Kakamega Counties against the decreasing trend in Migori County during the study period. This kind of observation was also made by Kipruto *et al.* (2017) but in a different way. From the findings, malaria transmission cases increased in the highland and mid altitude zones instead of the lowlands. This was a contradiction of what was observed by this study where increases were observed in the lowlands as opposed to the highlands.

4.5 Spatiotemporal Relationship between Variability in Climate Parameters and Malaria Transmission in Different Altitudes of the LLVB

During the study period (2011 – 2020), the relationship between variability in climate parameters (temperature, relative humidity and rainfall) and malaria transmission (morbidity) were established using Pearson's Product Moment correlation coefficient and regression analyses. Following were the observations made:

4.5.1 Relationship between Monthly Climatic Elements and Malaria Transmission

4.5.1.1 Kakamega County

In Kakamega County, Mumias West -Sub County, temperature ($r = 0.0071$), RH ($r = 0.4003$) and rainfall ($r = 0.4511$) all correlated positively with malaria transmission. Of those relationships, none was significant (Table 4.19) implying that none of the parameters could confidently be used to explain the behavior of malaria transmission in Kakamega County. However, unlike M'Bra *et al.* (2018) established in West Africa that transmission mostly depended on temperature and rainfall, in

Kakamega County, the three climate parameters were always optimal and positively influenced transmission. This implies that although the relationship was not significant, malaria transmission cyclically followed the climate trends.

Table 4.19: Correlation analysis for Relationship between Mean Monthly Malaria and climatic parameters in Kakamega

```
. pwcorr Malaria Temp Rainfall RH, obs sig
```

	Malaria	Temp	Rainfall	RH
Malaria	1.0000			
	12			
Temp	0.0071	1.0000		
	0.9825	12		
		12		
Rainfall	0.4511	-0.1244	1.0000	
	0.1410	0.7001	12	
		12	12	
RH	0.4003	-0.7208	0.7188	1.0000
	0.1973	0.0082	0.0084	12
		12	12	12

The relationship between temperature and malaria transmission and between RH and malaria transmission in Kakamega County were confirmed to be positive following regression models of, $Y = - 50050.63 + 1761.63X_2$ Where $Y =$ Cases of confirmed malaria, $X_2 =$ temperature, and $Y = - 50050.63 + 226.7999X_3$ Where $Y =$ Cases of confirmed malaria, $X_3 =$ RH. Rainfall on the other hand regressed negatively with $Y = - 50050.63 - 5.26488X_1$ Where $Y =$ Cases of confirmed malaria, $X_1 =$ rainfall. None of the relationships was significant, adding to the regression R^2 value of the line of best fit at 38.09%, none of the parameters could confidently be used to explain the behavior of malaria transmission in Kakamega County. However, at this stage, transmission was attributed to temperature and RH because they maintained a positive relationship through the correlation and regression (Table 4.20).

Table 4.20: Regression analysis for monthly malaria in Kakamega

```
. regress Malaria Temp Rainfall RH
```

Source	SS	df	MS	Number of obs	=	12
Model	2919297.85	3	973099.283	F(3, 8)	=	1.64
Residual	4744037.34	8	593004.667	Prob > F	=	0.2556
Total	7663335.19	11	696666.835	R-squared	=	0.3809
				Adj R-squared	=	0.1488
				Root MSE	=	770.07

Malaria	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
Temp	1761.63	1204.647	1.46	0.182	-1016.291 4539.551
Rainfall	-5.26488	7.437219	-0.71	0.499	-22.41514 11.88538
RH	226.7999	151.5196	1.50	0.173	-122.605 576.2047
_cons	-50050.63	35182.16	-1.42	0.193	-131180.8 31079.59

Monthly RH and rainfall in Kakamega County had rising trends while temperature was decreasing towards the end of the year. All climate elements had positive monthly correlation with malaria transmission in Kakamega County. On the other hand, temperature and RH regressed positively with the transmission while rainfall and transmission regressed negatively. From these results, it is temperature that consistently compared with malaria transmission in this area. The study therefore attributed the monthly malaria transmission dynamics in Kakamega County to the influence of temperature which had remained consistent at all levels.

Roser *et al.* (2020) recognized malaria as a tropical disease meaning it would thrive best under the tropical climate where temperatures and rainfall are relatively high. According to this study, Kakamega temperature peaks in February. This gives way to the long rains whose onset is March, cyclically setting the most conducive environment for malaria transmitting vectors in May hence the escalated transmissions which come in early or at the middle of every year. These monthly

trends confirmed the predictions by LVBC 2018-2023 of annual seasonality, cyclical patterns and strong but temporally varying trends.

Nissan *et al.* (2021) observed a set of transmission windows typical to India in terms of different temperature ranges. Kapesa *et al.* (2018) strengthened spatial variations. This study adds temporal variations based on conducive transmission environments monthly created by temperature and rainfall.

4.5.1.2 Kisumu County

Correlation analysis between spatiotemporal variability of Climate Parameters and total Confirmed malaria transmission in Kisumu County revealed a negative relationship between malaria transmission and temperature ($r = - 0.3697$), and a negative relationship between malaria transmission and rainfall ($r = - 0.3794$). The relationship between malaria transmission and RH was however positive ($r = 0.1025$). Given the two tailed significance test of 0.05, the relationships between malaria transmission and temperature, malaria transmission and RH and malaria transmission and rainfall were not significant. The implication here was that none of these selected climate parameters could confidently explain the monthly variability of malaria transmission in Kisumu County (Table 4.21).

Table 4.21: Correlation analysis for Monthly Relationship between Malaria cases and climatic parameters in Kisumu

```
. pwcorr malariaksm TempKsm RainKsm RHKsm, obs sig
```

	malariaksm	TempKsm	RainKsm	RHKsm
malariaksm	1.0000			
	12			
TempKsm	-0.3697	1.0000		
	0.2369	12		
		12		
RainKsm	-0.3794	0.1991	1.0000	
	0.2239	0.5349	12	
		12	12	
RHKsm	0.1025	-0.6469	0.5503	1.0000
	0.7513	0.0230	0.0637	12
		12	12	12

Regression conducted involving the three selected climatic parameters and malaria transmission revealed positive but not significant relationship between malaria transmission and temperature, positive but not significant relationship between RH and malaria transmission and a negative but not significant relationship between rainfall and malaria transmission. The models were: $Y = -18987.43 + 555.6542X_2$ where $Y =$ cases of confirmed malaria transmission, $X_2 =$ temperature; $Y = -18987.43 + 214.1365X_3$, $X_3 =$ RH and $Y = -18987.43 - 23.54156X_1$, $X_1 =$ rainfall. The regression R^2 value of the line of best fit was 29.65% meaning less than half of the observations could be explained by the data (Table 4.22). From such observations, the study again concluded that the selected climate variability (rainfall, temperature and RH) could not confidently explain malaria transmission trends in Kisumu County.

Table 4.22: Regression analyses for Monthly Relationship between Malaria cases and climatic parameters in Kisumu

```
. regress malariaksm TempKsm RainKsm RHKsm
```

Source	SS	df	MS	Number of obs	=	12
				F(3, 8)	=	1.12
Model	5039009.34	3	1679669.78	Prob > F	=	0.3953
Residual	11953510.3	8	1494188.78	R-squared	=	0.2965
				Adj R-squared	=	0.0327
Total	16992519.6	11	1544774.51	Root MSE	=	1222.4

malariaksm	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
TempKsm	555.6542	1409.808	0.39	0.704	-2695.369	3806.678
RainKsm	-23.54156	19.53225	-1.21	0.263	-68.583	21.49988
RHKsm	214.1365	253.9267	0.84	0.424	-371.4195	799.6926
_cons	-18987.43	45416.8	-0.42	0.687	-123718.8	85743.91

The climate elements, rainfall and RH had rising trends while temperature was decreasing. All elements had positive correlations with transmission. Temperature and rainfall had negative regression with transmission while RH and transmission were positive. From these observations, the study found temperature to be the only element consistent with malaria transmission dynamics in Kisumu County. Like M’Bra *et al.* (2018) established that transmission rate mostly depended on rainfall, in Kisumu County, monthly malaria transmission was defined by temperature. Kipruto *et al.* (2017) strengthened the one climatic element determination aspect when he observed that all the three identified climate parameters might simultaneously present an enabling transmission environment while elsewhere, one or two may over - ride others in providing such environments as was the case in Kisumu County where temperature over - rode rainfall and RH.

4.5.1.3 Migori County

In Migori County, the analysis of Monthly Climate Parameters and the monthly total confirmed Malaria Transmission revealed positive relationships between malaria transmission and temperature ($r = 0.3076$). The correlation was however negative between malaria transmission and RH ($r = -0.1550$), and negative between malaria transmission and rainfall ($r = -0.2986$) (Table 4.23). This implied that Malaria Transmission increased with increase in temperature while it decreased with increase in RH and rainfall. However, considering the 2-tailed test of significance level at 0.05, none of these relationships was found to be significant. At this level of observation, monthly malaria transmission was attributed to temperature although none of the climate parameters confidently explained malaria transmission trends in Migori County.

Table 4.23: Correlation analysis for Monthly Relationship between Malaria cases and climatic parameters in Migori

. pwcorr MalariaMig TempMig RainMig RHMig, obs sig

	MalariaMig	TempMig	RainMig	RHMig
MalariaMig	1.0000			
	12			
TempMig	0.3076	1.0000		
	0.3307			
	12	12		
RainMig	-0.2986	0.2113	1.0000	
	0.3458	0.5098		
	12	12	12	
RHMig	-0.1550	0.7321	0.7290	1.0000
	0.6304	0.0068	0.0071	
	12	12	12	12

In regression, positive and significant relationship was established between total malaria transmission cases and temperature, and a positive but not significant

relationship between total malaria transmission and rainfall in Migori County. RH on the other hand had negative but not significant relationship with malaria transmission. These were explained by the following models: $Y = -2405.911 + 1566.32X_2$ Where $Y =$ Cases of confirmed malaria, $X_2 =$ temperature; $Y = -2405.911 + 3.683698X_1$ Where $Y =$ Cases of confirmed malaria, $X_1 =$ rainfall; $Y = -2405.911 - 469.6379X_3$ Where $Y =$ Cases of confirmed malaria, $X_3 =$ RH. The R^2 value was 45.30%. In Migori County, malaria transmission trends were confidently defined by temperature according to regression (Table 4.24).

Table 4.24: Regression analysis for monthly malaria in Migori County

. regress MalariaMig TempMig RainMig RHMig

Source	SS	df	MS	Number of obs	=	12
Model	1778972.14	3	592990.715	F(3, 8)	=	2.21
Residual	2148417.47	8	268552.184	Prob > F	=	0.1648
Total	3927389.61	11	357035.419	R-squared	=	0.4530
				Adj R-squared	=	0.2478
				Root MSE	=	518.22

MalariaMig	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
TempMig	1566.32	687.032	2.28	0.052	-17.97884 3150.619
RainMig	3.683698	4.451356	0.83	0.432	-6.581147 13.94854
RHMig	-469.6379	261.8471	-1.79	0.111	-1073.458 134.1826
_cons	-2405.911	8474.486	-0.28	0.784	-21948.11 17136.29

The Migori climatic conditions depicted almost similar characteristics to those of Kisumu and Kakamega with small variations among R^2 values. Monthly temperature in Migori County indicated a reducing trend at an R^2 value of 16.03% towards the end of the year. Rainfall increased at an R^2 value of 3.58% while RH increased at R^2 value of 0.22%. Of all these climate elements, it is only temperature that had a positive correlation and regression with malaria, regression being positively significant. From this observation, the decreasing trend of temperature was used to explain the decreasing trend of malaria transmission in Migori County.

Once again as was observed by M'Bra *et al.* (2018) in Korhogo-West Africa where it was established that transmission rate mostly depended on rainfall, in Migori County, monthly transmissions were driven by Temperature.

4.5.2 Relationship between Annual Climatic Elements and Malaria

Transmission

During the study period (2011 – 2020), annual relationship between variability in climate parameters (temperature, relative humidity and rainfall) and malaria transmission (morbidity) were established using Pearson's Product Moment correlation coefficient and regression analyses. Following were the observations made.

4.5.2.1 Kakamega County

In Kakamega County, RH values correlated positively ($r = 0.105$) with malaria transmission. Temperature ($r = - 0.054$) and rainfall ($r = - 0.026$) on the other hand had negative correlations with the transmission. Of those relationships, none was significant (Table 4.25).

Table 4.25: Correlation Matrix showing relationship between total confirmed cases of malaria transmission and climate parameters in Kakamega County

		Correlations			
		MalMum	TempMum	RHMum	RainMum
MalMum	Pearson Correlation	1	-.054	.105	-.026
	Sig. (2-tailed)		.881	.774	.942
	N	10	10	10	10
TempMum	Pearson Correlation	-.054	1	-.690*	-.656*
	Sig. (2-tailed)	.881		.027	.039
	N	10	10	10	10
RHMum	Pearson Correlation	.105	-.690*	1	.215
	Sig. (2-tailed)	.774	.027		.551
	N	10	10	10	10
RainMum	Pearson Correlation	-.026	-.656*	.215	1
	Sig. (2-tailed)	.942	.039	.551	
	N	10	10	10	10

*. Correlation is significant at 0.05 level (2-tailed).

The relationships between rainfall and malaria transmission and between temperature and malaria transmission in Kakamega County were confirmed to be negative following regression models of, $Y = 1445.65 - 2697877X_1$ Where $Y =$ Cases of confirmed malaria, $X_1 =$ Rainfall and $Y = 1445.65 - 71.18992X_2$ (Table 4.26) Where $Y =$ Cases of confirmed malaria, $X_2 =$ temperature. RH on the other hand regressed positively $Y = 1445.65 + 63.65365X_3$ where $Y =$ Cases of confirmed

malaria, $X_3 = RH$. None of the relationships was significant. The regression R^2 value of the line of best fit was 1.4%. At R^2 value of 1.4% climate parameters confirmed least relationship with malaria transmission trends among the three selected counties of the LLVB, Kenya (Table 4.26).

Table 4.26: Rainfall/Malaria Regression for Kakamega County

Source	SS	df	MS			
Model	205160.764	3	68386.9213	Number of obs =	10	
Residual	14752777.1	6	2458796.18	F(3, 6) =	0.03	
Total	14957937.9	9	1661993.1	Prob > F =	0.9931	
				R-squared =	0.0137	
				Adj R-squared =	-0.4794	
				Root MSE =	1568.1	

KKmalaria	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
KKrainfal	-.2697877	2.350906	-0.11	0.912	-6.022247	5.482671
KKtemp	-71.18992	1772.514	-0.04	0.969	-4408.374	4265.995
KKRH	63.65365	408.2107	0.16	0.881	-935.202	1062.509
_cons	1445.656	65774.35	0.02	0.983	-159498.4	162389.7

From the above findings, there were no significant relationships between climate elements and malaria transmission in Kakamega County. The study therefore attributed insignificant role of climate elements to annual variation of malaria transmission in this area.

Rainfall and temperature negatively correlated with malaria transmission while RH was positive. When regressed, the results were the same as those of correlation. RH trend in Kakamega was rising. From these observations, the study concluded that although correlation and regression results were not significant, and given that all selected climate elements were within malaria transmission limits according to Nissan *et al.* (2021), the increase in annual malaria transmission in Kakamega County was most likely influenced by the increase in RH.

4.5.2.2 Kisumu County

Correlation analysis between spatiotemporal variability of Climate Parameters and total Confirmed malaria transmission in Kisumu County revealed a positive relationship between malaria transmission and temperature ($r = 0.557$), and a positive relationship between malaria transmission and rainfall ($r = 0.023$). The relationship between malaria transmission and RH was however negative ($r = -0.277$). This indicated that higher number of malaria transmission cases occurred when temperature and rainfall were high and vice versa. On the other hand, an increase in RH meant a decrease in malaria transmission. Given the two tailed significance test of 0.05, the relationships between malaria transmission and temperature, RH and rainfall were not significant (Table: 4.27). The implication here was therefore that none of these selected climate parameters could confidently define the annual variability of malaria transmission in Kisumu County.

Table 4.27: Correlation Matrix showing relationship between total confirmed cases of malaria transmission and climate parameters in Kisumu County

Correlations				
	malaKSM	TemKSM	RHKSM	RainKSM
malaKSM Pearson Correlation	1	.557	-.277	.023

	Sig. (2-tailed)		.095	.439	.949
	N	10	10	10	10
TemKSM	Pearson Correlation	.557	1	-.378	-.264
	Sig. (2-tailed)	.095		.282	.462
	N	10	10	10	10
RHKSM	Pearson Correlation	-.277	-.378	1	.636*
	Sig. (2-tailed)	.439	.282		.048
	N	10	10	10	10
RainKSM	Pearson Correlation	.023	-.264	.636*	1
	Sig. (2-tailed)	.949	.462	.048	
	N	10	10	10	10

*. Correlation is significant at the 0.05 level (2-tailed).

A regression was conducted involving the three selected climatic parameters and malaria transmission. The result was a positive but not significant relationship between malaria transmission and temperature, a positive but not significant relationship between rainfall and malaria transmission while a negative but not significant relationship between RH and malaria transmission. The models were: $Y = -383.77 + 1.66X_1$ where Y = cases of confirmed malaria transmission, X_1 = rainfall; $Y = -383.77 + 2317.46X_2$, X_2 = temperature and $Y = -383.77 + 2317.46X_3$, X_3 = RH. The regression R^2 value of the line of best fit was 40% meaning less than half of the observation could be explained by the data. From such observations, the study concluded that the selected climate parameters (rainfall, temperature and RH) could not confidently be used to explain annual malaria transmission trends in Kisumu County.

The study established that all the climate elements were increasing in Kisumu County. When correlated with malaria transmission, temperature and rainfall had positive correlations with the transmission while RH was negative. Regression result was the same as that of correlation (Table 4.28). The study thus attributed the annual increase of malaria transmission in Kisumu County to that of temperature and rainfall though the relationships were not significant. This observation still supported that of M'Bra *et al.* (2018) where only one element (rainfall) was responsible for defining the transmission trends in Korhogo-West Africa.

Table 4.28: Annual Climate/Malaria Regression for Kisumu County

Source	SS	df	MS			
Model	8553809.84	3	2851269.95	Number of obs =	10	
Residual	13348034.9	6	2224672.49	F(3, 6) =	1.28	
Total	21901844.7	9	2433538.31	Prob > F =	0.3628	
				R-squared =	0.3906	
				Adj R-squared =	0.0858	
				Root MSE =	1491.5	

KSMmalaria	Coef.	Std. Err.	t	P> t	[95% Conf. Interva]	
rainfall	1.656705	1.923272	0.86	0.422	-3.049373	6.362783
Temp	2317.462	1485.93	1.56	0.170	-1318.478	5953.402
RH	-261.6951	375.01	-0.70	0.511	-1179.311	655.9212
_cons	-38343.77	46126.3	-0.83	0.438	-151210.8	74523.23

4.5.2.3 Migori County

In Migori County, the analysis of Climate Parameters and the total confirmed malaria transmission revealed positive relationships between malaria transmission and temperature ($r = 0.147$) and between malaria transmission and RH ($r = 0.004$) while a negative relationship between malaria transmission and rainfall ($r = -0.442$) (Table 4.29). This implied that the higher the temperature and RH, the higher the malaria transmission. Malaria transmission on the other hand decreased with increase in rainfall. However, considering the 2-tailed test of significance level at

0.05, none of these relationships was significant. None of the climate parameters thus confidently explained malaria transmission trends in Migori County. Malaria transmission though on the decrease remained high with little influence from the varying climate parameters. The underlying parameters remained optimal and hardly went beyond the transmission thresholds.

All climate elements in Migori County had increasing trends. When correlated, malaria transmission correlated positively with temperature and RH whereas it correlated negatively with rainfall. In regression, RH and rainfall regressed negatively with malaria transmission. Temperature on the other hand was positive with malaria transmission (Table 4.29). From these results, it was only rainfall that was consistent in its relationship with transmission. The study therefore attributed the decreasing trends of annual malaria transmission in Migori County to increase in rainfall. This was a case that greatly resembled that of M'Bra *et al.* (2018) in Korhogo-West Africa where transmission was mostly defined by rainfall.

Table 4.29: Correlation Matrix showing relationship between total confirmed cases of malaria transmission and climate parameters in Migori County

		Correlations			
		MalaSONY	TempSON Y	RHSON Y	RainSON Y
MalaSONY	Pearson Correlation	1	.147	.004	-.442
	Sig. (2-tailed)		.685	.992	.201
	N	10	10	10	10
TempSON Y	Pearson Correlation	.147	1	.690*	.409
	Sig. (2-tailed)	.685		.027	.240
	N	10	10	10	10
RHSONY	Pearson Correlation	.004	.690*	1	.223
	Sig. (2-tailed)	.992	.027		.536
	N	10	10	10	10
RainSONY	Pearson Correlation	-.442	.409	.223	1
	Sig. (2-tailed)	.201	.240	.536	
	N	10	10	10	10

*. Correlation is significant at the 0.05 level (2-tailed).

When regressed, a positive but not significant relationship was established between total malaria transmission and temperature in Migori County. RH and rainfall on the other hand had negative relationships with malaria transmission. These were explained by the following models: $Y = -11238.41 + 1029.763X_2$ Where Y = Cases

of confirmed malaria, X_2 =temperature; $Y = -11238.41 - 97.14876X_3$ Where $Y =$ Cases of confirmed malaria, $X_3 =$ RH and $Y = -11238.41 - 1.812504X_1$ Where $Y =$ Cases of confirmed malaria, $X_1 =$ rainfall. The R^2 value was 3.5% (Table 4.30).

In Migori County, variability of annual malaria transmissions were not confidently defined by the selected climate parameters since less than half of the observations were defined by the data in question.

Table 4.30: Climate/Malaria Regression for Migori County

```
. regress MigoriMalaria Migorirain Migoritemp MigoriRH
```

Source	SS	df	MS	Number of obs = 10		
Model	5755539.11	3	1918513.04	F(3, 6) =	1.12	
Residual	10294150.2	6	1715691.71	Prob > F =	0.4130	
				R-squared =	0.3586	
				Adj R-squared =	0.0379	
				Root MSE =	1309.8	
Total	16049689.4	9	1783298.82			

MigoriMala~a	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
Migorirain	-1.812504	1.049473	-1.73	0.135	-4.380473	.7554651
Migoritemp	1029.763	863.0306	1.19	0.278	-1081.997	3141.523
MigoriRH	-97.14876	171.893	-0.57	0.592	-517.7558	323.4583
_cons	-11238.41	14016.05	-0.80	0.453	-45534.46	23057.64

In all the above cases, climate malaria transmission relationships depicted the findings made by Caminade *et al.*, (2014) that Malaria is one of the few climate – sensitive health outcomes that has been subjected to thorough global and regional assessments using a range of malaria impact models and climate scenarios with varying results. The correlation and regression results in Kakamega, Kisumu and Migori always varied and almost all were insignificant leaving none to confidently explain malaria transmission monthly and annually. However, the insignificant outcomes could be explained by the fact that the climatic conditions were most of the times within malaria transmission ranges as was explained by Kumar *et al.* (2022) hence the observed insignificant impacts during the malaria transmission periods.

4.6 Combined Relationships in the Entire LLVB, Kenya in Steps

All the selected climatic parameters had no significant correlation and regression with malaria transmission at the sampled altitudes except temperature that had a positive significant regression with monthly malaria transmission in Migori County ($P = 0.052$). However, at an R^2 value of 45.3%, this could have been a factor of chance.

As Bhattacharya *et al.* (2006) argued, for most *anopheles* vector species that transmit malaria, the optimal temperature range must be within 20°C to 30°C. This should extend over a period for completion of sporogony. According to that study, malaria transmission also depends on seasons with rainy period being preferred for vector multiplication. RH should neither be below 55% nor above 80%. Exceeding those limits, it becomes lethal for mosquitoes' survival. The three climate elements are the major climatic determinants of malaria transmission.

Studying spatiotemporal variation of temperature, RH and rainfall in the sampled counties of LLVB, it was established that in Kakamega County, temperature varied between 23.58°C and 21.69°C during the study period. Rainfall varied between 2823.7mm and 1674.4mm while RH varied between 68.96% and 64.42%. In Migori County, temperature varied between 24.12°C and 21.04°C. Rainfall varied between 2906.2mm and 1424.3mm while RH varied between 72.22% and 62.17%. The situation in Kisumu County was not far as temperature varied between 24.63°C and 23.21°C. Rainfall varied between 2125.9mm and 981.0mm, RH varied between 62.96% and 56.33%. From this study, climate parameters operated within malaria transmission thresholds in all the sampled counties and although malaria

transmission levels varied significantly among the counties, the variations could not have been confidently defined by climate elements whose variations remained optimal and hardly went beyond malaria transmission limits.

Due to the fact that none of the relationships between climate and malaria transmission in all the sampled counties were significant, they could not be used to give substantive conclusions on spatiotemporal malaria transmission variability. The study thus decided to explore further investigative mechanisms in steps as follows:

4.6.1 Correlation of Malaria Transmission, Temperature, Rainfall, RH and Altitude

Pearson's correlation analysis for the entire LLVB, Kenya revealed that Malaria transmission was negatively affected by Relative Humidity and altitude. This was a significant outcome with RH ($r = -0.461$, $P = 0.01$) and Altitude ($r = -0.475$, $P = 0.008$) (Table 4.31). The significance observed in RH could have been a factor of figures from one or two counties overcoming the others in the process of combination from different altitudes hence elevating RH to become a significant climatic determinant in the entire LLVB, Kenya. This outcome supports the proposal of the study that large - scale climatic occurrences do affect the micro - scale occurrences differently. This undermined blanket assumption.

Table 4.31: Correlation result for the effect of temperature, relative humidity, rainfall and altitude on malaria in the entire LLVB, Kenya (2011 – 2020)

		Correlations				
		Malaria	RH	Temp	Rainfall	Altitude
malaria	Pearson Correlation	1	-.461*	.208	-.227	-.475**

	Sig. (2-tailed)		.010	.271	.229	.008
RH	Pearson Correlation	-.461*	1	-.388*	.532**	.872**
	Sig. (2-tailed)	.010		.034	.002	.000
Temp	Pearson Correlation	.208	-.388*	1	-.464**	-.436*
	Sig. (2-tailed)	.271	.034		.010	.016
Rainfall	Pearson Correlation	-.227	.532**	-.464**	1	.368*
	Sig. (2-tailed)	.229	.002	.010		.046
Altitude	Pearson Correlation	-.475**	.872**	-.436*	.368*	1
	Sig. (2-tailed)	.008	.000	.016	.046	
	N	30	30	30	30	30

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

4.6.2 Regression of Malaria Transmission, Temperature, Rainfall and RH

Overall regression result for the combined total malaria case transmission in the lake region and combined climate parameters (Relative humidity, temperature and Rainfall) during the period 2011 – 2020, were evaluated. The result showed that in the lake region during the year 2011 – 2020, a number of malaria transmission cases were positively affected by temperature and rainfall. The cases were affected negatively by the relative humidity. Effects were shown by R^2 value of 19.61% in a regression model equation $Y = 5448.22 + 228.299X_1 + 0.0272X_2 - 117.896X_3$ (Where Y = Malaria cases in the region, X_1 = temperature, X_2 = rainfall, X_3 = relative humidity (Table 4.32). This overall effect indicated that malaria transmission increased with increase in temperature and rainfall. However, decrease in relative humidity resulted into an increase in malaria transmission. None of these results was significant.

Table 4.32: Regression result for the effect of temperature, relative humidity and rainfall on malaria in the region (2011 – 2020)

Source	SS	df	MS			
Model	13636128.8	3	4545376.27	Number of obs =	30	
Residual	55891224.8	26	2149662.49	F(3, 26) =	2.11	
Total	69527353.6	29	2397494.95	Prob > F =	0.1227	
				R-squared =	0.1961	
				Adj R-squared =	0.1034	
				Root MSE =	1466.2	

Malaria	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
RH	-117.896	60.83847	-1.94	0.064	-242.9513	7.159235
Temp	228.2998	391.5903	0.58	0.565	-576.6257	1033.225
Rainfall	.0271715	.6902272	0.04	0.969	-1.391611	1.445954
_cons	5448.22	10834.69	0.50	0.619	-16822.8	27719.24

From these observations, the study adopted the hypothesis, “There is no significant relationship between variability in climate parameters and malaria transmission in different altitudes of the LLVB, Kenya”. The insignificant correlations implied that the observed relationships might have occurred on account of chance and could not be used to make any significant conclusions regarding the relationship between climate and malaria transmission in different altitudes of the LLVB, Kenya. It must however be born in mind that although the relationships were not significant, climatic elements remained optimal for malaria transmission in the LLVB throughout the study period. This could make the relationships remain insignificant.

4.6.3 Regression of Malaria Transmission, Temperature, Rainfall, RH and Altitude

Overall effects of the climatic conditions on malaria transmission were further evaluated using stepwise linear regression. The finding showed that only altitude had a significant effect on spatiotemporal malaria transmission variability with a regression R^2 value of 22.6% (Table 4.33). The effect of the altitude adopted the

equation model of; $Y = \text{Constant} + \beta_1 X_1$. Where Y = Malaria cases in the region, X_1 = altitude, β_1 is the gradient of X_1 on Y . $Y = 9593.413 - 5.060X_1$ (Table 4.34).

Table 4.33: Stepwise Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.475 ^a	.226	.198	1386.75274

a. Predictors: (Constant), Altitude

Table 4.34: Stepwise linear Regression Results

Model	Unstandardized Coefficients		Standardized Coefficients		t-value	Sig.
	B	Std. Error	Beta			
(Constant)	9593.413	2273.925			4.219	.000
1 Altitude	-5.060	1.772	-.475		-2.856	.008

a. Dependent Variable: malaria

Effects of other climatic parameters were eliminated during computation (Table 4.35). This left only altitude as the major determinant of malaria transmission variability in the study area. This outcome confirmed the observation made by Ewnetu *et al.* (2022) that transmission differs by altitude such that the higher the altitude, the lower the transmission. The study thus zoned LLVB, Kenya into altitudes according to transmission levels: 1001m to 1200m – high transmission zones; 1201 to 1400 - medium transmission zones; 1401 to 1600 – low transmission zones.

Table 4.35: Zones of malaria transmission in the LLVB

Altitude (m)	Zone	Description
1001 – 1200	Zone 1	High transmission level
1201 – 1400	Zone 2	Medium transmission level
1401 - 1600	Zone 3	Low transmission level

In line with the argument raised by Ewnetu *et al.* (2022), this study revealed that climate parameters operated within malaria transmission thresholds at all the sampled altitudes of the LLVB, Kenya. Although transmission levels varied significantly among the sampled altitudes, they might not have been effectively defined by the optimal climate variations. Spatial malaria transmission was thus defined by altitude while temporal malaria transmission was insignificantly defined by temperature as was seen in the monthly transmissions. WHO (2019) confirmed endemic transmission due to the optimal climate factor, and given the temperature (20⁰C - 30⁰C) and RH (55% - 80%) transmission ranges, transmission is likely to continue, and even rise at differing altitudes of the LLVB, Kenya.

4.7 Prediction of Future Malaria Transmission in the Study Area

LVBC (2018-2023) proposed a temperature rise of up to 3⁰C by the year 2100 in the Lake Victoria Basin (LVB). As Tonnang *et al.*, (2010) put it, vector borne diseases are climate sensitive implying that if climate in the LLVB, Kenya was changing, then it was expected to have either a negative or positive effect on malaria transmittance in the area.

4.7.1 Kakamega County

In the Descriptive Time Series for Kakamega County, malaria transmission had increasing trends ($R^2 = 68.3\%$). Climate variables also increased except Temperature that was decreasing ($R^2 = 15.7\%$). RH and rainfall increased at $R^2 = 13.1\%$ and $R^2 = 4.1\%$ respectively. However, the R^2 values indicated that the increasing occurrences were not significant i.e. temperature had the highest among climate elements ($R^2 = 15.8\%$) on the decreasing side. At R^2 of 68.3% , the increase in malaria transmission was significant (Figure 4.21). In this study, as Tonnang *et al.*, (2010) put it, Malaria transmission increased alongside the increase of rainfall and RH in Kakamega County.

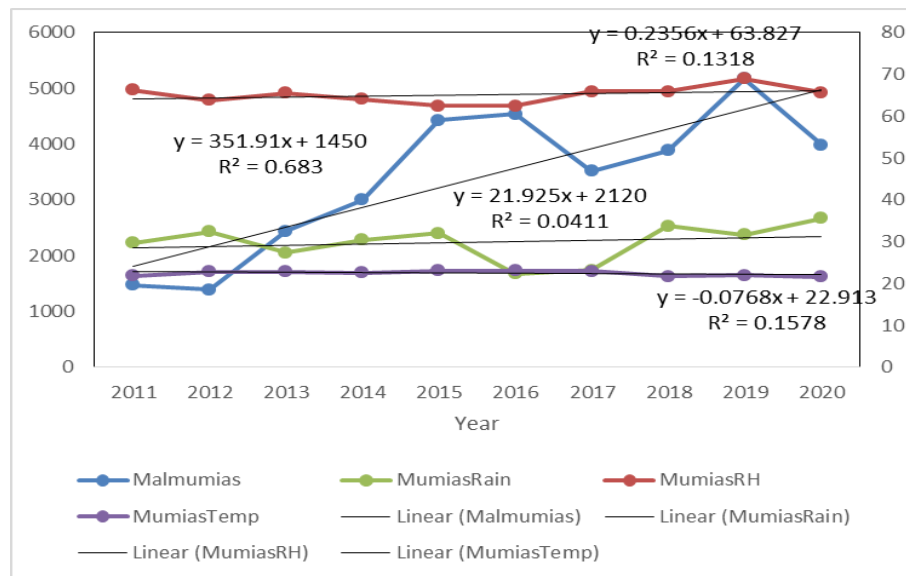


Figure 4.21: Trends of climate variability and malaria transmission in Kakamega County

Table 4.36 “Climate/Malaria ARIMA Regression for Kakamega County”, showed that the effect of RH on malaria transmission was positive but not significant at P value of 0.893, effect of rainfall was negative but not significant at P value of 0.878

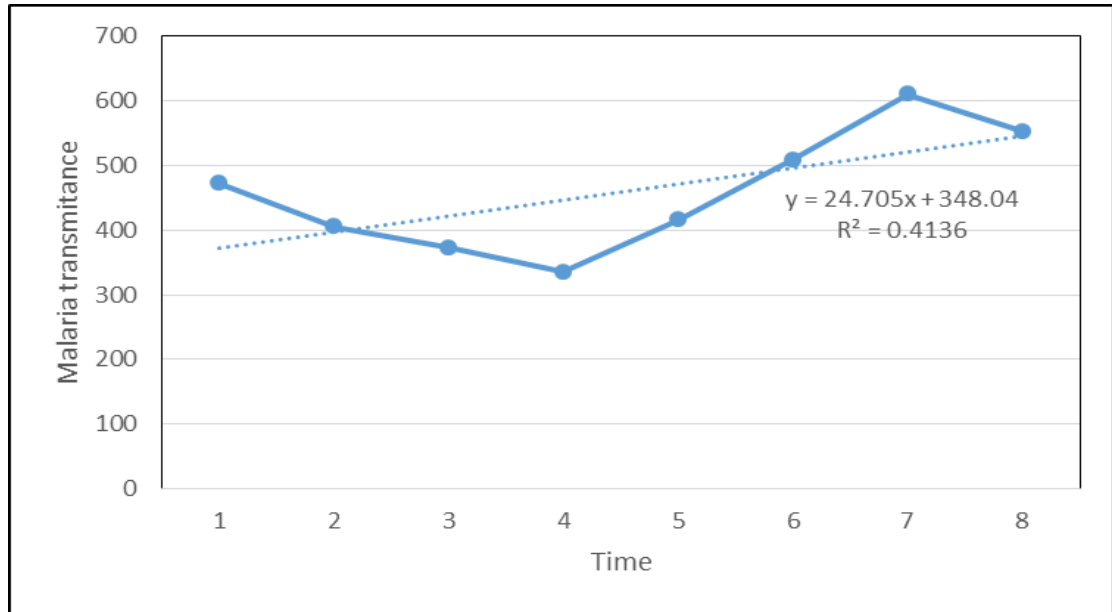


Figure 4.22: Predicted Future malaria transmission in Kakamega County

Descriptive Time Series for Kakamega County indicated increasing trends in all the variables except temperature which indicated a decrease. Malaria transmission increased with an R^2 Value of 68.3%. This was significant. Using ARIMA model, the three climate elements had influence on malaria transmission but the effects were not significant. The ARIMA model equation however gave an overall increasing malaria transmittance for the subsequent years. According to the climate transmission limits observed by Kumar *et al.* (2022), the study confidently concluded that malaria transmission in Kakamega County was on the increasing trend during the study period and would do so in future given the observed positive moving averages and the rising Descriptive Time Series. The rate of the rise however may not be significant considering the less than 50% R^2 value of the moving averages (41.36%). Although Kakamega County indicated temperature decline, the 3°C temperature increase proposed by LVBC (2018 - 2023) means that Kakamega County will still be well within temperature transmission limits. This was

an indication that the future climate would be more conducive for malaria transmission in Kakamega County.

4.7.2 Kisumu County

In Kisumu, all the variables had increasing trends when analyzed using Descriptive Time Series. Malaria transmission increased at $R^2 = 55.6\%$, RH increased at $R^2 = 1.1\%$, Temperature increased at $R^2 = 0.1\%$ while rainfall increased at $R^2 = 20\%$. As can be observed, climate parameters depicted insignificant trends while malaria transmission had more than half ($R^2 = 55.6\%$) hence significant (Figure 4.23). Even then, the outcome was that malaria transmission in Kisumu County increased alongside all climate parameters.

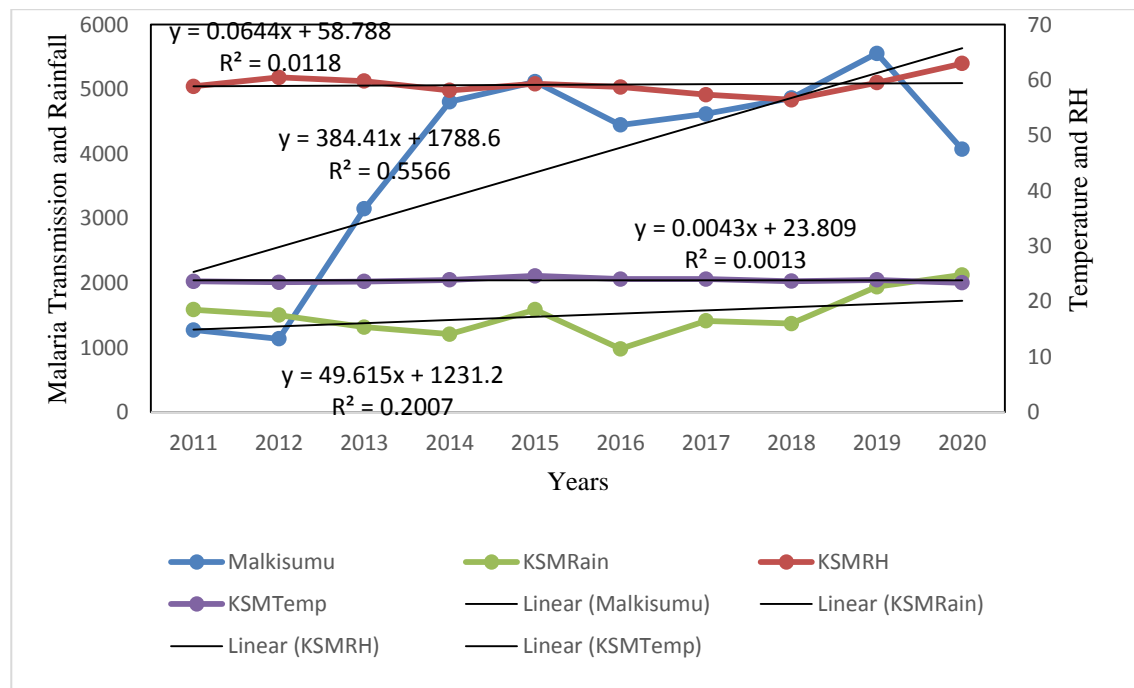


Figure 4.23: Trends of climate variability and malaria transmission in Kisumu County

Table 4.37 “Climate/Malaria ARIMA Regressions for Kisumu County”, indicated that none of the climate elements had a significant effect on malaria transmission.

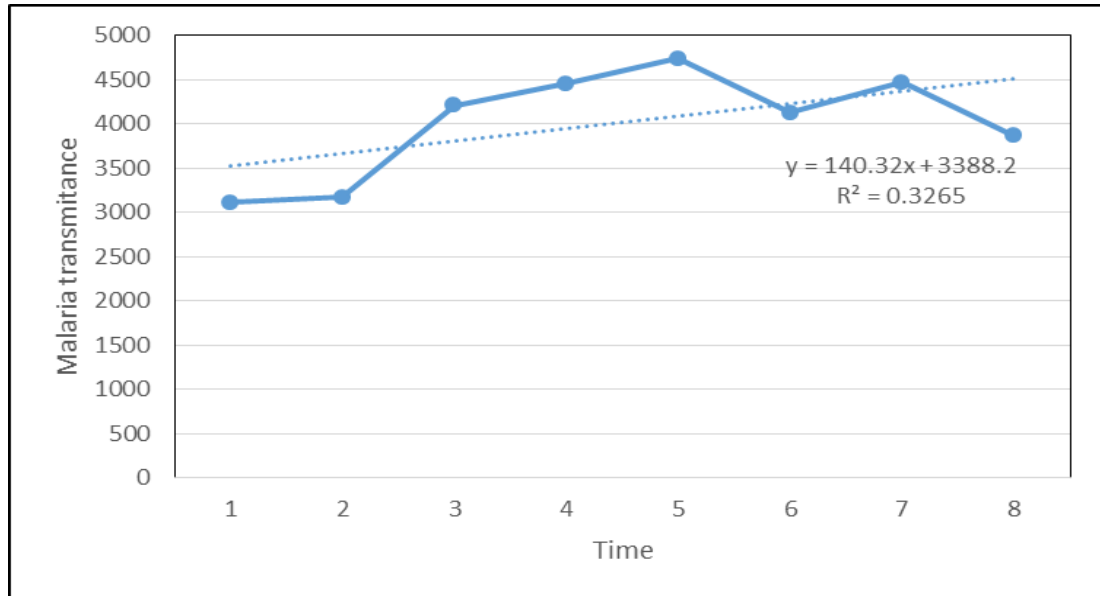


Figure 4.24: Predicted Future malaria transmission in Kisumu County

Descriptive Time Series for Kisumu County indicated increasing trend with R^2 value of 55.6% alongside the climate variables which also increased but with very low R^2 values meaning the increases were not significant. The 55.6% rise for malaria transmission could not have been a factor of chance. It was an indication that despite the low climatic R^2 values, they still effectively supported malaria transmission. The low R^2 values for climate parameters also meant that if ever they were changing with time, then the changes must have been very insignificant hence very insignificant effects on change in malaria transmission.

According to Parihar *et al.* (2022), the rising malaria trend was justified since the County's climate was within malaria transmission limit. Climate signals in the last 100 years showed an increasing trend in surface temperature by 0.3°C , a change in the spatial rainfall patterns with respect to normal, and occurrence of more intense

and frequent extreme temperature, rainfall and cyclone events (Parihar *et al.* (2022), these were meant to predict rising malaria transmission trends in the study area.

ARIMA regression model on the other hand indicated that the climate elements influenced malaria transmission though the effects were not significant. However, using the ARIMA model equation for prediction, the moving averages revealed a positive malaria transmittance for the future years. Supported with the increasing trend of the Descriptive Time Series, the study confidently concluded that malaria transmission in Kisumu County was on the rising trend and would continue to do so in future though insignificantly considering the R^2 values (32.65%) (Figure 4.24 above).

LVBC (2018-2023) proposed a temperature increase of 3°C in the next 100 years and according to Chaturvedi *et al.* (2022), increases in transmission will still be observed since the transmission limit will not have been surpassed. The implication is that transmission will still be on the increase in the next 100 years since the environment will continue being more conducive for transmission in Kisumu County.

4.7.3 Migori County

Unlike in the other two counties, in Migori County, malaria transmission had a decreasing trend with ($R^2= 2.7\%$). All the climatic variables had increasing trends i.e. RH ($R^2= 0.781$), Rainfall ($R^2= 31.5\%$) and temperature ($R^2= 71.1\%$) (Figure 4.25). The R^2 values for the climatic variables as can be seen were significant except for rainfall. Malaria R^2 value was equally insignificant at (2.7%) compared to those

of Kisumu and Kakamega (Figure 4.25). The Migori situation differed from that of Kakamega and Kisumu in that malaria transmission was decreasing instead of rising.

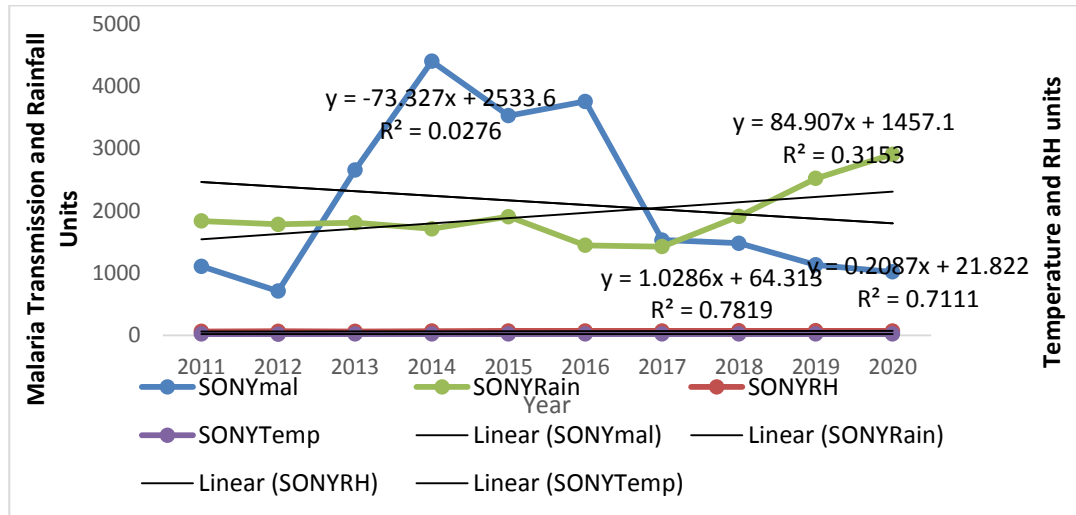


Figure 4.25: Trends of climate variability and malaria transmission in Migori County

As can be observed in Table 4.38 “Climate/Malaria ARIMA Regressions for Migori County”, the effect of RH on malaria transmission was negative but not significant at P value of 0.603, effect of rainfall was negative but not significant at P value of 0.271 and that of temperature was positive but not significant at P value of 0.449.

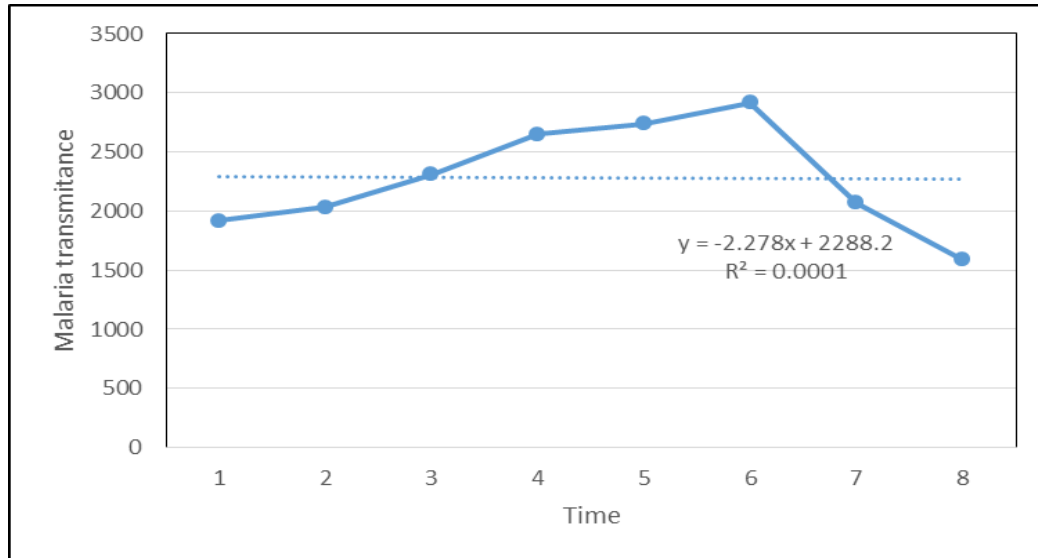


Figure 4.26: Predicted Future malaria transmission in Migori County

When analyzed using Descriptive Time Series, malaria transmission in Migori County indicated a decreasing trend at an R^2 Value of 2.7%. This was insignificant and the decrease could have been a factor of chance. All the other variables however had increasing trends with RH and temperature indicating significant R^2 values (78.1% and 71.1% respectively). Rainfall had an R^2 value of 31.5%. At these rates, they should have had significant effect on malaria transmission in the study area.

Using ARIMA time series regression model, none of the variables indicated a significant relationship with malaria transmission. Rainfall and RH had negative while temperature had positive effects. Given that from the ARIMA regression model, Migori County revealed no significant variation in malaria transmission, the study concluded that malaria transmission in Migori County decreased with time as was confirmed by the negative Descriptive Time Series. At an R^2 value of 2.7%, it could have been a factor of chance. A Descriptive Time Series using moving averages revealed even a much insignificant R^2 value (0.01%). The Migori

transmission situation could thus be defined as that of an almost “stable transmittance”.

The observations confirmed strong but temporally varying trends in malaria cases at different sites according to LVBC (2018 – 2023). Migori County experienced a decreasing trend while Kisumu and Kakamega had increasing trends. It also confirmed the observations by Hemingway *et al.* (2018) that while some parts of the country were experiencing increases others like Migori County experienced reductions.

According to Chaturvedi *et al.* (2022), malaria transmission is most effective within temperature ranging from 20⁰C to 30⁰C, RH ranging from 55% to 80% and moderate rainfall, the entire LLVB, Kenya will still be within climatic/malaria transmission ranges by the year 2100 and malaria will remain a challenge that may even expand to higher altitudes under the influence of climate change, unless stern measures are taken to ensure reduction and if possible complete eradication in the study area.

CHAPTER FIVE: SUMMARY OF FINDINGS, CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

Chapter five summarizes the entire body of the study. It gives conclusions and finally gives recommendations that may offer possible solutions to the problems that prompted the study, and the possible ways forward. This is the section that also suggests gaps for related further studies

5.2 Summary of Findings

Mean temperature was significantly higher in Kisumu County (23.77°C) compared to Kakamega County (22.61°C) and Migori County (22.52°C), ($F = 120.87$, $P = 0.0001$). The trends in Migori and Kisumu Counties increased while it decreased in Kakamega County. Temperature was highest in Kakamega County (23.58°C) in the year 2004 and lowest in the year 2020 (21.69°C). It was highest in Migori County in the year 2020 (24.12°C) and lowest in 2001 (21.04°C). In Kisumu County, mean annual temperature was highest in the year 2010 at 24.33°C and lowest in 2001 (23.21°C). There was a negative correlation ($r = - 0.896$) among the means and the altitudes indicating a positive lapse rate. Monthly trends cyclically peaked in February and March while they were low in June and July then peaking again in October. That is to say, temperature divided a year into three seasons by being high, low then high again.

Mean annual rainfall in Kisumu County ($1455.3 \pm 59\text{mm}$) was significantly lower compared to Migori County ($1885.8 \pm 77\text{mm}$) and Kakamega County ($2192.6 \pm 76\text{mm}$). Unlike temperature, rainfall did not pattern up with altitude. Both annual and monthly trends were increasing. Migori County recorded the highest (2906.2

mm) annual rainfall in the year 2020 and the lowest (1424.3mm) in 2017. In Kakamega County, the highest rainfall was recorded in the year 2010 (2823.7 mm) and lowest (1674.4mm) in the year 2016. Kisumu had the highest (2125.9 mm) occurring in year 2020 and the lowest (981.0mm) in 2016. In the three counties, monthly rainfall cyclically peaked in April, but was lowest in July (Appendix III).

Mean RH in Kisumu County was 58.77%, Kakamega County 67.74% and Migori County 66.88%. Both annual and monthly trends were increasing. The highest case in Kakamega County was in 2019 (68.96%) and the lowest in 2005 (62.42%). In Kisumu County it was highest in the year 2020 (62.96%) and lowest in the year 2009 (56.33%). In Migori County RH was highest in the year 2018 (74.22%) and lowest in the year 2002 (62.17%). In Migori County, RH was lowest in the month of June (63.98%) and August (63.85%), and highest in October (68.98%). Monthly, RH in Kakamega County was found to be relatively low (57.51%) and (56.59%) in January and February respectively. In Kisumu County, RH was observed from the year 2009 to 2020 and the lowest case occurred in February after which it rose sharply to the month of April.

There was a significantly higher mean malaria transmission in Kisumu County (3902.87 ± 493.3) followed by Kakamega County (3385.53 ± 407.7) then Migori County (2130.330 ± 422.3) ($F = 4.240$, $P = 0.025$). Annual transmission trends were increasing in Kisumu and Kakamega Counties while it was decreasing in Migori County. All monthly trends were higher early in the year but decreased towards the end.

The relationship between malaria morbidity and climate elements, in Kakamega, Kisumu and Migori significantly varied and almost all were insignificant leaving none of the climate elements to confidently explain spatiotemporal variability in malaria transmission both monthly and annually. It was only temperature that had a positive significant regression with monthly malaria transmission in Migori County. However, there was evidence that transmission in Kakamega was defined by RH, in Kisumu by temperature and rainfall, while in Migori, by rainfall though all were insignificant.

When data from all the sampled counties was put together, the result showed that in the LLVB, Kenya, spatiotemporal variability of malaria transmission was positively affected by temperature and rainfall. Using stepwise linear regression, the findings showed that only altitude had a significant effect on spatiotemporal malaria transmission variability. LLVB, Kenya was thus zoned into the following transmission zones according to altitude and transmission levels: 1001m to 1200m – high transmission zones; 1201 to 1400 - medium transmission zones; 1401 to 1600 – low transmission zones. When predicted, it was established that malaria transmission in high and medium zones will be increasing while it will be decreasing in the low transmission zones. This was an indication that with climate change, transmission is likely to increase towards the low transmission areas.

5.3 Conclusion

Basing on the findings, climate elements (Temperature, Rainfall and RH) significantly varied in space and time within different altitudes. Temperature means correlated with the altitudes revealed normal lapse rates in the LLVB, Kenya.

Extreme events in rainfall were indicators of climate change taking place in the area since climate change manifests in extreme weather events.

Increasing trends of malaria transmission in Kisumu and Kakamega Counties, the decrease observed in Migori County, alongside the endemic and epidemic nature of transmission, were significant indicators that transmission varied by altitude (space) and time. Instead of malaria transmission free periods, low and peak malaria transmission periods alternated (endemic and epidemic characteristics) in the LLVB, Kenya.

The study area was well within climatic thresholds for malaria transmission at all altitudes throughout the year. LLVB thus had high potential for malaria transmission rising. None of the selected climate elements had significant relationships with malaria transmission except monthly regression of temperature and malaria transmission in Migori County. All climatic elements remained optimal for malaria transmission throughout the year at all the selected altitudes. However, there was evidence that transmission in Kakamega was defined by RH, in Kisumu by temperature and rainfall, while in Migori, by rainfall.

In the entire study area, malaria transmission significantly decreased with increase in altitude implying that altitude and temperature were the major determinants of spatiotemporal malaria transmission variability in the LLVB, Kenya. Spatiotemporal Variability in Malaria transmission was therefore best defined by altitude, temperature and proximity to the lake. This made the study zone LLVB, Kenya into three based on altitude, temperature and malaria transmission rates as follows:

1001m to 1200m – high transmission zones; 1201 to 1400 - medium transmission zones; 1401 to 1600 – low transmission zones.

Malaria transmission was predicted to increase in Kisumu (a high transmission zone) and Kakamega (a medium transmission zone) Counties. The status in Migori (a low transmission zone) County was predicted to decrease. However, neither increase nor decrease was significant. At an R^2 value of 0.0001, the Migori case might continue decreasing, change and increase or assume a stable state of transmission in future depending on interventions. Reduction will only be a factor of medical or preventive interventions. Transmission in the entire LLVB is thus predicted to vary in future by being stationery, rising or decreasing depending on where it will be being experienced, and on the sensitivity of the people there in.

Transmission hot spots in LLVB, Kenya were determined by altitudinal and transmission zoning. Kisumu County and areas within high and medium transmission zones were therefore considered hot spots in the LLVB, Kenya. Kisumu County - a high transmission zone was followed by Kakamega - a medium transmission zone and Migori – a low transmission zone in that order. This zoning was important for determining necessary interventions according to the transmission rate in any given zone.

5.4 Recommendations

Temperature indicated normal lapse rate in the study area. This could be inferred within the LLVB and other places with different altitudes when fighting malaria transmission. Given that all the observations confirmed the varying nature of malaria

transmission in relation to altitude, the aspect of blanket assumption concerning malaria transmission in the LLVB, Kenya should be stopped.

Awareness should be created by the health sector collaborating with the meteorologists on the observed endemic and epidemic nature of transmission to help the population of the LLVB, Kenya remain vigilant throughout the year with particular attention to peak periods. The health sector should remain vigilant about malaria transmission and reduction by focusing on the early months of the year, a time when transmissions are at their peaks.

Since climate remained optimal for transmission throughout the year and during the entire study period, emphasis should be put on preventive and medical interventions throughout the year. Interventions should however consider different transmission rates at different times under different altitudes since transmission varied by time and altitude - the lower the altitude, the higher the transmission and the higher the need for surveillance.

Whatever approach is to be used, should be guided by the zonings suggested by the study: 1001m to 1200m – high transmission zones; 1201 to 1400 - medium transmission zones; 1401 to 1600 – low transmission zones. The aspect of altitude zoning also needs to consider time as regards climatic variations, and proximity to the lake. Climate variation however small may have a significant impact on transmission.

County governments of Kisumu and Kakamega to put more emphasis on malaria surveillance in order to curb the rising trends observed. The same should happen in Migori, to completely stop any possible reversal of the observed decreasing trends.

Meteorologists and medics should collaborate to monitor future influences of climate on malaria transmissions in the LLVB, Kenya since as WHO (2019) confirmed, malaria transmission depends on the three climatic elements. With evidence that there is climate variability in different altitudes, meteorologists should frequently publish meteorological information to help the medics relate the meteorological reports with the malaria transmission outcomes. This will help in enhancing surveillance processes.

5.5 Suggestions for Further Study

- i. Since rainfall and RH were inconsistent and did not have any clear relationships with altitude, there is need to establish their occurrences elsewhere at different altitudes within the study area.
- ii. Given that the selected areas met malaria transmission thresholds, further research is necessary for Migori County to establish factors underlying her decreasing trends while other counties are experiencing increasing trends. The findings may guide transmission management in the entire LLVB, Kenya.
- iii. Investigations should also be initiated to establish facts underlying positive indications on transmission among the > 5 year olds compared to the < 5 year olds in the LLVB, Kenya.

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APPENDICES

APPENDIX I: Temperature (2001 – 2020)

Year	Temperatures (^o C) Mean \pm SE		
	Kakamega County	Kisumu County	Migori County
2001	23.18 \pm 0.170	23.28 \pm 0.151	21.04 \pm 0.172
2002	23.37 \pm 0.223	23.67 \pm 0.193	22.01 \pm 0.181
2003	23.43 \pm 0.196	23.45 \pm 0.151	22.11 \pm 0.166
2004	23.58 \pm 0.231	23.68 \pm 1.149	21.84 \pm 0.166
2005	23.14 \pm 0.358	24.18 \pm 0.298	22.35 \pm 0.261
2006	22.32 \pm 0.297	23.83 \pm 0.324	22.00 \pm 0.194
2007	22.28 \pm 0.238	23.35 \pm 0.154	21.64 \pm 0.155
2008	21.78 \pm 0.379	23.46 \pm 0.215	21.98 \pm 0.126
2009	22.14 \pm 0.068	24.06 \pm 0.174	22.73 \pm 0.189
2010	22.03 \pm 0.070	24.33 \pm 0.128	22.76 \pm 0.291
2011	21.93 \pm 0.156	23.65 \pm 0.256	22.33 \pm 0.378
2012	22.85 \pm 0.293	23.47 \pm 0.235	21.45 \pm 0.225
2013	22.83 \pm 0.161	23.62 \pm 0.205	22.60 \pm 0.379
2014	22.64 \pm 0.157	23.91 \pm 0.184	22.96 \pm 0.160
2015	23.11 \pm 0.223	23.63 \pm 0.120	22.54 \pm 0.278
2016	23.14 \pm 0.270	24.05 \pm 0.220	23.51 \pm 0.349
2017	22.99 \pm 0.241	24.05 \pm 0.226	23.03 \pm 0.256
2018	21.77 \pm 0.245	23.66 \pm 0.285	23.69 \pm 0.245
2019	21.94 \pm 0.313	23.90 \pm 0.289	23.16 \pm 0.399
2020	21.69 \pm 0.183	23.39 \pm 0.151	24.12 \pm 0.456
MEAN	22.61 \pm 0.062a	23.77 \pm 0.05b	22.52 \pm 0.08a
F-value	120.87		
P-value	0.0001		

Sources: Mumias Sugar Company Meteorological Station (8934 - 133)
SONY Central Meteorological Station (9034145)
Kisumu International Airport Meteorological Station
(637080 - 9999)

APPENDIX II: Mean annual rainfall (2001 – 2020)

Year	Mean monthly rainfall (mm) Mean \pm SE		
	Kakamega County	Kisumu County	Migori County
2001	148.9 \pm 29.1	124.3 \pm 24.1	144.2 \pm 21.0
2002	184.0 \pm 28.0	135.1 \pm 25.4	159.8 \pm 37.2
2003	189.0 \pm 30.3	104.3 \pm 20.6	135.6 \pm 119
2004	167.3 \pm 17.6	118.8 \pm 24.9	152.3 \pm 212
2005	141.1 \pm 22.4	96.3 \pm 22.9	131.6 \pm 19.9
2006	223.7 \pm 26.6	142.2 \pm 29.6	179.8 \pm 32.7
2007	162.2 \pm 30.4	98.0 \pm 12.3	165.7 \pm 20.1
2008	172.1 \pm 22.4	113.3 \pm 13.9	135.7 \pm 18.9
2009	163.6 \pm 28.8	116.9 \pm 25.2	164.3 \pm 30.5
2010	235.3 \pm 36.9	123.0 \pm 23.5	170.5 \pm 25.0
2011	186.1 \pm 30.8	132.3 \pm 33.2	152.8 \pm 24.9
2012	202.6 \pm 37.7	125.3 \pm 26.9	148.5 \pm 32.0
2013	171.4 \pm 31.3	109.9 \pm 18.7	150.5 \pm 36.5
2014	190.2 \pm 27.3	100.8 \pm 18.0	142.5 \pm 19.7
2015	200.4 \pm 42.5	132.3 \pm 23.8	158.7 \pm 33.5
2016	139.5 \pm 28.6	81.8 \pm 16.6	120.4 \pm 25.0
2017	144.8 \pm 22.1	117.8 \pm 14.9	118.7 \pm 17.8
2018	211.1 \pm 43.6	114.3 \pm 22.4	159.2 \pm 32.2
2019	198.3 \pm 31.4	161.8 \pm 32.5	209.9 \pm 43.6
2020	222.8 \pm 31.6	177.2 \pm 24.8	242.2 \pm 49.8
MEAN	182.7\pm 6.81c	121.3\pm5.22a	157.2\pm 6.53b
F-value	24.56		
P-value	0.0001		

Sources: Mumias Sugar Company Meteorological Station (8934 - 133)
SONY Central Meteorological Station (9034145)
Kisumu International Airport Meteorological Station
(637080 - 9999)

APPENDIX III: Total annual rainfall (2001 – 2020)

Year	Annual rainfall (mm) Mean \pm SE		
	Kakamega County	Kisumu County	Migori County
2001	1786.4	1491.5	1730.0
2002	2208	1620.8	1918
2003	2268.5	1252.1	1627.1
2004	2007.5	1425	1828.0
2005	1693.7	1155.9	1579.5
2006	2684.4	1706.6	2157.1
2007	1945.9	1176.2	1988.4
2008	2065.1	1359.1	1627.8
2009	1962.7	1402.9	1971.8
2010	2823.7	1476.1	2046
2011	2233.3	1587.4	1834.4
2012	2431.2	1503.2	1781.4
2013	2056.3	1318.3	1806.2
2014	2282.3	1209.6	1710.5
2015	2405.1	1587.5	1905
2016	1674.4	981	1444.2
2017	1737.5	1414.2	1424.3
2018	2532.7	1372.1	1910.7
2019	2380	1941.5	2518.9
2020	2673.2	2125.9	2906.2
Mean	2192.6 \pm 76.3c	1455.3 \pm 59.6a	1885.8 \pm 77.4b
F -value	26.79		
P -value	0.0001		

Sources: Mumias Sugar Company Meteorological Station (8934 - 133)
SONY Central Meteorological Station (9034145)
Kisumu International Airport Meteorological Station
(637080 - 9999)

APPENDIX IV: Mean annual relative humidity (2001 – 2020)

Year	Annual relative humidity (%) Mean \pm SE		
	Kakamega County	Kisumu County	Migori County
2001	66.83 \pm 1.48	-	64.13 \pm 0.655
2002	65.96 \pm 1.65	-	62.17 \pm 1.66
2003	64.33 \pm 1.81	--	62.58 \pm 0.671
2004	63.91 \pm 0.91	-	63.04 \pm 1.14
2005	62.42 \pm 1.75	-	63.71 \pm 1.170
2006	67.96 \pm 1.84	-	64.58 \pm 1.16
2007	68.63 \pm 2.07	-	66.21 \pm 0.914
2008	66.42 \pm 1.98	-	64.44 \pm 0.686
2009	66.17 \pm 2.02	56.33 \pm 1.55	63.21 \pm 1.02
2010	68.25 \pm 1.05	59.50 \pm 1.42	63.88 \pm 0.779
2011	68.54 \pm 1.39	58.83 \pm 1.70	63.88 \pm 1.31
2012	66.25 \pm 2.41	60.46 \pm 2.35	67.00 \pm 0.751
2013	63.79 \pm 1.11	57.79 \pm 1.71	65.37 \pm 0.170
2014	65.58 \pm 1.81	58.13 \pm 1.12	69.15 \pm 1.69
2015	64.08 \pm 2.46	59.29 \pm 2.92	70.98 \pm 1.34
2016	62.42 \pm 2.29	58.71 \pm 1.51	71.36 \pm 1.97
2017	62.50 \pm 2.42	57.33 \pm 2.65	72.65 \pm 1.93
2018	65.99 \pm 2.81	56.42 \pm 2.90	74.22 \pm 1.55
2019	65.88 \pm 3.05	59.50 \pm 2.29	73.48 \pm 0.984
2020	68.96 \pm 1.83	62.96 \pm 0.83	71.48 \pm 1.91
Mean	67.74\pm 0.471b	58.77\pm 0.53a	66.876\pm 0.907b
F -value	30.37		
P -value	0.0001		

Sources: Mumias Sugar Company Meteorological Station (8934 - 133)
SONY Central Meteorological Station (9034145)
Kisumu International Airport Meteorological Station
(637080 - 9999)

APPENDIX V: Mean annual Malaria in Kakamega County (Mean \pm SE)

Period	Suspected malaria < 5 years)	Confirmed Positive cases < 5 years	Suspected malaria > 5 years)	Confirmed Positive cases > 5 years	Malaria in pregnancy
2011	1324.7 \pm 97.6	587.8 \pm 52.6	2532 \pm 156	885.6 \pm 52.6	48.08 \pm 3.66
2012	739.8 \pm 64.8	514.9 \pm 46.6	1840 \pm 107	873.8 \pm 43.6	42.83 \pm 4.01
2013	339.9 \pm 35.3	951.5 \pm 98.0	1433.8 \pm 91.3	1486 \pm 143	35.50 \pm 4.25
2014	513 \pm 103	1089.1 \pm 93.7	1527 \pm 176	1917 \pm 102	34 \pm 5.27
2015	95.7 \pm 17.4	1670 \pm 188	587 \pm 126	2764 \pm 300	49.42 \pm 5.28
2016	557 \pm 166	1390.3 \pm 93.8	1106 \pm 319	3151 \pm 309	54.25 \pm 5.50
2017	1241 \pm 209	1015 \pm 144	2614 \pm 413	2506 \pm 295	52.92 \pm 9.50
2018	1438.3 \pm 95.3	1049.9 \pm 98.3	3675 \pm 214	2835 \pm 235	36.42 \pm 8.42
2019	1943 \pm 217	1272 \pm 147	60.43 \pm 760	3904 \pm 491	68.0 \pm 18.6
2020	1412.8 \pm 79.7	874.5 \pm 60.8	5429 \pm 380	3118 \pm 166	105.0 \pm 28.9

Source: Kenya Health Information System (KHIS)

APPENDIX VI: Mean annual Malaria in Kisumu County (Mean \pm SE)

Period	Suspected malaria < 5 years)	Confirmed Positive cases < 5 years	Suspected malaria > 5 years)	Confirmed Positive cases > 5 years	Malaria in pregnancy
2011	216.8 \pm 29.5	381.1 \pm 42.1	189.2 \pm 26.4	244.1 \pm 22.1	8.08 \pm 0.93
2012	237.8 \pm 20.5	235.4 \pm 20.0	298.4 \pm 37.6	166.4 \pm 18.1	5.27 \pm 0.89
2013	227.5 \pm 25.9	252.7 \pm 24.2	152.8 \pm 25.7	137.9 \pm 14.6	3.46 \pm 0.93
2014	344.6 \pm 15.5	255.2 \pm 16.8	284.8 \pm 19.6	204.8 \pm 15.4	3.10 \pm 0.31
2015	169.6 \pm 30.3	123.6 \pm 20.2	216.6 \pm 30.7	121.2 \pm 19.4	7.55 \pm 1.31
2016	146.0 \pm 19.7	122.0 \pm 9.18	151.8 \pm 22.1	130.6 \pm 12.5	5.92 \pm 1.18
2017	258.1 \pm 42.9	113.7 \pm 16.9	327.2 \pm 58.4	121.6 \pm 20.9	3.25 \pm 0.92
2018	192.4 \pm 45.0	118.8 \pm 17.2	463.0 \pm 49.4	123.2 \pm 14.8	7.30 \pm 2.80
2019	292.4 \pm 43.1	120.6 \pm 19.1	732 \pm 110	221.4 \pm 41.7	4.17 \pm 0.44
2020	242.8 \pm 27.3	108.6 \pm 9.9	663.0 \pm 78.6	203.2 \pm 26.8	6.20 \pm 1.00

Source: Kenya Health Information System (KHIS)

APPENDIX VII: Mean Malaria in Migori County (Mean \pm SE)

Period	Suspected malaria < 5 years)	Confirmed Positive cases < 5 years	Suspected malaria > 5 years)	Confirmed Positive cases > 5 years	Malaria in pregnancy
2011	1374 \pm 126	335.8 \pm 52.7	2052 \pm 223	685 \pm 110	55.1 \pm 13.30
2012	1288.3 \pm 50.5	258.3 \pm 7.63	1827 \pm 114	453 \pm 26.2	36.7 \pm 3.32
2013	1324 \pm 110	1007.0 \pm 85.4	2108 \pm 179	1644 \pm 122	73.8 \pm 6.54
2014	705 \pm 152	1660 \pm 138	1411 \pm 258	2736 \pm 259	88.8 \pm 28.6
2015	190.3 \pm 25.5	1423 \pm 220	270.2 \pm 42.9	2101 \pm 283	140.8 \pm 38.2
2016	1049 \pm 153	1077 \pm 169	2879 \pm 453	2675 \pm 414	64.2 \pm 11.1
2017	611 \pm 121	434 \pm 109	1892 \pm 387	1096 \pm 234	27.8 \pm 3.7
2018	779.1 \pm 51.4	420.1 \pm 28.2	1808 \pm 174	1059.7 \pm 89.3	23.5 \pm 4.23
2019	584.3 \pm 67.9	328.5 \pm 29.9	1622 \pm 204	803.1 \pm 80.9	40.8 \pm 10.8
2020	530.7 \pm 39.3	243.3 \pm 29.3	1923 \pm 196	776 \pm 104	23.9 \pm 5.21

Source: Kenya Health Information System (KHIS)

**APPENDIX VIII: Mean Monthly Total Confirmed Malaria Transmission
(2011-2020)**

	K/MEGA	KISUMU	MIGORI
JAN	3399.1	5107.8	2624.6
FEB	3140.5	3941.3	2916.4
MARCH	3545.6	3833.3	2913.6
APRIL	3803	3430.8	2097
MAY	5053.3	5702.9	2536
JUNE	4532.6	4993.4	2437.9
JULY	3950.1	5936.4	2522.5
AUGAST	2924	3283.3	1676.9
SEPT	2578.7	2518.9	1387.6
OCT	2762.5	2473.5	1619
NOV	2631.6	2801	1422.4
DEC	2305.4	2811.8	1410.8

Source: Kenya Health Information System (KHIS)

**APPENDIX IX: MEAN ANNUAL TOTAL MALARIA CONFIRMED CASES
(2011 -2020)**

Year	Kisumu County	Kakamega County	Migori County
2011	1274.2 ± 92.1	1473 ± 103	1108 ± 123
2012	1135.7±99.1	1388.8±82.4	712.1±28.6
2013	3148±330	2438± 233	2651±204
2014	4805±611	3007 ±180	4397±329
2015	5116±541	4434±478	3523±481
2016	4447±671	4541±362	3752±574
2017	4618±783	3521±434	1530±340
2018	4863±540	3885±327	1480±104
2019	5553±1156	5176±628	1132±108
2020	4070±516	3992±222	1019±132
Mean	3902.87 ±493.3	3385.53 ± 407.7	2130.330 ± 422.3
F-Value	4.240		
P-Value	0.025		

Source: Kenya Health Information System (KHIS)

APPENDIX XI: RESEARCH AUTHORIZATION LETTER (KU)



**KENYATTA UNIVERSITY
GRADUATE SCHOOL**

E-mail: dean-graduate@ku.ac.ke

Website: www.ku.ac.ke

OUR REF: C82/27290/14

P.O. Box 43844, 00100
NAIROBI, KENYA
Tel. 8710901 Ext. 57530

Date: 1st March, 2021

The Director General,
National Commission for Science, Technology & Innovation
P.O. Box 30623-00100,
NAIROBI

Dear Sir/Madam,

RE: RESEARCH AUTHORIZATION FOR SAMWEL O. ODHIAMBO REG. NO. C82/27290/14

I write to introduce Odhiambo who is a Postgraduate Student of this University. The student is registered for Degree programme in the **Department of Geography in the School of Humanities & Social Sciences**.

Odhiambo intends to conduct research for project entitled, "**Climate Variability and Malaria Transmission Trends in Different Altitudes of Lower Lake Victoria basin, Kenya**"

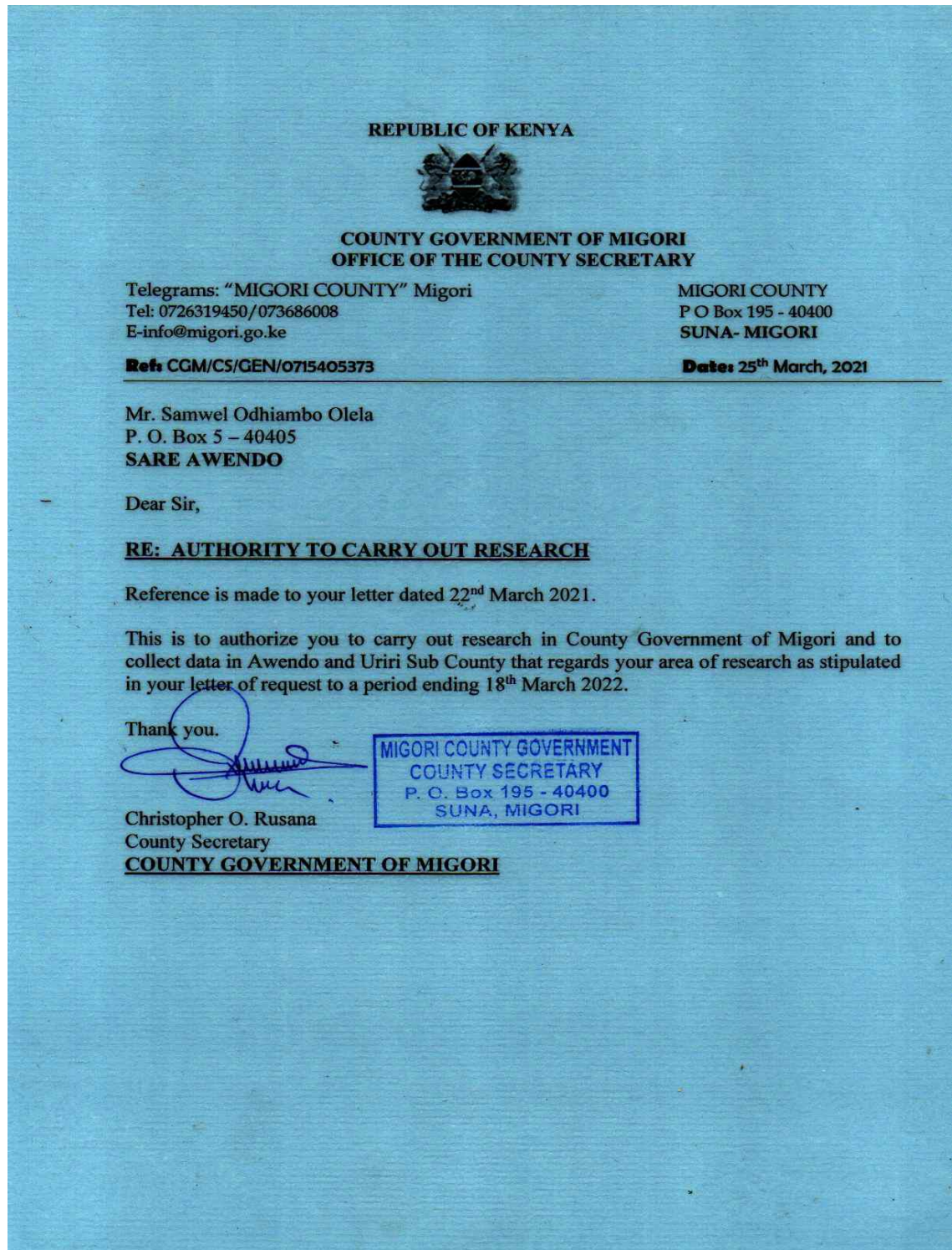
Any assistance given will be highly appreciated.

Yours faithfully,


**PROF. ELISHIBA KIMANI
DEAN, GRADUATE SCHOOL**

RM/cao

APPENDIX XIII: RESEARCH AUTHORIZATION LETTER (MIGORI COUNTY GOVERNMENT)



**APPENDIX XIV: RESEARCH AUTHORIZATION LETTER (MIGORI
COUNTY DIRECTOR OF EDUCATION)**



**MINISTRY OF EDUCATION
State Department of Early Learning and Basic Education**

Telephone: (059) 20420
Fax: 05920420
When replying please
quote

COUNTY DIRECTOR OF EDUCATION
MIGORI COUNTY
P.O. Box 466-40400
SUNA – MIGORI

REF: MIG/CDE/ADMN./73/VOL.II 180

DATE: 22nd March, 2021

Mr. Samwel odhiambo Olela
Kenyatta University

RE: RESEARCH AUTHORIZATION

Following your application for authority to carry out research on “Climate Variability and Malaria Transmission in Different Altitudes of Lower Lake Victoria Basin, in Migori County, Kenya” and subsequent approval by NACOSTI vide research license no.: NACOSTI/P/21/9466. I am pleased to inform you that you have been authorized to undertake research in Migori County for a period ending 18th March, 2022.

During the research, you are expected to exercise high levels of research integrity.


COUNTY DIRECTOR
MINISTRY OF EDUCATION
MIGORI COUNTY
P O Box 466-40400, MIGORI
Sign:.....

Elizabeth Otieno (Mrs.) Date.....
County Director of Education
MIGORI COUNTY

**APPENDIX XV: RESEARCH AUTHORIZATION LETTER (MIGORI
COUNTY DIRECTOR OF PUBLIC HEALTH)**



MIGORI COUNTY HEALTH DEPARTMENT

Telegrams:
Telephone:
Email: ndongakennedy@gmail.com

DIRECTOR PUBLIC HEALTH MANAGEMENT
MIGORI
P O BOX 1045-1045
SUNA -MIGORI
5th May 2021

MIG /CDPH/ST/VOL 3 /5/2021

TO WHOM IT MAY CONCERN

PERMISION TO UNDERTAKE HEALTH RESEARCH IN MIGORI COUNTY

This is to confirm that Mr. Samwel Odhiambo Olela of Kenyatta University has been granted permission to conduct Health related academic research in Migori County, Awendo and Uriri sub counties.

The research is titled; **A study on climate variability and malaria transmission trends in different attitudes of lower Lake Victoria basin, Kenya.**

Kindly accord him necessary assistance


Tom Odhiong
For: Director Public Health Management
MIGORI COUNTY

**DIRECTOR PUBLIC HEALTH
MIGORI COUNTY
Email: ndongakennedy@gmail.com
05 MAY 2021
Tel: 0722-961 226**

**APPENDIX XVI: RESEARCH AUTHORIZATION LETTERS (KAKAMEGA
COUNTY COMMISSIONER)**

REPUBLIC OF KENYA



**THE PRESIDENCY
INTERIOR AND CO-ORDINATION OF
NATIONAL GOVERNMENT**

Telegrams "DISTRICTER" Kakamega
Telephone 056 -31131
Fax 056 - 31133
Email: cckakamega12@yahoo.com
When replying please quote

COUNTY COMMISSIONER
KAKAMEGA
P O BOX 43 - 50100
KAKAMEGA.

Ref: ED/12/1/VOL.V/133


Date: 1st April, 2021

**Mr. Samwel Odhiambo Olela
P O Box 43844 - 00100
NAIROBI**

RE: RESEARCH AUTHORIZATION


Following your authorization vide letter Ref: NACOSTI/P/21/9466 dated 18TH March, 2021 by NACOSTI to undertake research on "*Climate variability and malaria Transmission Trends in Different altitudes of lower lake Victoria Basin, Kenya*" for the period ending 18th March, 2022.

I am pleased to inform you that you have been authorized to carry out the research on the same.


**P. A. DOLLA, MBS
COUNTY COMMISSIONER
KAKAMEGA COUNTY**

**APPENDIX XVII: RESEARCH AUTHORIZATION LETTERS
(KAKAMEGA COUNTY OFFICE OF THE GOVERNOR)**

**REPUBLIC OF KENYA
COUNTY GOVERNMENT OF KAKAMEGA**



**OFFICE OF THE GOVERNOR
COUNTY SECRETARY AND HEAD OF PUBLIC SERVICE**

Telephone: 056-31850/31852/31853
Website: www.kakamega.go.ke
E-mail: countysecretary@kakamega.go.ke

County Government of Kakamega
P.O. Box 36-50100
KAKAMEGA

When replying please Quote
REF NO. CGK/OCS/GEN CRR/04 (01)

Date: 1st April, 2021

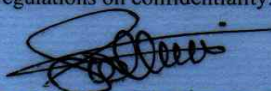
Mr. Samwel Odhiambo Olela
Kenyatta University
Geography Department
P.O Box 43844-00100
Nairobi.

RE: AUTHORITY TO COLLECT RESEARCH DATA

The above subject matter refers,

This is to inform you that you have been granted permission to collect data on "*Climate variability and Malaria Transmission Trends in different altitudes of lower Lake Victoria Basin, Kenya*" for your Postgraduate Degree in the Department of Geography in the School of Humanities & Social Science from Kenyatta University.


You are therefore required to adhere to Ethical standards and the County Government regulations on confidentiality.



Jacinta Aluoch Odhiambo (Mrs.)
County Secretary and Head of Public Service

Copy to: H.E the Governor

I hereby commit to share the findings with the County Government of Kakamega through the undersigned

Sign:  Date: 1/04/21 Phone No: 0715405373

**APPENDIX XVIII: RESEARCH AUTHORIZATION LETTERS
(KAKAMEGA COUNTY DIRECTOR OF EDUCATION)**

REPUBLIC OF KENYA



MINISTRY OF EDUCATION

STATE DEPARTMENT OF EARLY LEARNING AND BASIC EDUCATION

Telephone: 056 -30411
Fax: 056 - 31307
E-mail: rceducation2016@gmail.com
When replying please quote our Ref.

County Director of Education
Kakamega County
P. O. BOX 137 - 50100
KAKAMEGA

REF: KAKA/C/GA/29/17/VOL.V/109

1st April, 2021

SAMWEL ODHIAMBO OLELA
KENYATTA UNIVERSITY
NAIROBI

RE: RESEARCH AUTHORIZATION

The above has been granted permission by National Council for Science & Technology vide letter Ref. NACOSTI/P/21/9466 dated 18th March, 2021 to carry out research on "*Climate Variability and Malaria transmission trends in different altitudes of lower Lake Victoria Basin- Kakamega County*" for the period ending 22nd March, 2022".

Please accord him/her any necessary assistance he may require.

 **COUNTY DIRECTOR OF EDUCATION
KAKAMEGA COUNTY**

**DICKSON O. OGONYA
COUNTY DIRECTOR OF EDUCATION
KAKAMEGA COUNTY**

CC
The Regional Director of Education
WESTERN REGION

**APPENDIX XIX: RESEARCH AUTHORIZATION LETTERS (KISUMU
COUNTY COMMISSIONER)**



THE PRESIDENCY

MINISTRY OF INTERIOR AND COORDINATION OF NATIONAL GOVERNMENT

Telephone: Kisumu 2022219/Fax: 2022219
Email: ckisumucounty@gmail.com

COUNTY COMMISSIONER
KISUMU COUNTY
P.O. BOX 1912-40100
KISUMU.

Ref: CC/KC/ RES/1/3/VOL IV/105

Date: 31st March, 2021

All Deputy County Commissioners
KISUMU COUNTY

RE: RESEARCH AUTHORIZATION: MR. SAMWEL ODHIAMBO OLELA

Reference is made to a letter from the National Commission for Science, Technology and Innovation no. NACOSTI/P/21/9466 of 18th March, 2021 on the above underlined subject matter.

The above named is from Kenyatta University. He has been authorized to carry out a research on "*Climate Variability and Malaria Transmission Trends in Different Altitudes of Lower Lake Victoria Basin, Kenya*". The research period ends on 18th March, 2022.

Kindly accord him the necessary assistance.

**JOSEPHINE OUKO
COUNTY COMMISSIONER
KISUMU COUNTY.**

✓ **Copy to:**
Samwel Odhiambo Olela
Kenyatta University

**APPENDIX XX: RESEARCH AUTHORIZATION LETTERS (KISUMU
COUNTY DIRECTOR OF PUBLIC HEALTH AND SANITATION)**

**REPUBLIC OF KENYA
COUNTY GOVERNMENT OF KISUMU**

Telegrams: "PRO (MED)"
Tel: 254-057-2020105
Fax: 254-057-2023176
E-mail: kisumuedh@gmail.com



Director of Public Health, Preventive/
Promotion and Environmental Health
P.O. Box 721 – 40100,
Kisumu.

DEPARTMENT OF HEALTH & SANITATION

Our Ref: GN 133 VOL.VII/(272)

Date: 20th April, 2021

To:

SCMOHs: - Kisumu West, Seme & Muhoroni

RE: APPROVAL TO CONDUCT RESEARCH IN KISUMU COUNTY

The Department of Health has reviewed and approved this research titled "Climate Variability and Malaria Transmission Trends in Different Altitudes of Lower Lake Victoria basin, Kenya".

This principal investigator for this research activity is **Samwel Odhiambo Olela**.


Kindly accord him all the necessary support

**Fredrick Oluoch
County Director Public Health & Sanitation
Kisumu County**



CC: ✓ Principal investigator – Samwel Odhiambo Olela

APPENDIX XXI: RESEARCH PERMIT (NACOSTI)

 REPUBLIC OF KENYA	 NATIONAL COMMISSION FOR SCIENCE, TECHNOLOGY & INNOVATION
Ref No: 501388	Date of Issue: 18/March/2021
RESEARCH LICENSE	
	
This is to Certify that Mr.. SAMWEL ODHIAMBO OLELA of Kenyatta University, has been licensed to conduct research in Kakamega, Kisumu, Migori on the topic: CLIMATE VARIABILITY AND MALARIA TRANSMISSION TRENDS IN DIFFERENT ALTITUDES OF LOWER LAKE VICTORIA BASIN, KENYA for the period ending : 18/March/2022.	
License No: NACOSTI/P/21/9466	
501388	
Applicant Identification Number	Director General NATIONAL COMMISSION FOR SCIENCE, TECHNOLOGY & INNOVATION
	Verification QR Code
	
NOTE: This is a computer generated License. To verify the authenticity of this document, Scan the QR Code using QR scanner application.	

THE SCIENCE, TECHNOLOGY AND INNOVATION ACT, 2013

The Grant of Research Licenses is Guided by the Science, Technology and Innovation (Research Licensing) Regulations, 2014

CONDITIONS

1. The License is valid for the proposed research, location and specified period
2. The License any rights thereunder are non-transferable
3. The Licensee shall inform the relevant County Director of Education, County Commissioner and County Governor before commencement of the research
4. Excavation, filming and collection of specimens are subject to further necessary clearance from relevant Government Agencies
5. The License does not give authority to transfer research materials
6. NACOSTI may monitor and evaluate the licensed research project
7. The Licensee shall submit one hard copy and upload a soft copy of their final report (thesis) within one year of completion of the research
8. NACOSTI reserves the right to modify the conditions of the License including cancellation without prior notice

National Commission for Science, Technology and Innovation
off Waiyaki Way, Upper Kabete,
P. O. Box 30623, 00100 Nairobi, KENYA
Land line: 020 4007000, 020 2241349, 020 3310571, 020 8001077
Mobile: 0713 788 787 / 0735 404 245
E-mail: dg@nacosti.go.ke / registry@nacosti.go.ke
Website: www.nacosti.go.ke