KWAME NKRUMAH UNIVERSITY OF SCIENCE AND TECHNOLOGY, KUMASI

COLLEGE OF SCIENCE

FACULTY OF PHYSICAL SCIENCES

DEPARTMENT OF MATHEMATICS

KNUST

ANALYSIS OF PREDICTORS OF MALARIA MORTALITY AMONG CHILDREN USING A LOGISTIC REGRESSION MODEL: A CASE STUDY AT TAMALE TEACHING HOSPITAL

BY

ABDUL-RAHAMAN ABDUL-AZIZ

OCTOBER, 2011

KWAME NKRUMAH UNIVERSITY OF SCIENCE AND TECHNOLOGY, KUMASI

COLLEGE OF SCIENCE

FACULTY OF PHYSICAL SCIENCES

DEPARTMENT OF MATHEMATICS

KNUST

ANALYSIS OF PREDICTORS OF MALARIA MORTALITY AMONG CHILDREN USING A LOGISTIC REGRESSION MODEL: A CASE STUDY AT TAMALE TEACHING HOSPITAL

BY

ABDUL-RAHAMAN ABDUL-AZIZ

A THESIS SUBMITTED TO THE DEPARTMENT OF MATHEMATICS, KWAME NKRUMAH UNIVERSITY OF SCIENCE AND TECHNOLOGY, IN PARTIAL FULFILLMENT OF THE REQUIREMENT FOR THE DEGREE OF MASTER OF PHILOSOPHY IN MATHEMATICS.

OCTOBER, 2011

DECLARATION

I hereby declare that this submission is my own work towards the award of MPhil. (Mathematics) degree and that, to the best of my knowledge, it contains no material previously published by another person nor material which had been accepted for the award of any other degree of the University, except where due acknowledgement had been made in the text.

KNUST

ABDUL-RAHAMAN ABDUL-AZIZ (20059126) …… ……

(Student Name and ID) Signature Date

Certified by:

MR. EMMANUEL HARRIS …… ……

(Supervisor) Signature Date

Certified by:

MR. K.F. DARKWA …… ……..

(Head, Department of Mathematics, KNUST) Signature Date

DEDICATION

This work is dedicated to my lovely and caring parents for their continuous support in my life.

Alhaji Abdul-Rahaman Ahmed

And

Afishetu Abdulai

KNUST

ACKNOWLEDGEMENT

My sincere thanks go to the Almighty God for His protection and guidance through the successful completion of the course.

My deepest and profound gratitude to Mr. Emmanuel Harris for spending a lot of his time reading this thesis, criticizing where necessary and offering very good suggestions and pieces of advice.

KNUST

I also wish to thank all the staff of the Statistics Department of Kumasi Polytechnic, especially Mr. Bashiru Imoro Ibn Saeed and Mr. Kwame Annin for their spirit of encouragement.

Further, I wish to express my appreciation to Ahmed Hafiz A. R. and Baba Ahmed A. R. and all my brothers for being there for me.

Also, I wish to express my gratitude to Sherifa Sani for her love and care during the defence.

Again, I am greatly indebted to Issah Mohammed Awal, a biomedical scientist at Tamale Teaching Hospital, for his effort in securing the data used for this thesis.

Finally, my gratitude go to all the 2011 final year students of the Statistics Department, especially Nketiah Edward Appau, Brenya Bernice Okarley, Gattor Jonas, Quason Forster Tandoh and Owusu Bernice Everlove for assisting in keying in the raw data into Microsoft Excel sheet.

To all other Tom, Dick and Harry who have in diverse ways contributed to this work but their names have not been mentioned, I deeply appreciate you all.

God bless you all.

ABSTRACT

The main objective of this study was to apply logistic regressions modeling to analyze predictors of malaria mortality among children. Secondary data was obtained from inpatient morbidity and mortality returns register at Tamale Teaching Hospital, from 1st January 2000 to 31st December 2010.

The findings indicated there is a linear relationship between malaria mortality and predictors such as referral status, distance, treatment type and length of stay of children administered as malaria patients at the Tamale Teaching hospital from 2000 – 2010. The overall logistic model obtained was

$$\log it\left(P(y=1)\right) = -3.192 + 2.741\text{Referral status} + 1.947\text{Distance} - 0.898\text{Treatment} - 0.102\text{Length}$$

Again, it was found that the predictors; age, sex and season were not good predictors of malaria mortality. However, the predictors; referral status, distance, treatment type and length of stay were relevant in predicting malaria mortality.

KNUST

TABLE OF CONTENTS

KNUST

KNUST

KNUST

LIST OF TABLES

KNUST

LIST OF FIGURES

KNUST

CHAPTER ONE

INTRODUCTION

1.1Background of the Study

It is believed that human malaria began in Central and West Africa. According to the article, "Evolutionary and Historical Aspects of the Burden of Malaria" (Martinez, 2009), one of the four types of human malaria, Plasmodium malariae (a parasitic protozoa that causes malaria in humans), is found in apparently indistinguishable form as a natural parasite of chimpanzees in West Africa. The beginning of agricultural practices in central and western Africa, 8,000 years ago, brought about the human malaria parasite to this warm, temperate climate. These agricultural practices were one of the main components in the evolution of human malaria.

In the 19th century, during expansion of the world, malaria had spread especially to those who lived or visited Western Africa. The use of Dichlorodiphenyl Trichloroethane (DDT) was introduced to western Africa in the 1950s. This was the World Health Organization's solution to malaria control; although it worked on other continents, the introduction of DDT to Africa didn't work. Even with this failure, Africa was introduced to new anti-malarial drugs which resulted in fewer malaria related deaths through the 1980s. Today, Africa "carries by far the greatest burden of malaria today." The situation of malaria is relatively unchanged especially in tropical areas of the continent. http://www.ehow.com/facts_5545060_history-malaria-ghana.

Malaria is a persistent public health problem and is the leading cause of death among young African children, killing one child every second. More than a million deaths each year are attributed to malaria and 90 percent of those occur in Africa. The disease is present in over 100

countries, threatening 40 % of the world's population. So far malaria remains the single largest cause of death for children under five in Africa. The disease also seriously affects children's future: they may suffer neurological after-effects and impaired learning ability. Malaria does not only cut lives short but has a huge socio-economic impact: patients are often bedridden and incapable of carrying out normal activities. This causes considerable loss of income and places a heavy burden on families, heath systems and society as a whole.

KNUST

In Ghana, malaria is a significant cause of adult morbidity and the leading cause of workdays lost to illness. The disease is hyper endemic accounting for 40% (38.68% in 2006) of all outpatients seen at health facilities and 19 % of under-five mortality in Ghana.

Malaria presents a serious health problem in Ghana; it is hyper-endemic with a crude parasite rate ranging from 10 – 70% and plasmodium falciparum the major malaria parasite, dominating. Although numerous efforts have been made to fight malaria in the country as in many endemic countries, achievements have been minimal. It is the number one cause of morbidity accounting for 40% of outpatient attendance with annual reported cases of 2.2 million between 1995 -2001, and over 10% ending up on admission. From the United Nations (UN) classification of childhood diseases it ranks third in Africa (Ministry of Health 2002).

It is known that initial management and treatment of the disease often takes place outside formal service without consulting trained professionals largely because of transportation, finance, and time, social and physical distance, among others. Treatment received from these sources is often inappropriate leading to clinical complications such as severe anaemia, cerebral malaria, which may lead to coma and/or other parasitological complication such as the development of drug resistant parasites, whose emergence in the country in 1986 has been a major obstacle to the control strategy of prompt recognition and adequate treatment. It is also the leading cause of

workday loss due to illness in the country. For instance, it accounts for 3.6 ill days in a month, 1.3 workdays absent and 6.4% of potential income loss to Ghana for 1998/99. The disease is again responsible for 10.2% of all healthy life lost from other diseases making it the chief cause of lost days of healthy life in Ghana it concluded.

As part of measures to eradicate the disease, WHO initiated a "Roll Back Malaria" (RBM) project, of which Ghana is benefiting, to expand availability and coverage of insecticide-treated mosquito nets which includes forecasting and procurement of these nets by Non Governmental Organizations (NGOs). As a result of this effort, the Ministry of Health has drafted a policy on insecticide treated bed nets, and is adopting these nets as an additional control measure to back the RBM project (Chinbuah 1999). The Volta Region, a beneficiary of the project, has so far shown no significant improvement in combating malaria. This is reflected in the 2003 Ghana Demographic Health Survey (GDHS) report, which shows that Northern Region has one of the highest prevalent cases of malaria in the country. It is therefore important to find out why Northern Region is one of the hardest hit in the prevalence of malaria in Ghana for possible policy interventions.

Malaria contributes substantially to the poor health situation in Africa. It is on record that, Sub-Saharan Africa accounts for 90% of the world's 300 – 500 million cases and 1.5 – 2.7 million deaths annually. About 90% of all these deaths in Africa occur in young children. This has serious demographic consequences for the continent. Between 20 and 40 percent of outpatient visits and between 10 and 15 percent of hospital admissions in Africa is attributed to malaria (WHO, 1999). This burdens the health system. In general, it is estimated that malaria accounts for an average of 3% of the total global disease burden as a single disease in 1990. In Sub-Saharan Africa (SSA), 10.8% of all Disability – Adjusted live years (DALYs) were lost to

malaria in 1990. Again, among the ten leading causes of DALYS in the world in 1998, malaria ranked eighth with a share of 2.8% of the global disease burden. In SSA however, Malaria is ranked second after HIV/AIDS accounting for 10.6% of the disease burden.

According to the World Bank, Malaria accounted for an estimated 35 million DALYs lost in Africa in 1990 due to ill health and premature deaths (World Bank, 1993). This loss was again estimated at 39 million DALYs in 1998 and 36 million DALYs in 1999 (WHO, 1998, 1999, 2000). Furthermore, while malaria contributed 2.05% to the total global deaths in 2000, it was responsible for 9.0% of all deaths in Africa (WHO, 2002). The World Health Organization also estimated that the total cost of malaria to Africa was US$ 1.8 billion in 1995 and US$ 2 billion in 1997 (WHO, 1997). Malaria is therefore a massive problem, which plagues all segments of the society.

The effect of malaria on people of all ages is quite immense. It is however very serious among pregnant women and children because they have less immunity. When malaria infection is not properly treated in pregnant women, it can cause anemia and also lead to miscarriages, stillbirths, underweight babies and maternal deaths. Also, frequent cerebral malaria can lead to disabling neurological sequelae. Further, malaria in school children is a major cause of absenteeism in endemic countries. It is estimated that about 2% of children who recover from cerebral malaria suffer brain damage including epilepsy (WHO/UNICEF, 2003). Hence, among young children, frequent episodes of severe malaria may negatively impact on their learning abilities and educational attainment. This is a threat to human capital accumulation, which constitutes a key factor in economic development.

KNUST

The debilitating effects of malaria on adult victims are very much disturbing. In addition to time and money spent on preventing and treating malaria, it causes considerable pain and weakness among its victims. This can reduce peoples working abilities. The adverse impact of the disease on household production and gross domestic product can be substantial. Malaria therefore is not only a public health problem but also a developmental problem. At the national level, apart from the negative effect of lost productivity on the major sectors of the economy, malaria has negative effects on the growth of tourism, investments and trade especially in endemic regions.

KNUST

Malaria presents a major socio-economic challenge to African countries since it is the region most affected. This challenge cannot be allowed to go unnoticed since good health is not only a basic human need but also a fundamental human right and a prerequisite for economic growth (Streeten, 1981).

1.2 The Problem Statement

In Tamale, despite many years of prevention and control measures, malaria still remains a public health problem in low lying and water logged areas. In some areas across the metropolis, the transmission persistently occurs throughout the year.

It is interesting to note that Tamale Teaching Hospital (TTH) posses' large amount of data on diseases, in particular malaria, on its hospital register. These data is usually compiled and submitted to the district and the regional Ghana Health Service directorate for preparation of quarterly and annual reports. Though records on malaria disease and its covariates are usually not studied, yet it serves as a rich source of information for the stakeholders in the field.

Indeed, as far as my knowledge is concerned, it is surprising to note that no research has been carried out on the covariate influencing malaria mortality using hospital admission data at the Tamale Teaching Hospital (TTH) context to date.

Malaria therefore, is a complex problem that demands mobilization in all areas of public policy in order to facilitate appropriate decision-making towards the creation of malaria-free communities. It is in this vein that this study, which main objective is to apply a logistic regression model, as a case study, to analyze predictors influencing malaria in-hospital mortality using pediatric hospital data from the TTH in the northern region of Ghana.

KNUST

1.3 Objectives

The main objective of this study is to apply logistic regression modeling to analyze predictors of malaria mortality among children.

Also, this study would seek to;

i. Examine the significant predictors/variables in the model;

ii. Determine whether or not type of malaria treatment depends on individual's (child's) age.

1.4 Research Methodology

1.4.1 Scope and Study Area

Tamale metropolis, one of the 20 districts located in Northern Region, is generally classified as malaria endemic, although the highland zones in the central parts of the district are of low transmission and may be prone to epidemic malaria.

KNUST

The Tamale Teaching Hospital is a state run teaching and referral hospital built in 1974. It was one of the admired medical complexes in Ghana. It has a capacity of about 380 patient beds; a four -storey structure that houses four wards, the general purpose theatre and an X-ray Unit. The obstetric/gynecology ward; and antenatal Units (Gunu, 2009).

Tamale has a total population of 474,600 people as per the recent 2010 census. Currently the growth rate of Tamale is about 2.5% per annum. The climate of Ghana is tropical generally, but temperature varies from season and elevation. The city of Tamale experiences one rainy season beginning April and lasting until Novermber with rainfall averaging 1,100mm (about 43 inches). The dry desert wind (harmattan), blows from northeast from December to March, lowering humidity and creating hot days and cool nights in the north in general. The temperature of the area can be described as hot and dry ranging between 23ºC to 40ºC.

Tamale is one of the fastest growing cities in West Africa. It is the capital of the northern region of Ghana and the third largest city in the country after Accra and Kumasi. Livelihood in the city is largely dependent on agriculture (crop, livestock/poultry, and agro-processing) despite its Metropolitan status. The population of the city grew by 48.8% between 1984 and 2000 (population census, 2000) placing considerable challenges such as unprecedented demand on

land for residential and industrial development, unemployment especially for the poor and vulnerable , slum development, environmental degradation and poverty in general.

1.4.2 Data Collection

Data used for this study were obtained as secondary data from inpatient morbidity and mortality returns register at Tamale Teaching Hospital, from 1st January 2000 to 31st December 2010. Tamale Teaching Hospital, with about 380 patient beds is the largest facility in the metropolis which serves both as the first consultation point for patients within its catchment, and as a referral centre for other 15 primary health centers.

For this study, cases with primary diagnosis as malaria, from the hospital wards, were used. Each case was clinically assessed and definitively confirmed as malaria on admission. The registers included patients' age, sex, date of admission and discharge, outcome (i.e. death, discharged home, or absconded), village or location of residence, cost (i.e. for treatment), referral status and treatment given.

1.5 Justification of The Study

Measuring malaria burden in a population is a challenge in most of the region in Ghana. Routine hospital data, reported through the health management information system (HMIS), provide a proxy for measuring the covariate influencing malaria mortality using hospital admission data and for crudely measuring morbidity rates.

The study is immensely significant in diverse ways to policy makers and stakeholders. To the management of World Health Organization (WHO) , the findings and results of this study will provide a more reliable scientific measure and perspective for describing and evaluating the level of malaria mortality among children in the in the metropolis and their monitoring and evaluation operations. Particularly, it will facilitate immensely the World Health Organization in Ghana in achieving some of its policy goals, which include: reducing child's mortality due to malaria and enhancing the reliability and efficiency in the provision of malaria drugs.

KNUST

It would also serve as an invaluable source of information that brings to lime light the treatment type in terms of drugs administered to malaria patients and their efficacy or potency in curing the disease.

It will essentially uncover the state of other health delivery facilities in the metropolis in dealing with malaria cases among children. This will provide empirical support for management strategic decisions in several critical areas of their operations, and above all, provide a justifiably valid and reliable guide to supplying the children's hospital and other health clinics to get the requisite equipment in handling malaria cases.

To policy makers like government agencies such as the Ministry of Health and the Ghana Health Service, the findings and results of this study will provide invaluable insights and a more reliable guide to monitoring the impact of the operations of National Malaria Control Program (NMCP). It will also be a yardstick for measuring partly their respective policy goals and objectives.

To stakeholders like investors, employees such as doctors and nurses, the pharmaceutical association of Ghana, politicians, development partners etc., the study will provide invaluable information that will allow them to provide useful suggestions to the improvement in service

delivery of malaria related issues among children in the metropolis and Ghana at large. Describing such data could assist in monitoring and planning resource needs in a health system. In particular, explaining geographical variation in such outcomes is important to identify children at high risk, to assist in designing appropriate interventions, or lead to further investigations to identify important risk factors.

Additionally, it is important to contribute to knowledge on the covariate influencing malaria mortality with a view to, among other things, stimulate further research and to devote the needed attention to this dreadful disease.

KNUST

Since the cost of treatment of the disease is directly proportional to the size of the potential benefits to be derived for the country, for a successful malaria control programs, this study will try to identify covariates of malaria mortality in the region. Without a continuous assessment or provision of baseline data, the Region will not be able to effectively plan, implement and evaluate programs. If the Roll Back Malaria (RBM) initiative is to succeed in Northern Region, some empirical information on the covariates influencing the disease is needed and since no specific study has been done in this direction, the present study is timely.

1.6 Important Malaria Related Issues

Malaria is a parasitic disease transmitted through mosquito bites. Malaria is an infection caused by a protozoan of the genus Plasmodium. It is transmitted through the bite of an infected female Anopheles mosquito. There are three species that transmit human malaria in Ghana: Anopheles gambiae, Anopheles arabiensis and Anopheles funestus. There are four species of parasites that cause infections in humans but in Ghana only three are found; these are Plasmodium falciparum,

Plasmodium malariae and Plasmodium ovale. Plasmodium falciparum is responsible for most of the deaths and morbidity associated with malaria in Ghana, accounting for about 90- 98% of malaria cases.

Malaria is hyper-endemic in Ghana. It remains a major public health problem, requiring focused interventions including prompt and effective case management. Following the widespread development of chloroquine resistance in Africa, ACTs (Artemisininbased Combination Therapies) have become the drugs of choice for uncomplicated malaria. Ghana began implementing an ACT-based Anti-Malaria Drug Policy (AMDP) in 2004. At the time, Artesunate/Amodiaquine was the only ACT officially promoted for the treatment of uncomplicated malaria. The policy however faced challenges because it made no provision for those who could not tolerate the recommended drug. The policy has therefore since been revised to include alternate ACTs for uncomplicated malaria. The options for treatment of severe malaria and of malaria in pregnancy were also expanded (MOH, 2009).

Late in 2009, the World Health Organization (WHO) issued new recommendations calling for laboratory confirmation for malaria cases in all age groups. In Ghana, malaria testing in all age groups is indeed the goal in the long term, consistent with these recommendations. However, in the near term, epidemiologic and practical considerations require that emphasis be placed on laboratory confirmation in patient above 5. Testing in these older patients is the national policy, as reflected in implementation on a wide scale has scarcely begun.

For the time being, health care workers may continue to apply the empiric (IMCI) approach for patients under 5, as described in this document. However, health care workers are encouraged to consider laboratory confirmation of malaria in under 5's on a case-by-case basis, if their practice

settings are favorable. In case of a negative test, treatment may be withheld in patients under 5 when the following conditions are met: There are no signs of severe disease. Close clinical follow-up of the patient is assured. Reliable laboratory testing is readily available (RDT or microscopy). The prescriber has been adequately trained in the case management of malaria according to the new (2009) national guidelines, including the interpretation of test results.
In the future, when laboratory confirmation in patients above 5 has been put into wider practice in Ghana, priority will be given to testing the less than 5 years age group as well.

KNUST

After the malaria plasmodia parasites enter the human bloodstream, they travel to the liver and reproduce quickly. In most forms of malaria, some parasites stay in the liver to multiple while others flow into the bloodstream. Once in the blood, the malaria parasites destroy the red blood cells, which carry vital oxygen to the tissues of the body. The malaria plasmodia parasites that stayed in the liver also continue to reproduce and send more parasites into the blood.

This process of malaria results in repeated attacks of symptoms each time the malaria parasites are released into the blood. Symptoms first appear in about eight to 30 days after a bite from an infected mosquito. Symptoms are flu-like and can include fever, fatigue, nausea and chills.

Malaria can result in anemia (a decreased number or red blood cells). The remains of the destroyed red blood cells clump together and cause blockages in the blood vessels. This can result in brain damage or kidney damage, which is potentially fatal. A particularly serious, potentially life-threatening, form of malaria is called falciparum malaria.

Attacks of malaria can occur for years if it is not diagnosed and treated. Eventually, the body's immune system may develop a defense against malaria attacks, and they may become less severe in some people. If a person can survive a bout of falciparum malaria, repeat attacks do not recur.

Malaria is most common and a serious public health threat in warm in tropical and subtropical countries. About half of the world's population lives in at-risk areas of the world. Malaria is extremely rare in the U.S., although the Anopheles mosquito is found in the western and southeastern part of the country. Mosquito control programs have basically wiped-out the disease in the U.S. Most cases in the U.S. occur in people who have travelled outside the country to high-risk areas.

Making a diagnosis of malaria begins with taking a thorough personal and family medical history, including symptoms and travel history, and completing a physical examination. Recent travel to sub-tropical or tropical areas of the world is an important clue that may increase the suspicion of a diagnosis of malaria.

Diagnostic testing includes blood tests that check for the plasmodia parasites that cause malaria. A series of tests may need to be done to definitely rule-out or diagnose malaria. A complete blood count (CBC) can detect anemia (low red blood cell count), which can occur with malaria. A diagnosis of malaria can easily be missed or delayed in areas of the world, such as the U.S., where it is rare. For more information on misdiagnosis, refer to misdiagnosis of malaria below.

Treatment of malaria includes preventing the disease when travelling to high risk areas of the world with anti-malarial drugs. Anti-malarial drugs are also used in the treatment of malaria.

1.6.1 Preamble

The incubation period of malaria is from 10 to 14 days. The first attacks are usually more severe and may persist for weeks, if untreated. Malaria characteristically presents as a fever. The onset of falciparum malaria may be insidious and fever continues, remittent or irregularly. If the acute attack is treated rapidly, the disease is usually mild and recovery uneventful.

If left untreated, sequestration of infected red blood cells in the deep tissues can cause serious complications. *Falciparum* malaria during pregnancy is extremely dangerous to both mother and foetus. Malaria is also particularly dangerous in children under 5 years of age.

KNUST

1.6.2 Classification of Malaria

Cases of malaria are categorized as either "uncomplicated" or "severe," based on the clinical severity. Uncomplicated malaria is the presence of fever or a recent history of fever, in the absence of any signs of severe disease. On the other hand, severe malaria is the presence or history of fever, plus any life threatening condition. A person presenting with a history of fever within the last 2-3 days, or found to have fever on examination (axillary temperature > 38.5ºC or rectal temperature >37.5ºC), in the absence of any other cause shall be considered a suspected case of malaria. In the absence of signs of severe disease, a case of malaria is considered to be "uncomplicated."

1.6.3 Signs and Symptoms

The patient suffering from uncomplicated malaria commonly complains of:

- Fever or a history of fever within the preceding 2-3 days
- Chills (feeling unusually cold)

- Rigors (shivering)
- Headache

Other clinical features may include:

- Generalized body and joint pain
- Nausea with or without vomiting
- Loss of appetite
- Sweating
- Abdominal Pain (especially in children)
- Bitterness in the mouth
- Irritability and refusal to feed (in infants)
- Dizziness/fatigue

These features may occur singly or in combination. The presentation of malaria varies and may resemble other locally important disease such as pneumonia, meningitis, typhoid fever and septicemia. In the case of malaria, the fever may be initially intermittent.

KNUST

1.6.4 Diagnosis of Malaria

In Ghana, diagnosis is progressively being shifted from clinical to laboratory confirmation as the basis for treatment. This means that in patients with suspected malaria, a confirmed diagnosis is recommended, wherever possible, before giving anti-malarial treatment. Consistent with WHO and IMCI guidelines, and given the epidemiological distribution of malaria in Ghana, children under 5 years of age are exempted from being tested and can be treated presumptively.

The definitive diagnosis of malaria can be made with microscopy or rapid diagnostic test (RDT) to determine the presence of malaria parasites in the blood. A microscopic diagnosis should be carried out when possible. Microscopic testing should be the standard at health facilities, including district hospitals and higher level facilities. In general, RDTs shall be deployed at sub-district level health facilities, such as health centers and CHPS compounds. When laboratory diagnosis is not possible (neither microscopy nor RDT), treatment should be given on the basis of presumptive diagnosis of malaria. Community-based management (also called Home Management of Malaria) will depend mainly on the presence or history of fever for diagnosis.

A negative result from a properly performed test should greatly raise the suspicion of an illness other malaria, and these patients should be investigated for other causes. Malaria treatment should generally be withheld for a patient who has a negative laboratory test, provided the patient is older than 5 and is lacking signs of severe disease. As always, clinical judgment can be applied when interpreting test results and deciding on treatment for a patient.

1.6.4.1 Use and Interpretation of Diagnostic Tests for Malaria

The following guidelines apply to the use and interpreting diagnostic tests (microscopy or RDT).

a) Children Under 5 Years of Age

In young children, fever or history of fever in the absence of other causes of fever should be considered malaria and treatment commenced immediately without waiting for laboratory results. This is done in the context of Integrated Management of Childhood Illnesses (IMCI). Confirmatory testing in this age group is not required, but may be considered where available.

Fever in this age group may also be caused by other infections including pneumonia, measles, meningitis, otitis media, tonsillitis, etc. and the child should be thoroughly assessed, and treated, for these conditions.

In febrile infants less than 3 months, malaria may not be the first consideration as a cause of fever. Confirmatory testing in this age group is recommended to exclude malaria.

b) Children Aged 5 Years or More and Adults

KNUST

All febrile patients who are 5 years and older and all adults should be carefully examined for other causes of fever. These conditions should be treated, if present. When a malaria diagnostic test is available:

- If the test is positive, treat.
- If a correctly performed test is negative and danger signs are absent, clinicians should in general withhold anti-malarial treatment and follow the patient.
- When a malaria diagnostic test is not available, the patient should be examined carefully for other causes of fever. These patients may be treated for malaria in addition to any other cause of fever.
- In all pregnant women with fever or history of fever, a confirmatory diagnostic test for malaria is strongly recommended. However, in cases where laboratory testing is unavailable anti-malaria treatment should not be withheld.

Additional information on diagnostic tests is provided in the Annexes, including abbreviated SOPs (Standard Operating Procedures) and a flow chart to aid in decision-making. For a fuller presentation of the subject, refer to the National Guidelines for Laboratory Diagnosis of Malaria (Ghana Health Service, 2009).

1.6.5 Treatment of Malaria

The first step in treating malaria is prevention. Prevention measures include controlling mosquito populations in warm sub-tropical and tropical areas of the world. This includes draining areas and objects that can hold standing water and become a breeding ground for mosquitoes, such as old tires, puddles, and bird baths. Wearing insect repellent that contains DEET, picaridin etc also helps a lot.

KNUST

1.6.5.1 Goals of Treatment of Uncomplicated Malaria

The primary goals of treatment of a case of uncomplicated malaria are to:

- Treat promptly and effectively to avoid progression to severe disease
- Limit the duration of disease
- Minimize the risk of developing and spreading drug resistant parasites.

1.6.5.2 Artemisinin Combination Therapies (ACTs)

Since 2004, it has been national policy to use Artemisinin-based combination therapies (ACTs) for the treatment of uncomplicated malaria. This change was necessary because the malaria parasite was becoming resistant to Chloroquine and other monotherapies. Artemisinin and its derivatives are the most rapidly acting anti-malaria's available. They are administered in combination with second, long-acting anti-malaria in order to enhance treatment and to protect against the development of drug resistance.

As per the revised treatment policy (2007), three ACT products have been selected for national use:

- The drug of choice for the treatment of uncomplicated malaria is *Artesunate-Amodiaquine.*
- For those who cannot tolerate Artesunate-Amodiaquine, two alternative ACTs can be used: either *Artemether-Lumefantrine or Dihydroartemisinin-Piperaquine*.

All three drugs are safe for use in children. Either Artesunate-Amodiaquine or Artemether Lumefantrine combination may be used in 2 or 3 trimester of pregnancy. (Quinine should be used in the 1st trimester). Artesunate-Amodiaquine is still a cost-effective drug and should be used as a first-line drug for treating uncomplicated malaria in Ghana.

KNUST

1.6.5.3 General Guidelines for Treatment Using ACTs

(a) Drug Administration

The first oral dose of the ACT should be given under the supervision of a health worker especially for children. It is preferable to administer the medicines after meals.

(b) Management of Vomiting

If vomiting occurs within 30 minutes, the dosage of the ACT should be repeated. If vomiting stops, you can give the patient the second and third doses to take home if you are sure that your instructions will be followed. Ask the patient to return to the clinic if vomiting persists. Persistent vomiting is an indication for referral.

In children, apply tepid sponging, and continue to breast feed where applicable. You must ensure adequate fluid intake. In children, repeated vomiting sometimes results from high fever and can be reduced by tepid sponging and Paracetamol.

(c) Other Supportive Treatment

1. If a child or adult has an axillary temperature of > 37.5 C or feels very hot to touch on examination give an antipyretic, preferably Paracetamol. Treatment of fever is especially important for children. In adults only (not in children) Aspirin may be given as an alternative to Paracetamol.
2. Tepid sponge children with high fever.
3. Advise mothers/ caregivers to give extra fluids, such as breast milk, drinking water, diluted fruit juices, coconut water, oral rehydration salt solution (ORS), etc.
4. Feed the child during illness.
5. In case of itching, give an antihistamine. Explain that itching is a possible drug side effect. If itching is mild, patients should continue taking the drug.

(d) Patient Counseling

Advise the patient to return for medical attention immediately (within the same day) if symptoms get worse, and especially if signs of severe disease develop. The patient should also return to medical attention if fever has not resolved by the last day of treatment.

1.6.5.4 Dosing Guidelines for Artesunate-Amodiaquine

Artesunate-Amodiaquine is the first-line ACT. It should be given either once per day or in divided doses twice per day, and always for a total of three days. The dose of Artesunate is 4 mg per kg body weight per day, and the dose of Amodiaquine is 10mg per kg body weight per day.

It is given orally. The dosing should be done strictly according to weight. Health facilities therefore need to have weighing scales.

KNUST

1.6.5.4.1 Artesunate-Amodiaquine Co-Blistered Formulation

In the co-blistered formulation, tablets of each drug come packaged together. The Artesunate and the Amodiaquine should always be given together. They may be administered either as *one single dose* each day or as *divided doses*. In the case of divided doses, half the total daily dose is given in the morning, and half in the evening. Refer to Table 1a and Table 1b.

KNUST

1.6.5.4.2 Artesunate-Amodiaquine Fixed Dose Combination Therapy

In 2007-2008 a fixed dose combination formulation has been prequalified by WHO and adapted for use in Ghana. The tablets are water soluble (dispersible). The dose for the fixed dose combination is Artesunate 4mg/kg body weight and Amodiaquine 10mg /kg body weight, administered concurrently as *single daily treatment* for three (3) consecutive days. The product is available in 4 presentations for 4 age ranges (infants, small children, children, adolescents and adults), and each presentation is easily identified with a specific color code and pictograms to ensure appropriate usage in the field. These 4 presentations make possible a simple once daily dosing regimen as shown in Table1.1 below.

Table1.1 Artesunate and Amodiaquine Co-Blistered Formulation

Weight (kg)	**Age (yr)**	**Artesunate 50 mg tablets**			**Amodiaquine 150 mg base tablets**		
		Day 1	Day 2	Day 3	Day 1	Day 2	Day 3
5-10 kg	Under 1	½ tab	½ tab	½ tab	½ tab	½ tab	½ tab
11-24 kg	1-6	1 tab	1 tab	1 tab	1 tab	1 tab	1 tab
24-50 kg	7-13	2 tabs	2 tabs	2 tabs	2 tabs	2 tabs	2 tabs
50-70 kg	14-18	3 tabs	3 tabs	3 tabs	3 tabs	3 tabs	3 tabs

KNUST

1.6.6 Misdiagnosis of Malaria

A diagnosis of malaria can easily be missed or delayed in temperate or Northern areas of the world, such as the U.S., where it is extremely rare. In addition, the symptoms of malaria, such as fever, nausea and fatigue closely mimic symptoms of more common infectious diseases, such as influenza and hepatitis. Malaria may also resemble other infectious diseases, such as flu, typhoid fever and dengue.

1.6.7 Complications of Malaria

Review medical complications possibly associated with Malaria:

- Cerebral malaria

- Death
- Mother-infant transmission - pregnant mother can infect the fetus.
- Low birth weight

1.7 Structure of The Study

KNUST

Chapter one, which is the introduction, entails the background of the study, the problem statement, the objectives, the research methodology, the justification of the study and important malaria related issues.

In Chapter two, that is the literature review, related previous researches or literature on the disease were obtained and reviewed to enrich this study.

Chapter three has the heading methodology, which deals with the data collection, data organization and also treated the logistic regression analysis as a subject matter for the statistical inferential tool used for the analysis.

Further, Chapter four deals with the analysis of the data using bar charts, averages, multiple logistic models and the Chi-square statistic. It also contains the results and the discussion of the study.

Finally, Chapter five comprises the findings, conclusions and recommendations.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

A number of researches have been carried out on the application of logistic regression in modeling malaria mortality and other related issues in individuals, in this Chapter a review of literature on these previous researches would be discussed.

KNUST

2.2 Review of Previous Studies

Kazembe et al. (2006) examined the patterns of malaria-related hospital admissions and mortality among Malawian children using spatial modeling of hospital register data. Malaria is a leading cause of hospitalization and in-hospital mortality among children in Africa, yet, few studies have described the spatial distribution of the two outcomes. They, therefore, applied spatial regression models, which was aimed at quantifying spatial variation and risk factors associated with malaria hospitalization and in-hospital mortality. The methods they adopted were using pediatric ward register data from Zomba district, Malawi, between 2002 and 2003, as a case study. Two spatial models were developed. The first was a Poisson model applied to analyze hospitalization and minimum mortality rates, with age and sex as covariates. The second was a logistic model applied to individual level data to analyze case-fatality rate, adjusting for individual covariates. It was then found that; rates of malaria hospitalization and in-hospital mortality decreased with age, case fatality rate was associated with distance, age, wet season and increased if the patient was referred to the hospital. Furthermore, death rate was high on first

day, followed by relatively low rate as length of hospital stay increased. Both outcomes showed substantial spatial heterogeneity, which they attributed to the varying determinants of malaria risk, health services availability and accessibility, and health seeking behavior. The increased risk of mortality of children referred from primary health facilities might due to inadequate care being available at the referring facility or the referring facility was referring the more severe cases which are expected to have a higher case fatality rate. Improved prognosis as the length of hospital stay increased suggests that appropriate care when available can save lives. However, they recommended that, reducing malaria burden could require integrated strategies encompassing availability of adequate care at primary facilities, introducing home or community case management as well as encouraging early referral, and reinforcing interventions to interrupt malaria transmission.

Riedel et al. (2010) used logistic regression models to develop geographical patterns and predictors of malaria risk in Zambia. The Zambia Malaria Indicator Survey (ZMIS) of 2006 was the first nation-wide malaria survey, which combined parasitological data with other malaria indicators such as net use, indoor residual spraying and household related aspects. The survey was carried out by the Zambian Ministry of Health and partners with the objective of estimating the coverage of interventions and malaria related burden in children less than five years. In their study, the ZMIS data were analyzed in order to first of all estimate an empirical high-resolution parasitological risk map in the country and secondly to assess the relation between malaria interventions and parasitaemia risk after adjusting for environmental and socio-economic confounders. They fitted bivariate logistic regression models to assess the relationship between the parasitaemia risk outcome and the environmental lag time variables. For each climatic factor, the lag time variable, which was further considered in the analysis, was the one giving a model

with the smallest Akaike's Information Criterion (AIC). All covariates which were significant in the bivariate analysis at 15% significance level, determined by likelihood ratio tests, were included in a multiple geo-statistical logistic regression analysis. They further fitted several geo-statistical multiple logistic regression models to assess and capture potential non-linearity in the malaria-environment relation. These models included covariates (i) in continuous scales (ii) in categorical scales with categories based on quartiles and (iii) fitted by penalized and basis spline (P- and B-splines) curves. Model validation procedure was then used to choose the model with the best predictive ability. In the geo-statistical model specification, spatial correlation was taken into account by including household location-specific random effects and assuming that they derive from a multivariate Gaussian spatial process with zero mean. The covariance between any pair of locations was assumed to be an exponential function of distance between the locations. Covariates and random effects were modeled on the logit scale of the parasitaemia risk parameters. Their geo-statistical models had at least as many parameters as the number of locations, but model fit was possible via Markov Chain Monte Carlo simulation methods. Exploratory analyses suggested weak spatial correlation therefore non-spatial models (having smaller numbers of parameters) were also fitted. The model with the best predictive ability was employed to predict the risk at the unsampled locations via Bayesian kriging. Predictions were made over a grid of around 100,000 pixels to obtain a parasitaemia risk map for Zambia. Their results showed that, model validation indicated that linear environmental predictors were able to fit the data as well as or even better than more complex non-linear terms and that the data do not support spatial dependence. Overall the averaged population-adjusted parasitaemia risk was 20.0% in children less than five years with the highest risk predicted in the northern (38.3%) province. The odds of parasitaemia in children living in a household with at least one bed net

KNUST

decreases by 40% (CI: 12%, 61%) compared to those without bed nets. In conclusion, the map of parasitaemia risk together with the prediction error and the population at risk gave an important overview of the malaria situation in Zambia. These maps can assist to achieve better resource allocation, health management and to target additional interventions to reduce the burden of malaria in Zambia significantly. Repeated surveys, by their recommendation, would enable the evaluation of the effectiveness of on-going interventions.

KNUST

Daliana et al. (2003) studied Infection Probability Score (IPS) as a method to help assess the probability of infection in critically ill patients. The objective was to develop a simple score to help assess the presence or absence of infection in critically ill patients using routinely available variables. The presence of infection was defined using the Centers for Disease Control definitions. Body temperature, heart rate, respiratory rate, white blood cell count, and C-reactive protein concentrations were measured, and the Sequential Organ Failure Assessment score was calculated throughout the intensive care unit stay. Infection was documented in 92 of the 353 patients (26%) in the developmental set and in 41 of the 140 patients (29%) in the validation set. They used univariate logistic regression to select significant predictors for infection. Each continuous predictor was then transformed into a categorical variable using a robust locally weighted least square regression between infection and the continuous variable of interest. When more than two categories were created, the variable was separated into iso-weighted dummy variables. A multiple logistic regression model predicting infection was calculated with all the variables coded 1 or 0 allowing for relative scoring of the different predictors. The resulting IPS consisted of six different variables and ranged from 0 to 26 points (0-2 for temperature, 0-12 for heart rate, 0-1 for respiratory rate, 0-3 for white blood cell count, 0-6 for C-reactive protein, 0-2 for Sequential Organ Failure Assessment score). They observed that, best predictors for infection

were heart rate and C-reactive protein, whereas respiratory rate was found to have the poorest predictive value. The cutoff value for the IPS was 14 points, with a positive predictive value of 53.6% and a negative predictive value of 89.5%. Their model performance was very good (Hosmer-Lemeshow statistic, p = .918), and the areas under receiver operating characteristic curves were 0.820 for the developmental set and 0.873 for the validation set. They concluded that the Infection Probability Score (IPS) is a simple score that can help assess the probability of infection in critically ill patients. The variables used are simple, routinely available, and familiar to clinicians. Thus patients with score < 14 points have only a 10% risk of infection.

KNUST

Can emergency physicians identify a high mortality subgroup of patients with sepsis through the role of procalcitonin was investigated by Alain et al. (2008). Their objective was to assess the potential role of procalcitonin and tumor necrosis factor-α, interleukin-6 and interleukin-8, in the prognosis of patients with sepsis. Out of the 131 patients, 112 (85.5%) survived and 19 (14.5%) died. These two groups of patients differed with regard to simplified acute physiology score II, severity of infectious disease and underlying disease, bacteremia and type of micro-organisms. The mean serum levels of tumor necrosis factor, interleukin-6, interleukin-8, procalcitonin and lactates at study entry were higher in non-survivors than in survivors. Multivariate regression analysis showed the most significant of these variables to be serum procalcitonin level (*P*=0.0007), simplified acute physiology score II (*P*=0.03) and serum lactate level (*P*=0.03). Using a model incorporating these three variables, with a cut-off value corresponding to a 15% probability of predicting mortality, death could be correctly predicted in 99.5% of cases and survival in 95%. The cut-off value allowed them to maximize the prediction of death. When serum procalcitonin levels were not taken into account, the best model included simplified acute physiology score II and serum lactate and interleukin-6 levels, but the rate of correct prediction

of death then dropped to 84%. They further performed statistical analyses of clinical and laboratory data using Fisher's exact test for the comparisons of proportions (qualitative variable) and Student's *t*-test for the comparisons of means (quantitative variable). As some of the variables are intercorrelated, their joint effect on patient outcome could not be assessed in a univariate analysis. A stepwise multivariate logistic regression, including variables significant in the univariate analysis at a level of P=0.10, was consequently performed to select the variables most predictive of patient outcome (in terms of mortality) and then assessed their relative importance. The final model integrated variables that reached a probability level of 0.05. They validated the model using the technique of 'bootstrap' re-sampling. A total of 1000 samples, corresponding to 80% of the initial data set, were drawn at random with replacement. Model discrimination was assessed on the basis of area under the receiver operating characteristic curve. They concluded that, the stepwise multivariate logistic regression analysis showed serum procalcitonin level to be a valuable marker of sepsis severity, compared with the 15 other clinical, biochemical and bacteriologic variables tested.

Reid et al. (2010) developed mapping malaria risk in Bangladesh using Bayesian geo-statistical models. The background malaria-control programs are increasingly dependent on accurate risk maps to effectively guide the allocation of interventions and resources. Advances in model-based geo-statistics and geographical information systems (GIS) have enabled researchers to better understand factors affecting malaria transmission and thus, more accurately determine the limits of malaria transmission globally and nationally. They constructed Plasmodium falciparum risk maps for Bangladesh for 2007 at a scale enabling the malaria-control bodies to more accurately define the needs of the program. A comprehensive malaria-prevalence survey (N = 9,750 individuals; N = 354 communities) was carried out in 2007 across the regions of Bangladesh

known to be endemic for malaria. The data obtained were corrected to a standard age range of 2 to less than 10 years. Bayesian geo-statistical logistic regression models with environmental covariates were used to predict plasmodium falciparum prevalence for 2 to 10 years-old children (*Pf*$PR_{2–10}$) across the endemic areas of Bangladesh. The predictions were combined with gridded population data to estimate the number of individuals living in different endemicity classes. Across the endemic areas, environmental variables selected for prediction were vegetation cover, minimum temperature, and elevation. Model validation statistics revealed that the final Bayesian geo-statistical model had good predictive ability. Risk maps generated from the model showed a heterogeneous distribution of *Pf*P $R_{2–10}$ ranging from 0.5% to 50%; 3.1 million people were estimated to be living in areas with a *Pf*P $R_{2–10}$ greater than 1%. They recommended that contemporary GIS and model-based geo-statistics could be used to interpolate malaria risk in Bangladesh. Importantly, malaria risk was found to be highly varied across the endemic regions, necessitating the targeting of resources to reduce the burden in these areas.

Grillet et al. (2010) assessed disentangling the effect of local and global spatial variation on a mosquito-borne infection in a neo-tropical heterogeneous environment. They used local spatial statistics and geographically weighted regression (GWR) to determine the spatial pattern of malaria incidence and persistence in northeastern Venezuela. Seven to 11 hot spots of malaria transmission were detected by using local spatial statistics, although disease persistence was explained only for four of those hot spots. The GWR models greatly improved predictions of malaria risk compared with ordinary least squares (OLS) regression models. Malaria incidence was largely explained by the proximity to and number of Anopheles aquasalis habitats nearby (1–3 km), and low-elevation terrains. Disease persistence was associated with greater human population density, lower elevations, and proximity to aquatic habitats. However, they found

significant local spatial variation in the relationship between malaria and environmental variables. Thus they recommended that spatial modeling improves the understanding of the causal factors operating at several scales in the transmission of malaria.

Yabsley et al. (2005) used both logistic regression and kriging models to provide very reliable portrayals of ehrlichia chaffeensis occurrence and predicted that ehrlichia chaffeensis distribution had good concordance with human case data. Ehrlichia chaffeensis, which causes human monocytotrophic ehrlichiosis (HME), is an important emerging tick-borne pathogen in the southeastern and southcentral United States. The endemnicity probability of ehrlichia chaffeensis and, by implication, locations with risk for HME, was predicted by using two modeling methods. Their analyses included the ehrlichia chaffeensis serostatus for 563 counties from 18 states. They concluded that the integration of a deer surveillance system with geospatial analyses was useful in developing HME risk maps that will be useful for identifying high-risk areas for public health interventions such as prevention and control efforts.

Carneiro et al. (2006) modeled the relationship between the population prevalence of plasmodium falciparum malaria and anemia using logistic regression. More than half of all young children and pregnant women are affected by anemia. Although its etiology is multi-factorial, malaria was considered likely to be a major contributor to chronic anemia in endemic areas. Recent reviews have examined the effect of community-based malaria control interventions on anemia. They analyzed how the prevalence of anemia depends on that of Plasmodium falciparum malaria by developing models of the excess risk of anemia caused by malaria at a population level in 24 villages in northeastern Tanzania. In that setting, they estimated that the prevalence of a hemoglobin level < 8 g/dL attributable to malaria was 4.6% in

infants, 4.1% in children one year of age, 2.7% in children two years of age, and 3.3% in women of childbearing age. Successful validation of their models in other malaria endemic settings would enable its use for predicting the impact of malaria control interventions on anemia, and for long-term monitoring and surveillance of malaria. The parasitemia and anemia data were summarized within each survey and village by age-group, using one-year age groups up to four years and five-year age groups thereafter, leading to a total of 606 sub-groups. For their main analysis, they excluded the data of women 15–45 years of age, among whom anemia is specifically associated with menstruation and pregnancy, and carried out a separate analysis for these women. The prevalence of anemia, as a function of parasite prevalence, density, age group, and village, was analyzed using random effects logistic regression, with the full model of the form

$$\log it\left(p_A(a,i,s)\right) = \beta_{a0} + f\left(a, p_p(a,i,s)\right) + \beta_s I_s(s) + \gamma_t$$

Where $p_A(a,i,s)$ is the probability of being anemic in group with age-midpoint a, village i, and survey s, $p_p(a,i,s)$ is the corresponding parasite prevalence, β_{a0} is the intercept, β_s the regression coefficient for the survey effect where $I_s(s)$ is an indicator variable taking the value 0 for the first survey, and 1 for the second, and γ_t is a random effect corresponding to village i.

The models presented here enabled them to attribute a proportion of anemia to malaria in different age groups in northeastern Tanzania. It was interesting to note that peak anemia prevalence seems to be closely linked to the age of admission for severe anemia in hospitals in the same study area. Although there is no clear link between moderate anemia and mortality, there is evidence that anemia can have substantial effects on cognitive and motor development and on growth. Further investigations in the area supported the finding of a high excess risk of

anemia due to malaria in very young children. It was therefore essential that estimates of malaria burden and evaluation of malaria interventions include the contribution of malaria to chronic anemia in the community. They recommended that successful validation of the models in a range of settings across Africa, where the bulk of the malaria burden is currently concentrated, would allow prediction of the impact of different malaria interventions, including the introduction of malaria vaccines, under different transmission intensity scenarios.

KNUST

Hui et al. (2009) developed spatio-temporal distribution of malaria in Yunnan Province, China. The spatio-temporal distribution pattern of malaria in Yunnan Province was studied using a geographic information system technique. Both descriptive and temporal scan statistics revealed seasonal fluctuation in malaria incidences in Yunnan Province with only one peak during 1995–2000, and two apparent peaks from 2001 to 2005. Spatial autocorrelation analysis indicated that malaria incidence was not randomly distributed in the province. Further analysis using spatial scan statistics discovered that the high risk areas were mainly clustered at the bordering areas with Myanmar and Laos, and in Yuanjiang River Basin. There were obvious associations between Plasmodium vivax and Plasmodoium falciparum malaria incidences and climatic factors with a clear 1-month lagged effect, especially in cluster areas. It was recommended that all these could provide information on where and when malaria prevention and control measures would be applied. Their findings indicated that countermeasures should target high risk areas at suitable times, when climatic factors facilitate the transmission of malaria.

Gemperli et al. (2004) examined the spatial patterns of infant mortality in Mali by the effect of malaria endemicity. A spatial analysis was carried out to identify factors related to geographic differences in infant mortality risk in Mali by linking data from two spatially structured

databases: the Demographic and Health Surveys of 1995–1996 and the Mapping Malaria Risk in Africa database for Mali. They measured socioeconomic factors directly at the individual level and site-specific malaria prevalence predicted for the Demographic and Health Surveys' locations by a spatial model fitted to the Mapping Malaria Risk in Africa database were examined as possible risk factors. The analysis was carried out by fitting a Bayesian hierarchical geo-statistical logistic model to infant mortality risk, by Markov chain Monte Carlo simulation. Their model confirmed that mother's education, birth order and interval, infant's sex, residence, and mother's age at infant's birth had a strong impact on infant mortality risk in Mali. The residual spatial pattern of infant mortality showed a clear relation to well-known foci of malaria transmission, especially the inland delta of the Niger River. They also showed that spatial statistical models of malaria prevalence are useful for indicating approximate levels of endemicity over wide areas and, hence, for guiding intervention strategies. However, they recommended that points very remote from those sampled, it is important to consider prediction error.

Kleinschmidt et al. (2001) investigated the use of generalized linear mixed models in the spatial analysis of small-area malaria incidence rates in KwaZulu Natal, South Africa. Spatial statistical analysis of 1994–1995 small-area malaria incidence rates in the population of the northernmost districts of KwaZulu Natal was undertaken to identify factors that might explain very strong heterogeneity in the rates. Their paper described a method of adjusting the regression analysis results for strong spatial correlation in the rates by using generalized linear mixed models and variograms. The results of the spatially adjusted, multiple regression analysis showed that malaria incidence was significantly positively associated with higher winter rainfall and a higher average maximum temperature and was significantly negatively associated with increasing

distance from water bodies. They used the statistical model to produce a map of predicted malaria incidence in the area, taking into account local variation from the model prediction if this variation was supported by the data. Their predictor variables showed that even small differences in climate can have very marked effects on the intensity of malaria transmission, even in areas subject to malaria control for many years.

Alles et al. (1998) analyzed malaria mortality rates in South Asia and in Africa. Malaria mortality in human populations varies greatly under different circumstances. The intense malaria transmission conditions found in many parts of tropical Africa, the much lower malaria inoculation rates currently sustained in areas of southern Asia, and the epidemic outbreaks of malaria occasionally seen on both continents, present highly contrasting patterns of malaria-related mortality. They examined malaria-related mortality under different circumstances and discuss implications for the management of malaria in these settings. They emphasized on the power of rapid case treatment to save lives at risk under virtually all circumstances of malaria transmission.

Yé et al. (2007) assessed the risk of self-diagnosed malaria in urban informal settlements of Nairobi using self-reported morbidity survey. Because of the belief that Nairobi is a low risk zone for malaria, little empirical data exists on malaria risk in the area. Their aim was to explore the risk of perceived malaria and some associated factors in Nairobi informal settlements using self-reported morbidity survey. The survey was conducted from May to August 2004 on 7,288 individuals in two informal settlements of Nairobi. Participants were asked to report illnesses they experienced in the past 14 days. Logistic regression was used to estimate the odds of

perceived-malaria. The model included variables such as site of residence, age, ethnicity and number of reported symptoms.

$$\text{logit}(\pi_i) = \beta_0 + \beta_1 Slum\_Vivandani_i + \beta_2 Gender\_Male_i + \beta_3 AgeGroup\_15-24_i + \beta_4 AgeGroup\_24-39_i + \beta_5 AgeGroup\_40_i + \beta_6 Ethnicity\_Kamba_i + \beta_7 Ethnicity\_Luha_i + \beta_8 Ethnicity\_Luo_i + \beta_9 Symptom\_Score\_1_i + \beta_{10} Symptom\_Score\_2_i + \beta_{11} Symptom\_Score\_3_i + \beta_{12} Symptom\_Score\_4_i + \beta_{13} Symptom\_Score\_5 + {}_i$$

KNUST

Participants reported 165 illnesses among which malaria was the leading cause (28.1%). The risk of perceived-malaria was significantly higher in Viwandani compared to Korogocho (OR 1.61, 95%CI: 1.10–2.26). Participants in age group 25–39 years had significantly higher odds of perceived-malaria compared to those under-five years (OR 2.07, 95%CI: 1.43–2.98). The Kikuyu had reduced odds of perceived-malaria compared to other ethnic groups. Individuals with five and more symptoms had higher odds compared to those with no symptoms (OR 23.69, 95%CI: 12.98–43.23). Malaria was the leading cause of illness as perceived by the residents in the two informal settlements. This was rationalized by the fact that as the number of reported symptoms was highly associated with the risk of reporting the illness. Their results brought to fore the need for a more comprehensive assessment of malaria epidemiology in Nairobi to be able to offer evidence-based guidance to policy on malaria in Kenya and particularly in Nairobi.

Bryce et al. (2005) examined estimates of the causes of death in children. Child survival efforts can be effective only if they are based on accurate information about causes of deaths. WHO established the external Child Health Epidemiology Reference Group (CHERG) in 2001 to develop estimates of the proportion of deaths in children younger than age 5 years attributable to malaria, pneumonia, diarrhoea, measles, and the major causes of death in the first 28 days of life.

Various methods, including single-cause and multi-cause proportionate mortality models, were used. The role of undernutrition as an underlying cause of death was estimated in collaboration with CHERG. In 2000-03, six causes accounted for 73% of the 10.6 million yearly deaths in children younger than age 5 years: malaria (8%), pneumonia (19%), diarrhoea (18%), neonatal pneumonia or sepsis (10%), preterm delivery (10%), and asphyxia at birth (8%). The four communicable disease categories account for more than half (54%) of all child deaths. The greatest communicable disease killers were similar in all WHO regions with the exception of malaria; 94% of global deaths attributable to this disease occur in the Africa region. Undernutrition is an underlying cause of 53% of all deaths in children younger than age 5 years. They found that, in all regions, deaths in the neonatal period, primarily due to preterm delivery, sepsis or pneumonia, and birth asphyxia should also be addressed. From their results it was recommended estimates of the causes of child deaths should be used to guide public-health policies and programs.

Sacarlal et al. (2007) presented a 10 year study of the cause of death in children under 15 years in Manhiça, Mozambique. Child mortality is highest in Sub-Saharan Africa, although causes of mortality in this region are not well documented. The objective of their study was to describe the most frequent causes of mortality in children under 15 years of age in the demographic surveillance area of the Manhiça Health Research Centre, between 1997 and 2006. They employed verbal autopsy interviews for causes of death in children began in 1997. Each questionnaire was reviewed independently by three physicians with experience in tropical pediatrics, who assigned the cause of death according to the International Classification of Diseases (ICD-10). Each medical doctor attributed a minimum of one and a maximum of 2 causes. From January 1997 to December 2006, 568,499 person-year at risk (pyrs) and 10,037

deaths were recorded in the Manhiça DSS. 3,730 deaths with 246,658 pyrs were recorded for children under 15 years of age. 73.6% of deaths were attributed to communicable diseases, non-communicable diseases accounted for 9.5% of the defined causes of death, and injuries for 3.9% of causes of deaths. Malaria was the single largest cause, accounting for 21.8% of cases. Pneumonia with 9.8% was the second leading cause of death, followed by HIV/AIDS (8.3%) and diarrhoeal diseases with 8%. The results of their study stand out the big challenges that lie ahead in the fight against infectious diseases in the study area. The pattern of childhood mortality in Manhiça area is typical of developing countries where malaria, pneumonia and HIV/AIDS are important causes of death.

KNUST

Lindsay et al. (2010) assessed the future threat from vivax malaria in the United Kingdom using two markedly different modeling approaches. The world is facing an increased threat from new and emerging diseases, and there is concern that climate change will expand areas suitable for transmission of vector borne diseases. The likelihood of vivax malaria returning to the UK was explored using two markedly different modeling approaches. They used logistic-regression model to predict historical malaria incidence between 1917 and 1918 and simple temperature-dependent, process-based model of malaria growth transmitted in the UK, based on environmental and demographic data. The process-based model of climate suitability showed good correspondence with historical records of malaria cases. An analysis of the statistical models showed that mean temperature of the warmest month of the year was the major factor explaining the distribution of malaria, further supporting the use of the temperature-driven processed-based model. Confidence in these predictions was increased by the concordance between the processed-based and statistical models. They concluded that, although the future climate in the UK was favorable for the transmission of vivax malaria, the future risk of locally

transmitted malaria was considered low because of low vector biting rates and the low probability of vectors feeding on a malaria-infected person.

De La Cruz et al. (2006) used logistic regression among other tests to identify factors associated with bed net use among children less than five years of age and to compare the characteristics of mothers whose children use bed nets (doers) with those whose children do not (non-doers). Malaria prevention programs should be based in part on knowledge of why some individuals use bed nets while others do not. Their paper identified factors and characteristics of women that affect bed net use among their children less than five years of age in Ghana. They obtained data from the baseline component of an evaluation of Freedom from Hunger's malaria curriculum. A quasi-experimental design was used to select clients (n = 516) of *Credit with Education* (an integrated package of microfinance and health education) and non-clients (n = 535). The following factors were most closely associated with bed net use: region of residence; greater food security; and caregivers' beliefs about symptoms, causation and groups most vulnerable to malaria. Most respondents knew mosquitoes caused malaria; however, 20.6% of doers and 12.3% of non-doers (p = .0228) thought overworking oneself caused malaria. Ninety percent of doers and 77.0% of non-doers felt that sleeping under a net was protective against malaria (p = .0040). In addition, 16.5% of doers and 7.5% of non-doers (p = .0025) identified adult males as most vulnerable to malaria. The concluded that greater knowledge about malaria does not always translate into improved bed net use. Though culturally-based ideas about malaria may vary between communities, integrating them into traditional health education messages may enhance the effectiveness of public health efforts.

Karger (2005) assessed the impact on the mortality of young children in an area of intense transmission of malaria and no tradition of bed net use. A community-based randomized, controlled trial of permethrin impregnated bed nets was carried out in a rural area of northern Ghana, between July 1993 and June 1995, to assess the impact on the mortality of young children in an area of intense transmission of malaria and no tradition of bed net use. The district around Navrongo was divided into 96 geographical areas and in 48 randomly selected areas households were provided with permethrin impregnated bed nets which were re-impregnated every 6 months. A longitudinal demographic surveillance system was used to record births, deaths and migrations, to evaluate compliance and to measure child mortality. The use of permethrin impregnated bed nets was associated with 17% reduction in all-cause mortality in children aged 6 months to 4 years (RR=0.83; 95% CI 0.69–1.00; *P*=0.05). The reduction in mortality was confined to children aged 2 years or younger, and was greater in July-December, during the wet season and immediately after (RR=0.79; 95% CI 0.63–1.00), a period when malaria mortality is likely to be increased, than in the dry season (RR=0.92, 95% CI 0.73–1.14). The ready acceptance of bed nets, the high level of compliance in their use and the subsequent impact on all-cause mortality in this study has important implications for programs to control malaria in sub-Saharan Africa.

Kleinschmidt et al. (2000) developed a spatial statistical approach to malaria mapping. Good maps of malaria risk have long been recognized as an important tool for malaria control. The production of such maps relies on modeling to predict the risk for most of the map, with actual observations of malaria prevalence usually only known at a limited number of specific locations. Estimation is complicated by the fact that there is often local variation of risk that cannot be

accounted for by the known covariates and because data points of measured malaria prevalence are not evenly or randomly spread across the area to be mapped. They described in their methodology, by way of an example, a simple two-stage procedure for producing maps of predicted risk: they used logistic regression modeling to determine approximate risk on a larger scale since parasite prevalence data are binomial fractions and then employed geo-statistical ('kriging') approaches to improve prediction at a local level. Malaria prevalence in children under 10 was modeled using climatic, population and topographic variables as potential predictors. After the regression analysis, spatial dependence of the model residuals was investigated. Kriging on the residuals was used to model local variation in malaria risk over and above that which is predicted by the regression model. They found out that the method is illustrated by a map showing the improvement of risk prediction brought about by the second stage. The advantages and shortcomings of this approach are discussed in the context of the need for further development of methodology and software.

In sub-Saharan Africa, malaria is a leading cause of morbidity and mortality among young children. Meanwhile, detailed knowledge of spatial variation of malaria epidemiology and associated risk factors was important for planning and evaluating malaria-control measures. Therefore, Kreuels et al. (2008) determined the spatial variation of malaria incidence in young children from a geographically homogeneous area with high endemicity. In their methods, the spatial variation of malaria incidences and socioeconomic factors were assessed over 21 months, from January 2003 to September 2005, in 535 children from 9 villages of a small rural area with high Plasmodium falciparum transmission in Ghana. They mapped household positions by using a global positioning system, and then assessed the spatial effects on malaria rates by means of

ecological analyses and bivariate Poisson regression controlling for possible confounding factors. It was then observed that malaria incidence was surprisingly heterogeneous between villages, and ecological analyses showed strong correlations with village area and population size. Malaria risk was affected by a number of socioeconomic factors. Poisson regression showed an independent linear rate reduction with increasing distance between children's households and the fringe of the forest. They concluded that the exact location of households in villages is an independent and important factor for the variation of malaria incidence in children from high-transmission areas. Suggestion was made for the consideration of the findings in the planning of intervention trials and in spatial targeting of malaria interventions at a local level.

Clerk et al. (2009) described the factors associated with malaria infection and anemia in pregnancy in northern Ghana. They studied 3642 pregnant women of all gravidities and gestational age of 18–32 weeks who attended an antenatal clinic in the Kassena-Nankana district of Ghana between June 2004 and July2006. Blood samples were examined for haemoglobin concentrations and parasitaemia, and they obtained socio-demographic data, an obstetric history, and information on their past and current state of health and bed net use. The data was analyzed using Stata version 9. Proportions were compared using the chi-squared test or Fisher's exact test when appropriate. Univariate analysis was used to identify risk factors for anaemia and parasitaemia. They further used multiple logistic regression models to investigate the effect of the risk factors on anaemia and parasitaemia. Factors with P-values ≤ 0.1 were included in final regression models. In their risk factors model, a likelihood ratio with a P–value of < 0.05 was considered as statistically significant. The overall prevalence of malaria parasitaemia during pregnancy was 47%. Older age [adjusted odds ratio (AOR) 0.65, 95% CI 0.54–0.78], multigravidity (AOR 0.51, 95% CI 0.42–0.61) and third trimester of pregnancy (AOR 0.85, 95%

CI 0.73–0.99) were associated with a decreased risk of parasitaemia. Enrolment during the rainy or post-rainy season was associated with an increased risk of parasitaemia (AOR 2.59, 95% CI 2.20–3.04 and AOR 3.12, 95% CI, 2.60–3.74 respectively). Malaria infection was associated with an increased risk of anaemia among young women. The prevalences of anaemia (Hb<11.0 g ⁄ dl) and severe anaemia (Hb<7.0 g ⁄ dl) during pregnancy were 72% and 2% respectively. The risk of anaemia was lower in older women (AOR 0.79, 95% CI, 0.64–0.97), multigravidae (AOR 0.67, 95% CI 0.55–0.83) and in educated women (AOR 0.81, 0.68–0.98). They found out that, the prevalence of malaria parasitaemia and anaemia among pregnant women in Kassena-Nankana district is high with marked seasonal variation. Thus, it was recommended that targeting of interventions to the high transmission season and to paucigravidae might be appropriate.

Jack et al. (1998) studied the evaluation of Acute Physiology and Chronic Health Evaluation (APACHE) III predictions of hospital mortality in an independent database. The objective was to assess the accuracy and validity of APACHE III hospital mortality predictions in an independent sample of U.S. intensive care unit (ICU) admissions. They used demographic, clinical, and physiologic information recorded during ICU day 1 and the APACHE III equation to predict the probability of hospital mortality for each patient. They compared observed and predicted mortality for all admissions and across patient subgroups and assessed predictive accuracy using tests of discrimination and calibration. Aggregate hospital death rate was 12.35% and predicted hospital death rate was 12.27% (p = 0.541). Their model discriminated between survivors and non-survivors well (area under receiver operating curve = 0.89). A calibration curve showed that the observed number of hospital deaths was close to the number of deaths predicted by the model, but when tested across deciles of risk, goodness-of-fit (Hosmer-Lemeshow statistic, chi-

square = 48.71, 8 degrees of freedom, $p < 0.0001$) was not perfect. Observed and predicted hospital mortality rates were not significantly ($p < .01$) different for 55 (84.6%) of APACHE III's 65 specific ICU admission diagnoses and for 11 (84.6%) of the 13 residual organ system-related categories. The most frequent diagnoses with significant ($p < 0.01$) differences between observed and predicted hospital mortality rates included acute myocardial infarction, drug overdose, non-operative head trauma, and non-operative multiple trauma. In conclusions, APACHE III accurately predicted aggregate hospital mortality in an independent sample of U.S. ICU admissions. They recommended that, further improvements in calibration could be achieved by more precise disease labeling, improved acquisition and weighting of neurologic abnormalities, adjustments that reflect changes in treatment outcomes over time, and a larger national database.

KNUST

Malaria in humans is caused by four species of the plasmodium protozoa (single celled parasites) – plasmodium falciparum, plasmodium vivax, plasmodium ovale and plasmodium malariae. Of these species plasmodium falciparum accounts for the majority of infections and is the most lethal. Several studies have been done on different aspects of the disease, from parasitology to finding a cure with drugs (chemotherapy) and to eradication of the disease by the use of insecticide treated net and insecticides. Rashed et al. (2000) conducted a study which was aimed at determining the effect of Permethrin insecticide treated nets (PITN) used on the incidence of febrile episodes and non household malaria expenses in Benin. The study found out that, the use of PITNs decreased the risk of developing malaria by 34% in children in the rural areas; meanwhile, PITN use did not reduce prevention and treatment expenses. In a parasitology laboratory, malaria was found to be the major killer of paediatric illness and death in Kinshasa (Coene 1991). In view of this, the treatment of fevers as malaria with chloroquine was no longer acceptable because the plasmodium falciparum had a resistance to chloroquine. According to the

study, the differences in endemicity of malaria that existed between the various parts of town had to be taken into consideration alongside the ecological and socio-economic factors that mattered when planning for estimation of potential control methods.

The behavioral risk for malaria in the Machodinho resettlement area in the Amazonian forests of Brazil was examined by Castilla et al. (1993). Analysis of their study suggested that economic status and knowledge of the importance and behavior of the mosquito in transmitting malaria are significant factors in determining prevalence risk irrespective of whether preventive precautions, for example, dichlorodiphenyl trichloroethane (DDT) spraying of houses and cleaning of vector breeding sites are to be undertaken in the endemic areas. However, the researchers found out that a higher economic status combined with better knowledge of the vector and DDT spraying of houses decreased the risk of infection. They suggested that a more positive implication is that control programs must work harder and more intensively on behalf of poorer people especially migrants in order to diminish the disease burden for them.

Sharma et al. (2001) examined the socioeconomic factors as well as the human behavior towards malaria on cross section of the Sundargarh district in India. They argued that poor socioeconomic status and socio-cultural factors play an important role in maintaining high degree of malaria transmission. They found that human behaviors such as location of hamlets, type of malaria transmitted, sleeping habits, and outdoor activities after dusk, poor knowledge about the disease and treatment seeking behavior are of great significance as determinants of malaria transmission.

Malaria is also a major problem in Papua New Guinea as it accounts for a high proportion of sickness and death. This is because in addition to human suffering, it also put severe stress on the health facilities and directly hinders economic growth. It has been suggested that a malaria vaccine would be best, most cost effective and safe public health measure to reduce the burden of malaria according to Reeder (2001).

KNUST

A study was conducted in Benin on how to conceive and establish the importance of economic factors that contributed to malaria transmission by Mensah et al. (2004). According to their study, despite the endemic malaria situations, there was still little understanding of the relative importance of economic factors that contribute to people acquiring the disease in communities where malaria was endemic. The researchers contended that, predisposing characteristics of household's heads such as age, knowledge of malaria, education and size of household significantly affected the incidence of malaria as anticipated by economic theory.

A study by Asenso – Okyere (1994) on malaria in four districts namely Kojo Ashong, Barekese, Barekuma and Oyereko all from the Greater Accra Region of Ghana revealed that factors that were perceived as causing malaria are malnutrition, mosquitoes, excessive heat, excessive drinking, flies, fatigue, dirty surroundings, unsafe water, bad air and poor hygiene. Almost all the adolescents at that time had no idea how the disease was spread from person to person, while the symptoms of clinical malaria was also frequently considered to be yellowish eyeball, chills and shivering, headache, a bitter taste, body weakness and yellowish urine, the study added.

Yeboah-Antwi et al. (1997) examined the extent to which district health teams in Kintampo in the Brong Ahafo Region of Ghana could reduce the burden of malaria, which is a major cause of mortality and morbidity in a situation where severe resource constraints existed. It was found out that, compliance improve by approximately 20% in both adults and children but there was improvement to care about 50% for example in cost to patients, waiting time at dispensaries and drug wastage at facilities.

KNUST

Another case study in Ghana sought to compare household's data on acute morbidity and treatment seeking behavior in two districts using health facility data was investigated by Agyepong et al. (2004). For every case of febrile illness seen in the health facilities there were approximately 4-5 cases in the community, hence they concluded that every febrile episodes especially in children be treated with an anti-malarial drug. Since several countries extend malaria treatment to include the community and the home through public and private, formal and informal sectors, the need for more comprehensive estimates becomes urgent.

Appawu et al. (2004) studied malaria transmission dynamics in the Kassena Nankana District, a site in northern Ghana proposed for testing malaria vaccines. Intensive mosquitoes sampling was done for one year using human landing catches in three micro-ecological sites that is irrigated, lowland and rocky highlands. Transmission was highly seasonal and the heaviest transmission occurred from June to October. The intensity of transmission was higher for people in the irrigated communities than the non-irrigated ones. Approximately 60% of malaria transmission in KND occurred indoors during the second half of the night, peaking at daybreak between 04.00 to 06.00 hours.

Ross A. et al. (2008) in their study sort to modeling the epidemiological impact of Intermittent Preventive Treatment against malaria in Infants. The trials of intermittent preventive treatment against malaria in infants (IPTi) using sulphadoxine-pyrimethamine (SP) have shown a positive, albeit variable, protective efficacy against clinical malaria episodes. The impact of IPTi in different epidemiological settings and over time was unknown and predictions were hampered by the lack of knowledge about how IPTi works. They investigated mechanisms proposed for the action of IPTi and made predictions of the likely impact on morbidity and mortality. They used a comprehensive, individual-based, stochastic model of malaria epidemiology to simulate recently published trials of IPTi using SP with site-specific characteristics as inputs. Their baseline model was then modified to represent hypotheses concerning the duration of action of SP, the temporal pattern of fevers caused by individual infections, potential benefits of avoiding fevers on immunity and the effect of sub-therapeutic levels of SP on parasite dynamics. The baseline model reproduced the pattern of results reasonably well. None of the models based on alternative hypotheses improved the fit between the model predictions and observed data. Predictions suggested that IPTi had a beneficial effect across a range of transmission intensities. IPTi was predicted to avert a greater number of episodes where IPTi coverage was higher, the health system treatment coverage lower, and for drugs which were more efficacious and had longer prophylactic periods. The predicted cumulative benefits were proportionately slightly greater for severe malaria episodes and malaria-attributable mortality than for acute episodes in the settings modelled. Modest increased susceptibility was predicted between doses and following the last dose, but these were outweighed by the cumulative benefits. The impact on transmission intensity was negligible. They concluded that the pattern of trial results was accounted for by differences between the trial sites together with known features of malaria epidemiology and the

action of SP. Predictions suggested that IPTi had a beneficial impact across a variety of epidemiological settings.

Terlouw et al. (2010) investigated the impact of mass distribution of free long-lasting insecticidal nets on childhood malaria morbidity in Togo. They evaluated the short-term impact on childhood malaria morbidity of mass distribution of free long-lasting insecticidal nets (LLINs) to households with children aged 9-59 months as part of the Togo National Integrated Child Health Campaign. The prevalence of anemia and malaria in children aged zero to 59 months was measured during two cross-sectional household cluster-sample surveys conducted during the peak malaria transmission, three months before (Sept 2004, n=2521) and nine months after the campaign (Sept 2005, n=2813) in three districts representative of Togo's three epidemiological malaria transmission regions: southern tropical coastal plains (Yoto), central fertile highlands (Ogou) and northern semi-arid savannah (Tone). In households with children less than 5 years of age, insecticide-treated net (ITN) ownership increased from below 1% to more than 65% in all 3 districts. They reported that ITN use by children during the previous night was 35.9%, 43.8% and 80.6% in Yoto, Ogou and Tone, respectively. Rainfall patterns were comparable in both years. The overall prevalence of moderate to severe anemia (Hb <8.0g/dL) was reduced by 28% (prevalence ratio [PR] 0.72, 95% CI 0.62-0.84) and mean hemoglobin was increased by 0.35g/dL (95% CI 0.25-0.45). They observed that the effect was predominantly seen in children aged 18-59 months and in the two southern districts: PR (95% CI) for moderate to severe anemia and clinical malaria: Yoto 0.62 (0.44-0.88) and 0.49 (0.35-0.75); Ogou 0.54 (0.37-0.79) and 0.85 (0.57-1.27), respectively. Similar reductions occurred in children <18 months in Ogou, but not in Yoto. No effect was seen in the semi-arid northern district despite a high malaria burden and ITN

KNUST

coverage. They concluded that a marked reduction in childhood malaria associated morbidity was observed in the year following mass distribution of free LLINs in two of the three districts in Togo. Recommendation of sub national level impact evaluations would contribute to a better understanding of the impact of expanding national malaria control efforts was made..

In malaria-endemic areas, reliably establishing parasitaemia for diagnosis of malaria can be difficult. A retinopathy with some features unique to severe malaria with a predictive value on prognosis had been described. Therefore, Essuman et al. (2010) studied retinopathy in severe malaria in Ghanaian children - overlap between fundus changes in cerebral and non-cerebral malaria. Detection of this retinopathy could be a useful diagnostic tool. Their study was designed, first of all, to determine the diagnostic usefulness of retinopathy on ophthalmoscopy in severe malaria syndromes: Cerebral malaria (CM) and non-cerebral severe malaria (non-CM), i.e. malaria with respiratory distress (RD) and malaria with severe anaemia (SA), in Ghanaian children. Again, it was aimed at determining the association between retinopathy and the occurrence of convulsions in patients with CM. A cross-sectional study of consecutive patients on admission with severe malaria who were assessed for retinal signs, at the Department of Child Health, Korle-Bu Teaching Hospital, Accra, from July to August 2002 was done. All children had dilated-fundus examination by direct and indirect ophthalmoscopy. Fifty-eight children aged between six months and nine years were recruited. Twenty six(45%) had CM, 22 with convulsion; 26(45%) had SA and six(10%) had RD. Some amount of retinopathy was seen in: CM 19(73%), SA 14(54%), RD 3(50.0%), CM with convulsion 15(68%) and CM without convulsion 4(100%). They compared CM to non-CM groups which showed a significant risk relationship between retinal whitening and CM (OR=11.0, CI=2.2- 56.1, p= 0.001). There was

no significant association with papilloedema (OR=0.9, CI=0.3 – 3.0, p=0.9), macular whitening(OR=1.6, CI=0.5 – 4.8, p=0.4), macular haemorrhage(OR=0.28, CI=0.03 – 2.7 p=0.2), retinal haemorrhage(OR=1.9, CI=0.6 – 5.6, p=0.3), vessel abnormality(OR=1.9, CI=0.6 – 6.1, p=0.3) and cotton wool spots(OR not calculated, p=0.08). Tortuous and engorged retinal veins, not previously described as a feature of CM, was the most common vascular abnormality (15/58 = 26%) and was detected even in the absence of papilloedema. They found out that Retinal whitening, a sign suggestive of retinal ischaemia, was significantly more common in CM than in non-CM syndromes. However, the high prevalence of any retinopathy in the latter suggested that the brain and the retina may be suffering from ischaemia in both CM and non-CM.

KNUST

Hay S. I. et al. (1998) predicted malaria seasons in Kenya using multi-temporal meteorological satellite sensor data. The predictions were made using relationships established between long-term data on pediatric severe malaria admissions and simultaneously collected data from the Advanced Very High Resolution Radiometer (AVHRR) on the National Oceanic and Atmospheric Administrations (NOAA) polar-orbiting meteorological satellites and the High Resolution Radiometer (HRR) on the European Organization for the Exploitation of Meteorological Satellites' (EUMETSAT) geostationary Meteosat satellites. The remotely sensed data were processed to provide surrogate information on land surface temperature, reflectance in the middle infra-red, rainfall, and the normalized difference vegetation index (NDVI). They then subjected the variables to temporal Fourier processing and the fitted Fourier data were compared with the mean percentage of total annual malaria admissions recorded in each month. The NDVI in the preceding month correlated most significantly and consistently with malaria presentations across the three sites (mean adjusted $=0.71, range 0.61-0.79). Regression analyses showed that

an NDVI threshold of 0.35-0.40 was required for more than 5% of the annual malaria cases to be presented in a given month. These thresholds were then extrapolated spatially with the temporal Fourier processed NDVI data to define the number of months, in which malaria admissions were expected across Kenya in an average year, at an 8 x 8 km resolution. The resulting maps were compared with the only existing map (Butler's) of malaria transmission periods for Kenya, compiled from expert opinion. Conclusions were drawn on the appropriateness of remote sensing techniques for compiling national strategies for malaria intervention.

KNUST

The impact of permethrin impregnated bed nets on child mortality in Kassena-Nankana district, Upper East region-Ghana, using a randomized controlled trial was investigated by Binka et al. (2007) investigated. A community-based randomized, controlled trial of permethrin impregnated bednets was carried out in a rural area of northern Ghana, between July 1993 and June 1995, to assess the impact on the mortality of young children in an area of intense transmission of malaria and no tradition of bed net use. The district around Navrongo was divided into 96 geographical areas and in 48 randomly selected areas households were provided with permethrin impregnated bed nets which were re-impregnated every 6 months. They used longitudinal demographic surveillance system to record births, deaths and migrations, to evaluate compliance and to measure child mortality. They observed that the use of permethrin impregnated bed nets was associated with 17% reduction in all-cause mortality in children aged 6 months to 4 years (RR=0.83; 95% CI 0.69–1.00; *P*=0.05). Reduction in mortality, according to them, was confined to children aged 2 years or younger, and was greater in July-December, during the wet season and immediately after (RR=0.79; 95% CI 0.63–1.00), a period when malaria mortality was likely to be increased, than in the dry season (RR=0.92, 95% CI 0.73–1.14). They concluded that ready acceptance of bed nets, the high level of compliance in their use and the subsequent impact on

all-cause mortality in their study had important implications for programs to control malaria in sub-Saharan Africa.

Intermittent preventive anti-malarial treatment in infants (IPTi) is currently evaluated as a malaria control strategy. Among the factors influencing the extent of protection that is provided by IPTi are the transmission intensity, seasonality, drug resistance patterns, and the schedule of IPTi administrations. Kobbe et al. (2007) studied malaria incidence and efficacy of IPTi with the aim of determining how far the protective efficacy of IPTi depends on spatio-temporal variations of the prevailing incidence of malaria. One thousand and seventy (1,070) infants were enrolled in a registered controlled trial on the efficacy of IPTi with sulphadoxine-pyrimethamine (SP) in the Ashanti region, Ghana. Stratification for the village of residence and the month of birth of study participants demonstrated that the malaria incidence was dependent on spatial (range of incidence rates in different villages 0.6-2.0 episodes/year) and temporal (range of incidence rates in children of different birth months 0.8-1.2 episodes/year) factors. They observed that the range of spatio-temporal variation allowed ecological analyses of the correlation between malaria incidence rates, anti-Plasmodium falciparum lysate IgG antibody levels and protective efficacies provided by IPTi. Protective efficacy of the first SP administration was positively correlated with malaria incidences in children living in a distinct village or born in a distinct month (R2 0.48, $p<0.04$ and R2 0.63, $p<0.003$, respectively). They noticed corresponding trends after the second and third study drug administration. Accordingly, IgG levels against parasite lysate increased with malaria incidence. This correlation was stronger in children who received IPTi, indicating an effect modification of the intervention. It was found that spatial and temporal variations of malaria incidences in a geographically and meteorologically homogeneous study area exemplify the need for close monitoring of local incidence rates in all types of intervention studies.

Chucks et al. (2007) assessed the patterns, levels, and trends of malaria prevalence among inhabitants in the 12 districts of the region, and examines whether those at risk of malaria have assess to protective measures and have effective treatment for malaria in Volta Region. Their study focused on secondary analysis of data from the Volta Regional bio-statistical office, Ho, the region's capital, supplemented by the 2003 Ghana Demographic and Health Survey. Their results showed that malaria cases are prevalent in the Jasikan, Hohoe, Kpando, Ho and Keta Districts. Districts that lie within the middle and southern belts enjoy two rainy seasons that are conducive to the vector that causes malaria. Overwhelming majority of the in-patients (41.5%) are children aged 0 – 4 years, while the number of the in-patient cases generally decreases with advancing age. The majority of children who had fever in the last two weeks (34.8%) were aged 12 – 23 months, followed by 34.4% for age group 0 – 11 months. The highest malaria cases in the region are from the Hohoe district (24.2%) in year 2003, followed by Ho 20.1% in 2000 and 2002, and Keta (17.2%) also in 2003. The least recorded was the North Tongu with 0.9% for 2 different years (2000 and 2002). It was anticipated that with a considerable reduction in poverty levels, households and communities would become increasingly responsible for the improvement of their health status and quality of life.

KNUST

CHAPTER THREE

METHODOLOGY

3.1 Introduction

This Chapter deals with the method of data collection and how the data is organized for application logistic regression analysis. It also contains detailed discussion of the main statistical techniques and a review of the basic methods used for the analysis of the data.

KNUST

3.2 Data Collection

The data used in this study were obtained as secondary data from inpatient morbidity and mortality returns register at Tamale Teaching Hospital, from 1st January 2000 to 31st December 2010. Tamale Teaching Hospital, with about 380 patient beds is the largest facility in the metropolis which serves both as the first consultation point for patients within its catchment, and as a referral centre for other 15 primary health centers. These facilities are managed by the Ministry of Health and the Ghana Health Service with support from other some partners (Gunu, 2009).

For this study, cases with primary diagnosis as malaria, from the hospital wards, were used. Each case was clinically assessed and definitively confirmed as malaria on admission. The registers included patients' age, sex, date of admission and discharge, outcome (i.e. death, discharged home, or absconded), village or location of residence, cost (i.e. for treatment), referral status and treatment given.

3.2.1 Organization of Data

From the data, the following variables were derived: *outcome* (dead = 1 and alive = 0); *season* of the year when admitted (1 = wet season from April to October, 0 = dry season from November to March); *treatment* given (1 = artesunate amodiaquine, 0 = quinine); *distance* to the hospital (1 = distance > 5 km, 0 = distance ≤ 5 km). The distance of 5 km was chosen to reflect travel time of 1 hour. Also, length of hospital stay was derived. In addition, the variable *referral* was defined, with children who used the hospital as a first point of consultation given a code 0 and those referred to the hospital from peripheral health facilities in the metropolis given the code 1.

KNUST

Recall that in multiple linear regression, the basic activity is to draw the least square line around which the values of Y (the outcome variable) are distributed. In contrast to that, in logistic regression we are trying to estimate the *probability* that a given individual will fall into either dead (i.e mortality which is the event of interest) or alive. The probability helps to interpret the coefficients in the logistic regression model in a meaningful manner, in the same way as we attach meaning to the coefficients in linear regression.

As a measure of the probability we ask about the odds of an event occurring. If P is the probability of a given dead, then (1 − P) is the probability of the alive occurring.

Since this study considered several predictors in deciding the eventual outcome (dead or alive), we calculated the odds ratio for each one separately. The joint effect of all the predictors (independent variables) put together would be expressed mathematically by

$$Odds = P \Big/ (1-P) = e^{\alpha+\beta_1 x_1+\beta_2 x_2+\ldots+\beta_p x_p}$$

The independent contribution of each of the covariates (i.e. x_1, x_2 … x_p) in the above expression to the overall odds ratio was determined by taking the logarithms of both sides of the equation.

In this study, the logistic regression parameters were estimated such that the coefficients make our observed results most likely. The method is called the *maximum likelihood* method. What does it all mean? Suppose in the above equation the two possible values of the outcome variable are dead and alive, (dead = 1). Then α represents the overall malaria mortality risk, while β_1 is the fraction by which the risk is increased (or decreased) by every unit change in x_1; β_2 is the fraction by which the malaria mortality risk is altered by a unit change in x_2, and so on.

KNUST

Meanwhile, since children were used for the study, it is important to note that by definition a child is a person with the ages between 0 – 14 years.

The data obtained from the hospital register were analyzed using the Statistical Package for Service Solution (SPSS).

3.3 Logistic Regression

This section introduces logistic regression, which is a method for modeling the dependence of a binary response variable on one or more explanatory variables. It therefore allows one to predict a discrete outcome, such as group membership, from a set of variables that may be continuous, discrete, dichotomous, or a mix of any of these. For the purpose of this study, both continuous and categorical explanatory variables were considered.

Logistic regression is a specialized form of regression that is formulated to predict and explain a binary (two-group) categorical variable rather than a metric dependent measure. The form of the

logistic regression variate is similar to the variate in multiple regression. The variate represents a single multivariate relationship, with regression-like coefficients indicating the relative impact of each predictor variable. It also can accommodate non-metric variables through dummy-variable coding, just as regression can.

Logistic regression is limited, however, to prediction of only a two-group dependent measure. Logistic regression has widespread application in situations in which the primary objective is to identify the group to which an object (e.g., person, firm, or product) belongs. Potential applications include predicting anything where the outcome is binary (e.g., Dead/Alive or Yes/No). Such situations include the death or otherwise of administered malaria patient, the success or failure of a new product, deciding whether a person should be granted credit, or predicting whether a firm will be successful. In each instance, the objects fall into one of two groups, and the objective is to predict and explain the bases for each object's group membership through a set of independent variables selected by the researcher.

Logistic regression provides a method for modeling a binary response variable, which takes values 1 and 0. For example, we may wish to investigate how dead (coded 1) or alive (coded 0) of administered malaria patients can be predicted by certain factors. As an illustrative example, consider a sample of 2293 patients whose status (dead or alive) was known. We can predict the magnitude of effect each factor has on the administered malaria patient.

There are two types of logistic regression. **Binary logistic regression** is similar to linear regression except that it is used when the dependent variable is dichotomous. **Multinomial logistic regression** is used when the dependent/outcome variable has more than two categories, but that is complex and less common, so we will not discuss it here.

However, discriminant analysis is also used to predict group membership with only two groups. Discriminant analysis can only be used with continuous independent variables. Thus, in instances where the independent variables are a categorical, or a mix of continuous and categorical, logistic regression is preferred. It does have the advantage, however, of easily incorporating non-metric variables as independent variables, much like in multiple regression.

In a practical sense, logistic regression may be preferred because it does not rely on some of the assumptions on which multiple regression and discriminant analysis are based. Thus, logistic regression is much more robust when these assumptions are not met, making its application appropriate in many situations. It has straightforward statistical tests, similar approaches to incorporating metric and non-metric variables and nonlinear effects, and a wide range of diagnostics. Thus, for these and more technical reasons, logistic regression may be more suitable in many situations.

KNUST

3.3.1 Assumptions of Logistic Regression

There are fewer assumptions for logistic regression than for multiple regression and discriminant analysis, which is one reason this technique has become popular, especially in health related fields.

Binary logistic regression assumes that the dependent or outcome variable is dichotomous and, like most other statistics, that the outcomes are independent and mutually exclusive; that is, a single case can only be represented once and must be in one group or the other. Finally, logistic regression requires large samples to be accurate: Some say there should be a minimum of 20 cases per predictor, with a minimum of 60 total cases. These requirements need to be satisfied

prior to doing statistical analysis. As with multiple regression, multicollinearity is a potential source of confusing or misleading results and needs to be assessed.

3.3.2 The Decision Process for Logistic Regression

As noted in Hair Jr et al (2010), the application of logistic regression can be viewed from a six-stage model-building perspective. As with all multivariate applications, setting the objectives is the first step in the analysis. Then the researcher must address specific design issues and make sure the underlying assumptions are met. The binary measure is translated into the odds of occurrence and then a logit value that acts as the dependent measure. The model formed in terms of the independent variables is almost identical to multiple regression. Model fit is assessed by first looking for statistical significance of the overall model and then determining predictive accuracy by developing a classification matrix. Then, given the unique nature of the transformed dependent variable, logistic coefficients are given in their "original" scale, which is in logarithmic terms, and a transformed scale, which is interpreted more like regression coefficients.

Each form of the coefficient details a certain characteristic of the independent variable's impact. Finally, the logistic regression model should be validated with a holdout sample.

3.3.3 The logistic function

To explain the logistic regression, we show here the logistic function, which describes the mathematical form on which the logistic model is based. Let the function be called $f(z)$, is given by

$$f(z) = \frac{1}{1+e^{-z}} \qquad \text{---------- (3.1)}$$

When the values of this function are plotted, z varies from $-\infty$ to $+\infty$ and its shape is given figure 3.1

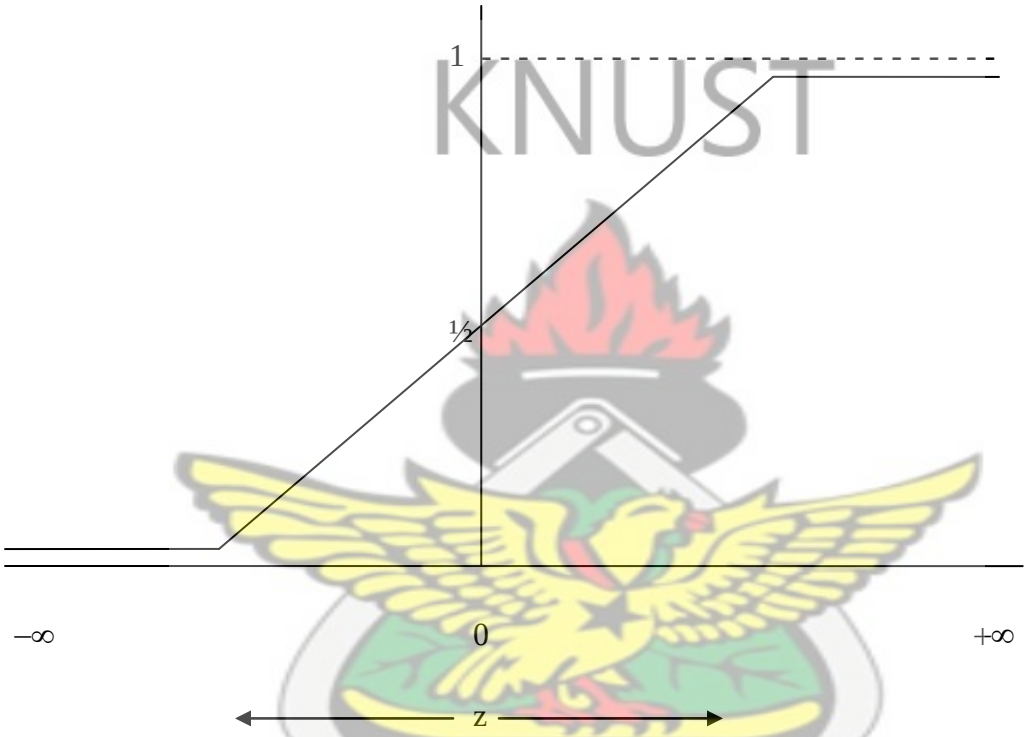

Figure 3.1 Shape of logistic function

From the graph, the range of *f* (z) is between 0 and 1, irrespective of the value of *z*. The model is designed to describe a probability, which is always some number between 0 and 1. Another characteristic of the logistic model is derived from the shape of the logistic function, which is an elongated S shape. As shown in Fig. 3.1, if we begin at $z = -\infty$ and move to the right, then as *z* increases, the value of ***f* (*z*)** hovers close to zero for a while, then starts to increase dramatically toward 1, and finally levels off around 1 as *z* increases toward $z = +\infty$.

3.3.4 The Logistic Model

The response variable in logistic regression is usually dichotomous, that is, the response variable can take the value 1 with a probability of success p, or the value 0 with probability of failure 1-p. This type of variable is called a Bernoulli (or binary) variable.

As mentioned previously, the independent or predictor variables in logistic regression can take any form. That is, logistic regression makes no assumption about the distribution of the independent variables. They do not have to be normally distributed, linearly related or of equal variance within each group. The relationship between the predictor and response variables is not a linear function in logistic regression, instead, the logistic regression function is used, which is the logit transformation of p:

KNUST

To obtain the logistic model from the logistic function, we write z as the linear sum

$$z = \alpha + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k \quad \text{---------- (3.2)}$$

Where the x's are independent variables of interest and α and the β_i's are constant terms representing unknown parameters.

Substituting equation 3.1 into 3.2 we obtain

$$f(z) = \frac{1}{1 + e^{-(\alpha + \sum \beta_i x_i)}}$$

For notational convenience, we will denote the probability statement as simply p(x) where x is a notation for the collection of variables x_1 through x_k.

Thus, the logistic model may be written as

$$p(x) = \frac{1}{1+e^{-(\alpha+\sum \beta_i x_i)}}$$

However, since the above logistic model is non-linear, the logit transformation would be used to make it linear, this is given by

$$Logit\ p(x) = In_e\left[\frac{p(x)}{1-p(x)}\right] \text{ ---------- (3.3)}$$

KNUST

Where $p(x) = \frac{1}{1+e^{-(\alpha+\sum \beta_i x_i)}}$ ---------- (3.4)

This transformation allows us to compute a number, called logit p(x), for an individual with independent variables given by x.

By substituting Equation 3.4 into Equation 3.3, we obtain

$$In_e\left[\frac{p(x)}{1-p(x)}\right] = In_e\left[\frac{\frac{1}{1+e^{-(\alpha+\sum \beta_i x_i)}}}{\frac{e^{-(\alpha+\sum \beta_i x_i)}}{1+e^{-(\alpha+\sum \beta_i x_i)}}}\right]$$

$$= In_e\left[e^{(\alpha+\sum \beta_i x_i)}\right]$$

$$= \alpha + \sum \beta_i x_i$$

$$Logit\ p(x) = \alpha + \sum \beta_i x_i$$

$$\therefore \quad Logit\ p(x) = \alpha + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_k x_k$$

Thus, the logit of p(x) simplifies to the linear sum.

The quantity p(x) divided by 1-p(x), whose log value gives the logit, describes the odds for a malaria patient being dead, with independent variables specified by x.

$$\frac{p(x)}{1-p(x)} = \text{ odds for individual x}$$

The goal of logistic regression is to correctly predict the category of outcome for individual cases using the most parsimonious model. To this end, a model is created that includes all predictor variables that are useful in predicting the response variable (Kleinbaum and Klein, 1994).

3.3.5 Logistic regression with a single variable

The logistic or logit function is used to transform an 'S'-shaped curve into an approximately straight line and to change the range of the proportion from 0–1 to -∞ to +∞.

The logit function is defined as the natural logarithm (ln) of the odds of an event. That is,

$$\log it = In\left(\frac{p}{1-p}\right)$$

Where p is the probability of an event.

$$\log it(p) = \alpha + \beta x$$

Although this model looks similar to a simple linear regression model, the underlying distribution is binomial and the parameters α and β cannot be estimated in exactly the same way as for simple linear regression. Instead, the parameters are usually estimated using the method of maximum likelihood, which is discussed below.

3.3.6 Logistic regression with several explanatory variables

We may wish to investigate how dead or alive of patients can be predicted by more than one explanatory variable. Like ordinary regression, logistic regression can be extended to incorporate more than one explanatory variable, which may be either quantitative or qualitative. For example, given that administered malaria patients at risk for death are influenced by predictors such as referral, distance, treatment type and length of stay. Two of these predictors are

categorical; these are referral and treatment type. Now, supposed that the results of our model fitting yielded the estimated parameters for the predictors as follows $\hat{\alpha} = -3.192$, $\hat{\beta}_1 = 02.741$, $\hat{\beta}_2 = 01.947$, $\hat{\beta}_3 = -0.898$ and $\hat{\beta}_4 = -0.102$

The logistic regression model can then be written as follows:

$$\log it\left(P(y=1)\right) = -3.192 + 2.741\text{Referral status} + 1.947\text{Distance} - 0.898\text{Treatment} - 0.102\text{Length}$$

where p is the probability of dead.

KNUST

The method of including variables in the model can be carried out in a stepwise manner going forward or backward, testing for the significance of inclusion or elimination of the variable at each stage. The tests are based on the change in likelihood resulting from including or excluding the variable or using the p-value or other test statistic.

3.3.7 Binomial distribution

The binomial distribution is a method sometimes used to compute the probability of an event under the logistic regression theoretically. When the response variable is binary (e.g. dead or alive), then the probability distribution of the number of deaths in a sample of a particular size, for given values of the explanatory variables, is usually assumed to be binomial. The probability that the number of deaths in a sample of size n is exactly equal to a value r is given by ${}_nC_r p^r (1 - p)^{n - r}$, where ${}_nC_r = n!/(r!(n - r)!)$ is the number of ways r individuals can be chosen from n and p is the probability of an individual dying. (The probability of survival is 1 - p.)

For example, using the probability that seven deaths occurred out of 182 patients is given by ${}_{182}C_7\, p^7\, (1 - p)^{175}$. If the probability of death is assumed to be 0.04, then the probability that seven

deaths occurred is ${}_{182}C_7 \times 0.04^7 \times 0.86^{175} = 0.152$. This probability, calculated on the assumption of a binomial distribution with parameter p = 0.04, is called a likelihood.

3.4 Maximum likelihood estimation

Maximum likelihood estimation involves finding the value(s) of the parameter(s) that give rise to the maximum likelihood. The method of maximum likelihood chooses that estimator of the set of unknown parameters θ which maximizes the likelihood function L(θ). The estimator is denoted as θ and its components are $\theta_1, \theta_2, \ldots, \theta_q$.

The standard approach for maximizing an expression like the likelihood function for the binomial example here is to use calculus by setting the derivative

$$\frac{dL}{dp} = 0$$

and solving for the unknown parameter or parameters.

In general, maximizing the likelihood function L(θ) is equivalent to maximizing In L(θ) which is computationally easier. That is by solving

$$\frac{\delta InL(\theta)}{\delta \theta_j} = 0, \quad j = 1, 2, \ldots, q$$

In more complicated situations, iterative techniques are required to find the maximum likelihood and the associated parameter values, and a computer package is required.

3.5 Assessment of the fitted model

After estimating the coefficients, there are several steps involved in assessing the appropriateness, adequacy and usefulness of the model. First, the importance of each of the

explanatory variables is assessed by carrying out statistical tests of the significance of the coefficients. The overall goodness of fit of the model is then tested. Additionally, the ability of the model to discriminate between the two groups defined by the response variable is evaluated. Finally, if possible, the model is validated by checking the goodness of fit and discrimination on a different set of data from that which was used to develop the model.

KNUST

3.6 Tests and confidence intervals for the parameters

3.6.1 The Wald statistic

A Wald test is used to test the statistical significance of each coefficient in the model. A Wald test calculates a *Z* statistic, which is:

$$z = \frac{\hat{\beta}}{SE}$$

This z value is then squared, yielding a Wald statistic with a Chi-square distribution as follows.

$$z^2 = \chi^2 = \left(\frac{\hat{\beta}}{SE}\right)^2$$

However, several authors have identified problems with the use of the Wald statistic. Menard (1995) warns that for large coefficients, standard error is inflated, lowering the Wald statistic (chi-square) value. Agresti (1996) states that the likelihood-ratio test is more reliable for small sample sizes than the Wald test.

Each Wald statistic is compared with a χ^2 distribution with 1 degree of freedom. Wald statistics are easy to calculate but their reliability is questionable, particularly for small samples. For data that produce large estimates of the coefficient, the standard error is often inflated, resulting in a lower Wald statistic, and therefore the explanatory variable may be incorrectly assumed to be unimportant in the model. Likelihood ratio tests are generally considered to be superior.

The constant has no simple practical interpretation but is generally retained in the model irrespective of its significance.

KNUST

Now, let us consider interval estimation when there is only one regression coefficient of interest. The procedure typically used is to obtain a large sample confidence interval for the parameter by computing the estimate of the parameter plus or minus a percentage point of the normal distribution times the estimated standard error.

$100(1-\alpha)\%$ CI for β_i:

$\hat{\beta}_i \pm Z_{1-\frac{\alpha}{2}} \times s_{\hat{\beta}_i}$ where $\hat{\beta}_i$ and $s_{\hat{\beta}_i}$ are obtained from printout and Z from N(0,1) tables.

CI for Odds Ratio: exp (CI for $\hat{\beta}_i$)

Thus, if we consider Model, and if X_i denotes a (0, 1) exposure variable of interest then a 95% confidence interval for the adjusted odds ratio is given by

$$\exp\left(\hat{\beta}_i \pm 1.96 \times s_{\hat{\beta}_i}\right)$$

3.6.2 Likelihood-Ratio Test

The likelihood ratio test for a particular parameter compares the likelihood of obtaining the data when the parameter is zero (L_0) with the likelihood (L_1) of obtaining the data evaluated at the Maximum Likelihood Estimate (MLE) of the parameter. The test statistic is calculated as follows.

$-2 \times \ln(\text{likelihood ratio}) = -2 \times \ln(L_0/L_1) = -2 \times (\ln L_0 - \ln L_1)$

It is compared with a χ^2 distribution with 1 degree of freedom.

KNUST

3.6.3 Goodness of fit of the model

The goodness of fit or calibration of a model measures how well the model describes the response variable. Assessing goodness of fit involves investigating how close values predicted by the model are to the observed values.

When there is only one explanatory variable, as for the example data, it is possible to examine the goodness of fit of the model by grouping the explanatory variable into categories and comparing the observed and expected counts in the categories.

The observed and the expected numbers of deaths can be compared using a χ^2 goodness of fit test, providing the expected number in any category is not less than 5. The null hypothesis for the test is that the numbers of deaths follow the logistic regression model. The χ^2 test statistic is given by

$$\chi^2 = \sum \frac{(observed - \exp ected)^2}{\exp ected}$$

The test statistic is compared with a χ^2 distribution where the degrees of freedom are equal to the number of categories minus the number of parameters in the logistic regression model. For

example, suppose the χ^2 statistic is 2.68 with 9 - 2 = 7 degrees of freedom, giving $P = 0.91$, suggests that the numbers of deaths are not significantly different from those predicted by the model.

3.6.4 The Hosmer-Lemshow Test

The Hosmer–Lemeshow test is a commonly used test for assessing the goodness of fit of a model and allows for any number of explanatory variables, which may be continuous or categorical. The test is similar to a χ^2 goodness of fit test and has the advantage of partitioning the observations into 10 ordered groups of subjects groups of approximately equal size, and therefore there are less likely to be groups with very low observed and expected frequencies. The observations are grouped into deciles based on the predicted probabilities. The test statistic is calculated, based on the data used for this study, using the observed and expected counts for both the dead and alive, and has an approximate χ^2 distribution with 8 (=10 - 2) degrees of freedom. The Hosmer–Lemeshow test (example $P = 0.167$) indicates that the numbers of deaths due to malaria are not significantly different from those predicted by the model and that the overall model fit is good.

Further checks can be carried out on the fit for individual observations by inspection of various types of residuals (differences between observed and fitted values). These can identify whether any observations are outliers or have a strong influence on the fitted model. For further details see, for example, Hosmer and Lemeshow (2000).

KNUST

CHAPTER FOUR

ANALYSIS, RESULTS AND DISCUSSION

4.1 Introduction

This Chapter, first of all, involves the exploration of the data for important features using summary statistics and histograms. The logistic model would be used to determine the factors influencing malaria in-hospital mortality among children at the Tamale Teaching hospital. Also, we would examine the significance of the coefficients of the predictors in the model. Further, we would determine whether or not the type of treatment depends on the age of children.

4.2 Analysis of Data and Results

4.2.1 Descriptive Analysis of Data

It was observed that out of 2293 number of administered malaria patients about 111 (4.8%) were dead. Thus, there were more children alive compared to those who were dead.

Moreover, about 2157 (94.1%) children called at the Tamale Teaching Hospital as their first consultation point where as 136 (5.9%) children were referred from other peripheral health facilities in and around the metropolis. Refer to graphical representation in appendix B.

It was noticed that there were 946 (41.3%) of female children as against 1347 (58.7) of their male counterparts. This shows that there were about 401 (17.4%) more male children than female children on admission. See bar graph representation in appendix B.

Again, it was seen that, about 1306 (57%) of children were on admission during the dry season whilst about 987 (43%) of children were on admission during the wet season. This shows that about 319 (14%) more children were admitted in dry season than wet season. See appendix B.

Further, it was observed that, about 1784 (77.8%) of children were residing at homes which are less than 5km to the Tamale Teaching hospital where as about 509 (22.2%) of children were living at homes which are greater or equal to 5km to the Tamale Teaching hospital. See bar graph representation in appendix B.

KNUST

Also, out of 2293 administered malaria cases 775 (33.8%) of them were treated with Artesunate ammodiaquine whilst 1518 (66.2%) were treated with Quinnine. This indicates that about 743 (32.4%) children more took Quinnine than Artesunate ammodiaquine. See appendix B for bar graph representation.

From Table 4.1 below, it shows that the mean age of the children was 3.69 years with about half (50%) of the children having ages below or equal to 3 years and about half (50%) of the children having their ages above or equal to 3 years. The age which was most common among the children was 2 years.

Table 4.1 Age Distribution of Patients

	Age
Mean	3.69
Median	3.00
Mode	2
Skewness	1.181
Std. Error of Skewness	0.051

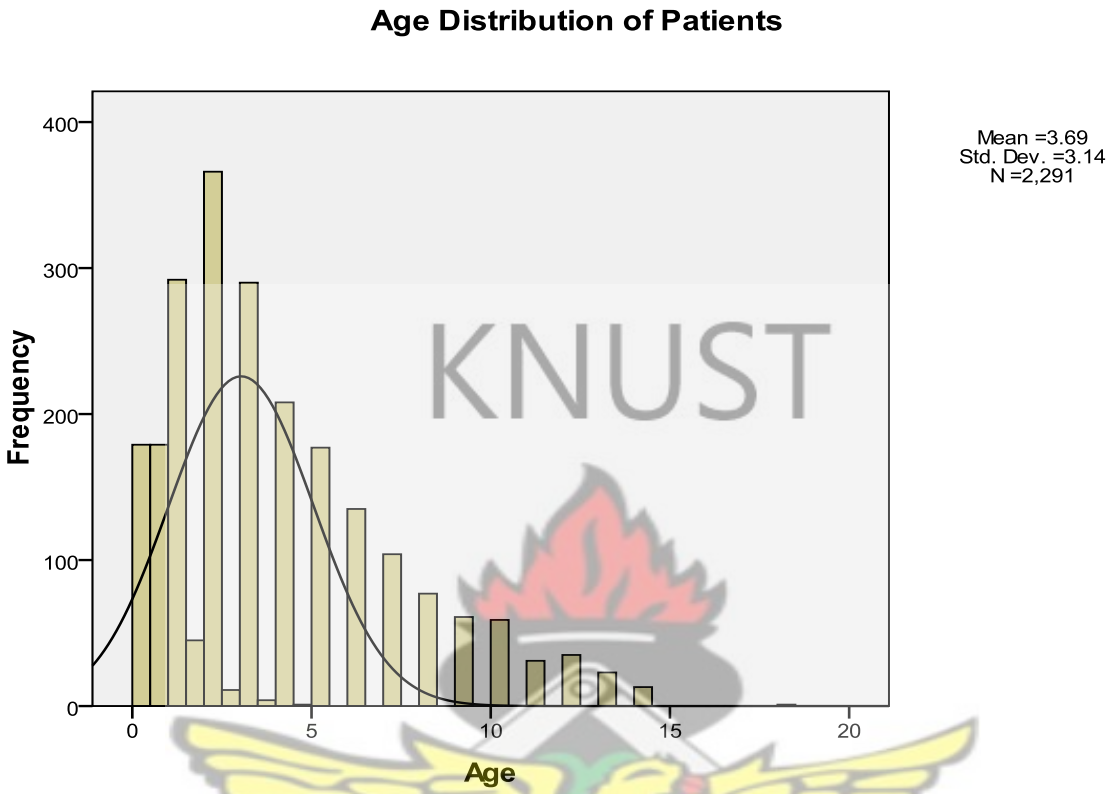

Fig. 4.1 The age distribution of administered malaria patients

Further, the age distribution of the children administered of malaria was about 1.181 positively skewed with standard error of 0.051. Again, Fig. 4.1 shows that about 50% of the children were aged from 0-5 years with the remaining 50% further divided into about 25% each for children from 6-10 years and 11-14 years.

It can be observed from Table 4.2 below that, the mean length of stay on admission of the children was 4.79 days with about half (50%) of the children having length of stay below or equal to 3 days and about half (50%) of the children having length of stay above or equal to 3 days. The most common length of stay on admission among the children was 3 days.

Table 4.2 Length of Stay on Admission

	Length of Stay on Admission
Mean	4.79
Median	3.00
Mode	3
Skewness	6.394
Std. Error of Skewness	0.051

KNUST

Further, the distribution of the length of stay on admission by children administered as malaria patients was about 6.394 positively skewed with an error of 0.051. It also indicates from Fig.4.2 that majority of days spent by were from 1-20 days on admission.

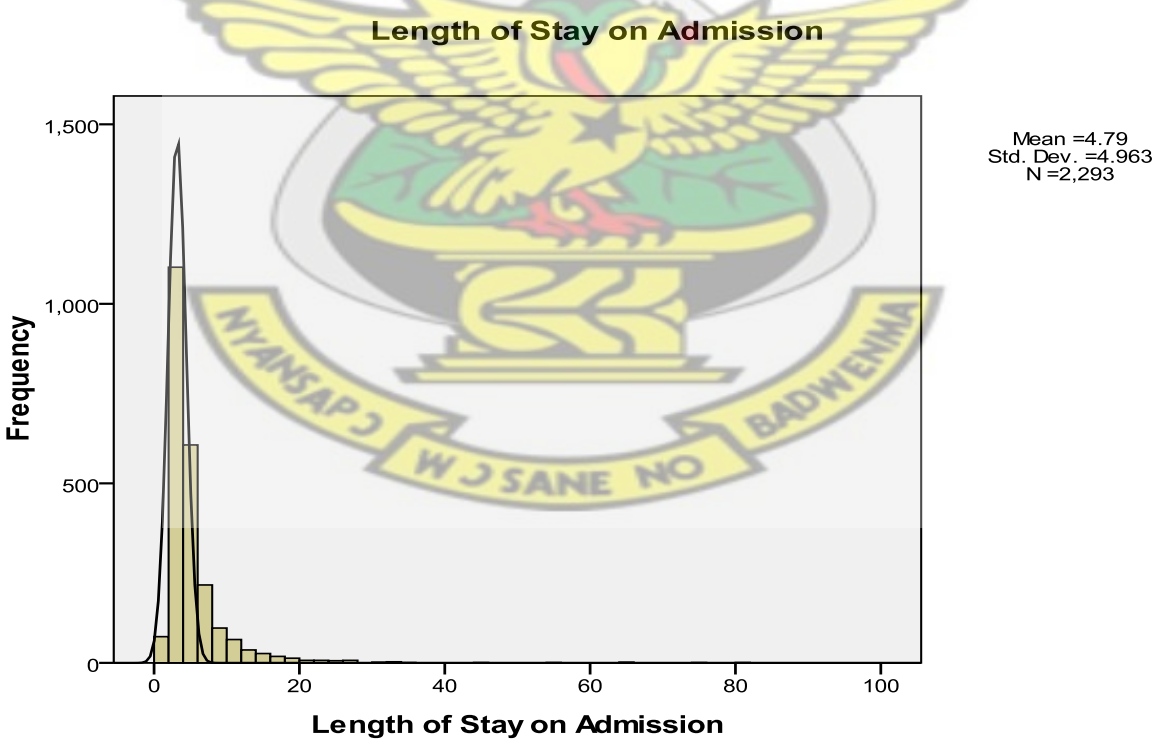

Fig. 4.2 Length of stay on admission of administered malaria patients

4.2.2 Inferential Analysis of Data

From Table 4.3, it can be seen that the Variance Inflation Factor (VIF) for each of the independent variables referral status, age, sex, season, length, distance and treatment type were each less than the reference value 10. This means that there is no interaction between the independent variables. Thus, all the independent variables are fit to be used for the modeling of malaria in-hospital mortality at the Tamale Teaching hospital from 2000-2010.

KNUST

Table 4.3 Collinearity Diagnostic Test

Model	Collinearity Statistics	
	Tolerance	VIF
Referral Status of Patient	0.859	1.164
Age	0.983	1.018
Sex of Patient	0.997	1.003
Season Of Admission	0.964	1.037
Length of Stay on Admission	0.987	1.014
Distance to Hospital	0.848	1.179
Treatment Type Given to Patient	0.975	1.026

The decision on which logit coefficient is significant to the model, is one of the challenges faced in logistic regression model building. This decision is arrived at by using the either the Wald test or the log likelihood (-2logL) or by comparing the p–value with the significance level (5%). Significance is established if p–value ≤ 0.05. The significance level used for the purpose of analysis was $\alpha = 0.05$.

From Table 4.4 below, the logistic model was obtained as follows

$$\log it\left(P(y=1)\right) = -3.192 + 2.741\text{Referral status} + 1.947\text{Distance} - 0.898\text{Treatment} - 0.102\text{Length} \quad (4.1)$$

Explanation of variables in the model:

It can be noted from Table 4.4 that, the predictors referral status, length of stay, distance and treatment type with the significance values 0.000, 0.003, 0.000 and 0.000 respectively are each less than $\alpha = 0.05$. Therefore we reject the null hypothesis (H_0) and conclude that there is enough evidence to show that these variables (predictors) are each not equal to zero at 95% confidence interval. This means that these predictors are each important to be included in the final model 4.1. Against this backdrop, therefore, there is enough basis to conclude that these predictors are relevant predictors in predicting malaria in – hospital mortality at the Tamale Teaching hospital from 2000 – 2010.

Interpretation of the Odds ratios:

As in Table 4.4, the strongest predictor of the outcome of malaria administered patient was referral status, recording an odds ratio of 15.506 (95 % C.I. = 9.290 – 25.883). This indicated that administered patients who had been referred were over 15 times as likely to estimate the success (mortality) of malaria as those who were not referred, controlling for all other factors in the model. The odds ratio 0.407 (95% C.I. = 0.254 – 0.652) for treatment was less than 1, indicating that for every treatment per patient, there were more malaria mortality due to quinine, controlling for other factors in the model.

Again, the odds ratio with respect to distance was 7.010 (95% C.I. = 4.092 – 12.006) meaning that more of the malaria mortality was estimated by distances greater than or equal to 5km compared to distances which are less than 5km, holding other factors constant.

Explanation of variables not in the model:

From the below Table 4.4, it is revealing to note that, the predictor's age, sex and season were dropped from the model. Since the p – values 0.183, 0.069 and 0.673 were each greater than $\alpha = 0.05$, we fail to reject the null hypothesis and conclude that there is sufficient evidence to indicate that each of the predictors age, sex and season are each equal to zero. This shows that these predictors were not important to be included in the model. Hence the predictors age, sex and season were not relevant in predicting malaria in – hospital mortality at the Tamale Teaching hospital from 2000 – 2010.

Table 4.4 Logistic Regression Predicting Likelihood of Malaria Mortality

	B	S.E.	Wald	P-value	Odds Ratio	95% C.I. for Odds Ratio	
						Lower	Upper
Referral Status	2.741	0.261	109.965	0.000	15.506	9.290	25.883
Age	-0.051	0.038	1.772	0.183	0.950	0.881	1.024
Sex	-0.427	0.235	3.297	0.069	0.652	0.411	1.034
Season	0.101	0.239	.178	0.673	1.106	0.693	1.766
Length	-0.102	0.035	8.652	0.003	0.903	0.844	0.967
Distance	1.947	0.275	50.304	0.000	7.010	4.092	12.006
Treatment	-0.898	0.240	13.989	0.000	0.407	0.254	0.652
Constant	-3.192	0.348	84.263	0.000	0.041		

H_0: The hypothesized model fits the data

H_1: The hypothesized model does not fit the data

From Table 4.5, since the p – value, 0.167, is greater than the significance level, α = 0.05, we fail to reject the null hypothesis (H_0) and conclude that there is enough evidence to show that the hypothesized model fits the data set used in predicting malaria in-hospital mortality. Hence, this indicates that the numbers of deaths due to malaria are not significantly different from those predicted by the model and that the overall model fit is good.

KNUST

Table 4.5 Assessing Model Fit by Hosmer and Lemeshow Test

Chi-square	df	P-value
11.662	8	0.167

It is worth noting from Table 4.6 that, between 13.1% and 40.8% of the variance in predicting whether or not administered malaria patient would be dead was explained by the predictors; referral status, distance, treatment and length of stay. Meanwhile, it can be seen that, the Nagelkerke R-Square (also known as Pseudo R-square) was 27.7% more than the Cox & Snell R-Square value.

Table 4.6 Model Summary

-2 Log likelihood	Cox & Snell R-Square	Nagelkerke R-Square
566.036	0.131	0.408

However, it was shown from the classification table (see appendix B) that, about 98.9% could be predicted alive whilst about 35.1% can be predicted dead. It is worth noting that, overall, about 95.8% of the cases were correctly classified.

The null and the alternative hypothesis for assessing the dependence or otherwise of treatment type on child's age are given by

KNUST

H_0: Treatment type of administered malaria patient is independent of the age of the child

H_1: Treatment type of administered malaria patient is dependent on the age of the child

From Table 4.7 below, since the p-value = 0.465 is greater than the significance level, $\alpha = 0.05$, we fail to reject the null hypothesis (H_0) and conclude that there is sufficient evidence to show that treatment type of administered malaria patients is independent of the child's age at 95% confidence level.

Table 4.7 Chi-Square Test on the Dependence of Treatment Type on Child's Age

	Value	Df	P-value
Pearson Chi-Square	83.050	1	0. 465
Likelihood Ratio	93.473	1	0. 466
Linear-by-Linear Association	8.546	1	0. 465
N of Valid Cases	2293		

4.3 Discussion

This study provides evidence of the predictors which influence in-hospital malaria mortality among children, between 0 – 14 years, at Tamale Teaching hospital in the northern region of Ghana. In-hospital deaths of about 35.1% were correctly predicted in the model when the relevant factors were added to predict mortality. The model indicates that distance contributes more, among other factors, in terms of influencing malaria in-hospital deaths. Distant villages or areas with ill resourced health centers or none at all suggest problems of access to health care, which does translate into high mortality rate in. Thus the further the village is from the health centre, the more disadvantaged the households are in terms of getting early health care. The study showed that patients within 5 km of hospital were less likely to die in hospital than those beyond 5 km, and does reflect the fact that nearness to the hospital improved early access to care, thus reduced the risk of in-hospital mortality.

It was also observed that referral children were at higher chance of dying in hospital, even after adjusting for distance. This seems to suggest that delayed effective treatment (in the process of being transferred to the Tamale Teaching hospital) increased the severity of the disease. This could be because most referring health facilities may often be faced with stock-out of effective drugs or may not have prompt access to ambulatory support when needed. This also suggests inadequate care being available at primary facilities, regardless of whether they are distant from the hospital or not. It is also possible that referring hospitals are referring the more severe cases which are expected to have a higher case facility rate. Further research is warranted to investigate the timing and availability of pre-referral drugs, and other health facility characteristics that may lead to delayed referral, and suggest ways of improving the referral system in the metropolis.

This challenge is similar to other districts and metropolis in the country and more familiar in most sub-Saharan countries as indicated by Kreuels et al. (2008) and Alles et al. (1998).

With regard to the length of hospital stay, it was found that the in-hospital malaria deaths were significantly associated with the length of hospital stay. This suggests that the sickest patients had a short length of stay terminating in death, with highest chance of dying in hospital the same day of admission. The high case fatality when distance was added to the model could be attributed to severe or complicated cases. However, as days of stay increased the risk diminished. This suggests that by and large the care that is provided in the hospital is effective and saves lives.

Although, there is the perception that malaria transmission is more intense in the wet season than the dry season, yet the study showed that there were 1306 (57%) cases in dry season and 987 (43%) cases in wet season. Thus, on the contrary, the results further indicated that the risk was lower in the wet season than the dry season. Season, surprisingly, was not even relevant predictor in the model. The three predictor's age, sex and season were excluded from the model 4.1, which suggest that they do not contribute to predicting deaths, though it was shown in Malawi that age and sex were predictors of malaria mortality. However, the findings showed that the remaining four factors (Table 4.6) affected in-hospital malaria mortality among children. This study provides evidence that mortality for malaria among children, in and around, Tamale metropolis could be describe as high.

These analyses depended on data collected from routine hospital registers. One major shortcoming of using such data is that they only represent those patients who visited the Tamale Teaching hospital. As demonstrated in other studies, and elsewhere in Africa for example in

Tanzania by Carneiro et al. (2006), most malaria treatments occur outside the formal curative care, and only do so if the illness is perceived to be near fatal. Hence, the true metropolitan in-hospital malaria mortality may be distorted and underestimated compared to similar tropical setting like Zomba district in Malawi by Kazembe et al. (2006).

KNUST

CHAPTER FIVE

FINDINGS, CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

Malaria is a complex problem that demands mobilization in all areas of public policy in order to facilitate appropriate decision-making towards the creation of malaria-free communities. It is in this vein that this thesis, with the main objective of applying logistic regression modeling framework to analyze predictors which affect in-hospital mortality among children at Tamale Teaching hospital. More specifically, the study sort to; analyze the coefficients of the model and determine whether type of treatment depends on individual's (child's) age.

5.2 Findings

The findings of this study include the following

- Many more children used the Tamale Teaching hospital as their first call for consultation.
- Most of the children were aged between 0 – 5 years and just few were above 10 years.
- The predictors referral status, distance to hospital, treatment type and length of stay were found to influence or affect malaria in-hospital mortality. The predictor's age, sex and season were not significant.
- Treatment type was found to be independent of child's age.

5.3 Conclusions

The findings of this thesis indicates there is a linear relationship between malaria mortality (dead) and predictors such as referral status, distance, treatment type and length of stay of children administered as malaria patients at the Tamale Teaching hospital between 2000 – 2010.

The overall logistic model obtained was

$$\log it\left(P(y=1)\right) = -3.192 + 2.741\text{Referral status} + 1.947\text{Distance} - 0.898\text{Treatment} - 0.102\text{Length}$$

Again, from the test of the significance of the coefficients of the predictors, the study found that the predictors; age, sex and season were not good predictors of malaria in-hospital mortality. However, the covariates; referral status, distance, treatment type and length of stay were relevant in predicting in-hospital malaria mortality. Therefore the predictors which actually influence malaria in-hospital mortality among children at the Tamale Teaching hospital were referral status, distance, treatment type and length of stay.

Also, it was found that there is sufficient evidence to show that treatment type of administered malaria patient was independent of the child's age.

5.4 Recommendations

- The Ministry of Health (MOH) could develop a strategic plan to build poly-clinics in every district capital and cheap-compound health facilities, at least in every community. This could help curb the long distance villagers staying around the metropolis have to travel to access health care.

- Other stake holders, such as the World Health Organization (WHO), should as a matter of urgency step up campaign to discourage, if not ban entirely, the use of quinine in treating malaria. Since this move would help WHO in their fight to reduce malaria mortality.
- The government should expand ambulance services as well as improve more assessable roads in and around the Tamale metropolis to facilitate timely transportation of referral cases.
- Ghana Health Service should improve case management at primary facilities by ensuring adequate stocks of anti-malarial drugs and encourage the use of artesunate ammodiaquine rather than quinnine, for the treatment of childhood malaria. This could curb malaria mortality due to treatment.
- Further research could be done in this area by considering malaria data from the clinics in and around the Tamale metropolis in order to examine the spatial variation. This would even improve upon the scope.

KNUST

REFERENCES

Agresti, A. (1996). An Introduction to Categorical Data Analysis. John Wiley and Sons, Inc. *http://lib.stat.cmu.edu/datasets/agresti*

Agyapong, I. A. and Kangeya-Kayonda, J. (2004). Providing Practical Estimates of Malaria Burden for Health Planners in Resource—Poor Countries. American Journal of Tropical medicine and Hygiene. pp.162-167.

Alain V., Guyomarc'h S., Marjollet O., Berger C., Carricajo A., Robert F., Laporte S., Lambert C., Page Y., Zéni F. and Bertrand J.C. (2008). Can emergency physicians identify a high mortality subgroup of patients with sepsis: role of procalcitonin. European Journal of Emergency Medicine. Volume 15, Issue 1. pp 26-33

Alles H. K., Mendis K. N., and Carter R. (1998). Malaria Mortality Rates in South Asia and in Africa: Implications for Malaria Control. Malaria Journal. Volume 3, issue 2. pp 125-131.

Apawu. M. et al. (2004). Malaria Transmission Dynamics at a Site in Northern Ghana Proposed For Testing Malaria Vaccine. Tropical Medicine for International Health. pp. 160-170.

Asenso-Okyere. W.K., (1994). Socioeconomic Factors in Malaria Control, World Health Organization Forum. 5(3): pp. 265-268. *http://www.ncbi.nlm.nih.gov/pubmed/7945758*

Binka F. N., Kubaj A., Adjuik M., Williams L. A., Lengeler C., Maude G. H., Armah G. E., Kajihara B., Adiamah J. H. and Smith P. G. (2007). Impact of permethrin impregnated bednets on child mortality in Kassena-Nankana district, Ghana: a randomized controlled trial. Tropical Medicine & International Health. Volume 1, Issue 2. pp 147–154.

Bryce J., Boschi-Pinto C., Shibuya K., and Black R.E. (2005). WHO estimates of the causes of death in children. WHO Child Health Epidemiology Reference Group. *http://www.ncbi.nlm.nih.gov/pubmed/15794969?dopt=Abstract&holding=f1000,f1000m,isrctn.*

Castilla R.E. and Sawyer D.O., (1993). Malaria Rate and Fate: A Socioeconomic Study of Malaria in Brazil. Social Sciences Medical Journal, pp 37.

Carneiro A. I., Thomas S., John P. A. L., Robert M., Jürg U., and Chris J. D. (2006). Modeling the relationship between the population prevalence of plasmodium falciparum malaria and anemia. American Journal of Tropical Medicine and Hygiene. Volume 75, Issue 2. pp. 82-89.

Chinbuah. M., (1999). "Knowledge And Acceptability And Use Of Insecticide Treated Bed net In The Cape Coast municipality". (Unpublished) Dissertation of School of Public Health, University Of Ghana, Legon.

Chuks J. Mba & Irene K. Aboh: Prevalence and Management of Malaria in Ghana: A Case Study of Volta Region. African Population Studies Journal, Vol. 22, No. 1, 2007, pp. 137-171. *http://www.bioline.org.br/abstract?ep07007*

Clerk C.A., Jane B., Brian G. and Daniel C. (2009). Factors associated with malaria infection and anemia in pregnancy in northern Ghana. Tropical medicine international health. Volume 14, Issue: 6, pp 688-695 *www.ncbi.nlm.nih.gov*

Daliana P. B., Mélot C., Ferreira F. L. and Vincent J. L. (2003). Infection Probability Score (IPS) as a method to help assess the probability of infection in critically ill patients. Critical Care Medicine. Volume 31, Issue 11. pp 2579-2584.

De La Cruz N., Benjamin C., Kirk D., Bobbi G., Natasha I., Stephen A., and Robb D. (2006). Who sleeps under bed nets in Ghana; A doer/non-doer analysis of malaria prevention behaviors. *Malaria Journal.* Volume 5, issue 1. pp 61-65.

Essuman V. A., Christine T. N. A., Birgitte S. A., George O. A., Jorgen A. K., Thomas A. N., and Bamenla G. (2010). Retinopathy in severe malaria in Ghanaian children - overlap between fundus changes in cerebral and non-cerebral malaria. *Malaria Journal.* Volume 9, issue 1. pp 232.

Gemperli P., Vounatsou P., Kleinschmidt I., Bagayoko M., Lengeler C., and Smith T. (2004). Spatial Patterns of Infant Mortality in Mali: The Effect of Malaria Endemicity. American Journal of Epidemiology. Volume159, Issue1. pp. 64-72.

Ghana Health Service, (2009).National Guidelines for Laboratory Diagnosis of Malaria. Accra, Ghana. Pp 5-10

Grillet M.E., Roberto B., Martínez J.E., Jesús B., and Fortin M.J. (2010). Disentangling the Effect of Local and Global Spatial Variation on a Mosquito-Borne Infection in a Neotropical Heterogeneous Environment. American Journal of Tropical Medicine and Hygiene. Volume 82, issue 2. pp. 194-201.

Gunu, O.M. (2009). The Deteriorating State of Tamale Teaching Hospital – Tamale, Ghana. Manassas, VA. *http://knol.google.com/k/the-deteriorating-state-of-tamale-teaching-hospital-tamale-ghana#2009*

Hair Jr. J. F., Black W.C., Babin B. J., and Anderson R. E. (2010). 7th ed. Multivariate Data Analysis. Pearson Prentice Hall. Pp 316-320

Hay S.I., Robert W. S. and David J. R. (1998). Predicting malaria seasons in Kenya using multitemporal meteorological satellite sensor data. Department of Zoology, University of Oxford, South Parks Road, Oxford, OX1 3PS, UK

Hosmer D.W and Lemeshow S. (2000). Applied Logistic Regression. 2nd ed. New York, USA: John Wiley and Sons.

Hui F.M., Bing X., Zhang-Wei C., Xiao C., Lu L., Hua-Bing H., Li-Qun F., Hong Y., Hong-Ning Z., Heng-Lin Y., Xiao-Nong Z., Wu-Chun C., and Peng G. (2009). Spatio-Temporal Distribution of Malaria in Yunnan Province, China. American Journal of Tropical Medicine and Hygiene. Volume 81, issue 3. pp. 503-509.

Jack E. Z., Wagner D. P., Draper E. A., Wright L., Alzola C., Knaus W. A. (1998). Evaluation of Acute Physiology and Chronic Health Evaluation (APACHE) III predictions of

hospital mortality in an independent database. Critical Care Medicine. Volume 26, Issue 8. pp 1317-1326.

Karger S. (2005). Assessing the impact on the mortality of young children in an area of intense transmission of malaria and no tradition of bed net use.

Kazembe L. N., Kleinschmidt I. and Sharp B. L. (2006). Patterns of malaria-related hospital admissions and mortality among Malawian children: an example of spatial modeling of hospital register data. *Malaria Journal.* Volume 5, issue 1. pp 93.

Kleinbaum D. G. and Klein M. (1994). 2nd ed. Logistic Regression: A Self-Learning Text. John Wiley and Sons Publishers, New York. pp 15-26.

Kleinschmidt I., Bagayokob M., Clarkec G.P.Y., Craiga M., and Le Sueura D. (2000). A spatial statistical approach to malaria mapping. International Journal of Epidemiology. Volume 29, Issue 2. pp. 355-361.

Kleinschmidt I., Sharp B. L., Clarke G. P. Y., Curtis B., and Fraser C. (2001). Use of Generalized Linear Mixed Models in the Spatial Analysis of Small-Area Malaria Incidence Rates in KwaZulu Natal, South Africa. American Journal of Epidemiology Volume153, Issue12. pp. 1213-1221.

Kobbe R., Samuel A., Christina K., Benno K., Benedicta T., Peter T., Florian M., Wibke B., Meral T., Nadine S., Ernest O., Ohene A., Christian M., Juergen M. (2007). Malaria incidence and efficacy of intermittent preventive treatment in infants (IPTi). *Malaria Journal.* Volume 9, issue 6 (1). pp 163

Kreuels B., Kobbe R., Adjei S., Kreuzberg C., Von Reden C., Bäter K., Klug S., Busch W., Adjei O. and May J. (2008). Spatial sariation of malaria incidence in young children from a geographically homogeneous area with high endemicity. *http://lib.bioinfo.pl/auth:Kreuels/1/197 (1)*

Lindsay S.W., David G. H., Robert A. H., Shane A. R., and Stephen G. W. (2010). Assesseing the future threat from vivax malaria in the United Kingdom using two markedly different modeling approaches. *Malaria Journal.* Volume 9, Issue 1. pp 70-79.

Menard, S. (1995). Applied Logistic Regression Analysis. Sage Publications.Series: Quantitative Applications in the Social Sciences, pp. 106.

Martinez, C. (2009). The History of Malaria in Ghana. eHow Contributor *http://www.ehow.com/facts_5545060_history-malaria-ghana.html#ixzz10RneCmew*

Mensah, O. and Kumaranyake L. (2004). Malaria Incidence in Rural Benin: Does Economic Matter in Benin Health Policy. Health Policy Journal. Volume 68, Issue 1, pp 93-102 *http://www.healthpolicyjrnl.com/article/S0168-8510%2803%2900172-6/abstract*

Ministry of Health (2002), Information for Action: A Bulletin of Health Information. MoH, Accra. *http://www.moh-ghana.org/UploadFiles/interagency*

Ministry of Health (2000). Roll Back Malaria Strategic Plan for Ghana 2001 - 2010. MoH, Accra.
http://www.eac.int/health/index.php?option=com_docman&task=doc_download&gid=40&Itemid=144

MOH, (2009). Revised Anti Malaria Drug Policy for Ghana, 2nd Revised Version.
http://www.ghanahealthservice.org/includes/upload/publications/ANTIMALARIA%20DRUG%20POLICY.pdf

MOH, (2009). Guidelines for Case Management of Malaria in Ghana. Accra, Ghana. pp 2-4
www.ghanahealthservice.org/includes/upload/.../GUIDELINESforman.pdf

MOH, (2007). 2nd ed. Anti Malaria Drug Policy. Accra, Ghana. *www.moh-ghana.org*

Rashed, S. et al. (2000). Economic impact of febrile morbidity and use of permethrin- treated bed nets in a malarious area II. Social Sciences Medical Journal. Toronto, Canada. pp49.

Reeder, J. C. (2001). Towards a Malarious Vaccine for Papua New Guinea. Papua New Guinea Medical Journal. pp 17-23.

Reid H., Haque U., Clements A. C. A., Tatem A., Vallely J. A., Ahmed S. M., Islam A., and Haque R. (2010). Mapping Malaria Risk in Bangladesh Using Bayesian Geostatistical Models. American Journal of Tropical Medicine and Hygiene. Volume 83, issue 4. pp. 861-867.

Riedel N., Penelope V. J. M. M., Laura G., Elizabeth C. K., Victor M. and Rick W. S. (2010). Geographical patterns and predictors of malaria risk in Zambia: Bayesian geo-statistical modeling of the 2006 Zambia national malaria indicator survey. Malaria Journal. Volume 9. pp 37.

Ross A., Penny M., Maire N., Studer A., Carneiro I., et al. (2008). Modeling the Epidemiological Impact of Intermittent Preventive Treatment against Malaria in Infants. PLoS ONE 3(7): e2661. doi:10.1371/journal.pone.0002661

Sacarlal J., Nhacolo A.Q., Sigaúque B., Nhalungo D.A., Abacassamo F., Sacoor C.N., Aide P., Machevo S., Nhampossa T., Macete E.V., Bassat Q., David C., Bardají A., Letang E., Saúte F., Aponte J.J., Thompson R., and Alonso P.L. (2007). A 10 year study of the cause of death in children under 15 years in Manhiça, Mozambique. *http://www.ncbi.nlm.nih.gov/pubmed/19236726.*

Sharma. S. K., Pradham. P., Pradhi. D. M., (2001). Socioeconomic Factors Associated with Malaria in a Tribal Area of Orissa, India. Indian Journal of Public Health, pp 93-98.

Streeten, Paul (1981). First thing first; meeting basic human needs in developing countries. The World Bank. Washington. pp 193-199 *http://www.getcited.org/pub/102141983*

Terlouw D. J., Kodjo M., Adam W., Aboudou D., Ameyo D., James E. M., Jodi V. E., Yao K. S., Feiko O. K. and William A. H. (2010). Impact of mass distribution of free long-lasting insecticidal nets on childhood malaria morbidity: the Togo National Integrated Child Health Campaign. *Malaria Journal.* Volume 9, issue 1. pp 199.

World Bank (1993). 'Investing in Health'. World Development Report 1993. Washington. Oxfold University Press. *http://www.getcited.org/pub*

World Health Organization, WHO, (1999). World Health Report, 1999: Making a Difference. *http:/www.who.int/whr/1999/*

WHO (2002); "Macroeconomics and Health Initiative in Accra". Press Release No.013/02. *http:/www.who.int/macrohealth/infocentre/press/bulletin/en/html*

WHO (1997). World Malaria Situation in 1994, part 1. WHO weekly Epidemiological Record 36: pp 269-274. *http://www.ncbi.nlm.nih.gov/pubmed/9293226*

WHO/UNICEF, (2003). Africa Malaria Report. WHO/CDS/MAL/2003.1093. 2003. Geneva. *http://www.rbm.who.int/amd2003/amr2003/ch3.htm*

Yabsley M.J., Michael C. W., David E. S., Susan E. L., and William R. D. (2005). Spatial analysis of the distribution of ehrlichia chaffeensis, causative agent of human monocytotropic ehrlichiosis, across a multi-state region. American Journal of Tropical Medicine and Hygiene. Volume 72, issue 6. pp. 840-850.

Yeboah-Antwi. K., et al. (1997). Impact of Prepackaging Anti-malarial Drugs on Cost to Patient and Compliance with Treatment. Social Sciences Medical Journal. pp. 659-67.

Yé Y., Elizabeth K.M., John K., and Frederick M. (2007). Assessing the risk of self-diagnosed malaria in urban informal settlements of Nairobi using self-reported morbidity survey. Malaria Journal. Volume 6, issue 1. pp 71-76.

KNUST

APPENDIX A

Tamale Teaching Hospital Inpatient Morbidity and Mortality Returns Register from 2000-2010.

(A Sample of Extracted Malaria Data Used)

Outcome	Referral Status	Age	Sex	Season	Length	Distance	Treatment
0	0	3.42	1	1	4	0	0
0	0	4	1	1	6	1	0
0	0	5	1	1	6	0	1
0	0	2	1	1	6	1	0
0	0	3	1	1	3	1	1
0	0	5	0	1	4	1	0
0	0	3	0	1	4	1	0
0	0	4	1	1	7	1	0
0	0	0.67	0	1	6	0	1
1	0	6	0	1	33	1	1
0	0	9	0	1	3	1	1
0	0	5	1	1	4	1	0
0	0	2.5	0	1	4	1	0
0	1	10	0	1	9	1	1
0	0	2	1	1	3	0	1
0	0	4	1	1	3	0	1
0	0	1	0	1	12	0	1
0	0	5	0	1	2	1	1
0	0	0.67	1	1	5	1	1
0	0	3	1	1	9	0	1
0	0	9	1	1	2	0	1
0	0	6	0	1	3	0	1
0	0	2	0	1	6	1	1
0	0	6	1	1	3	1	1
0	0	1	0	1	3	0	0
0	0	1.42	0	1	4	1	0
0	0	6	1	1	3	1	1
0	0	6	1	1	4	1	1
0	0	3	1	1	2	0	1
0	0	1	1	1	4	0	1
0	0	2	1	1	4	1	0
0	0	2	1	1	2	0	1
0	0	2	0	1	5	0	1
0	0	4	1	1	17	1	1

KNUST

0	1	4	1	1	3	1	1
1	1	8	1	1	2	1	0
1	1	0.1	0	1	3	1	0
1	1	0.3	0	1	2	0	1
0	0	3.5	1	1	3	1	1
0	0	0.25	1	1	3	0	1
0	0	1	0	1	4	1	1
0	0	3	1	1	4	1	1
0	0	2	1	1	2	0	1
0	0	3	0	1	3	0	1
0	0	10	1	1	4	1	0
0	1	3	0	1	4	1	1
0	0	9	0	1	2	1	0
0	0	1	0	1	3	0	0
0	0	9	1	1	3	0	1
0	0	6	0	1	9	1	0
0	0	0.67	0	1	6	0	0
0	0	7	1	1	4	0	0
0	0	3	1	1	4	0	1
0	0	2	0	1	3	1	1
0	0	4	1	1	6	1	1
1	0	6	1	1	3	0	1
0	0	2	0	1	3	0	1
0	0	6	0	1	3	0	1
0	0	3	1	1	3	0	1
0	0	2	1	1	4	1	1
0	0	4	1	1	3	0	1
0	0	8	0	1	4	0	0
0	0	0.67	1	1	10	0	1
0	0	3	1	1	33	0	1
0	0	11	1	1	5	0	1
0	0	6	1	1	1	0	1
0	0	8	1	1	2	0	0
1	0	3	0	1	2	0	1
0	0	6	0	1	5	0	1
0	0	3	1	1	11	0	0
0	0	7	1	1	3	0	1
0	0	3	1	1	6	0	1
0	0	2	1	1	2	0	1
0	0	7	0	1	6	0	1
0	0	1.5	0	1	2	0	1

KNUST
NYANSAPƆW ƆSANE NO BADWENMA

0	0	0.5	1	1	34	0	1
0	0	2	0	1	8	0	1
0	1	2	0	1	15	1	1
0	0	5	1	1	3	1	1
0	0	3	0	1	4	0	1
0	0	5	1	1	6	1	0
0	0	4	0	1	5	1	0
0	1	1	1	1	2	1	1
0	0	1.42	1	1	2	0	0
0	0	3	0	1	4	1	1
0	0	5	0	1	2	0	1
0	0	4	1	1	2	1	1
1	1	1	0	1	2	1	1
0	0	1	1	1	2	1	1
0	0	7	1	1	2	0	1
0	0	9	1	1	3	0	1
0	0	2	0	1	3	0	1
0	0	3.42	1	1	2	0	1
0	0	7	1	1	4	0	1
0	0	2	0	1	4	1	0
0	0	1	0	1	6	1	1
0	0	6	1	1	3	0	0
0	0	2	1	1	3	0	0
0	1	2	1	1	4	1	0
0	0	3	1	1	3	1	1
0	0	6	1	1	3	1	0
0	0	2	0	1	3	0	1
0	0	3	1	1	3	1	1
0	0	1.25	0	1	4	0	0
1	1	1	0	1	1	1	0
0	0	7	1	1	4	0	0
0	0	8	1	1	5	0	1
0	0	10	1	1	3	0	1
0	0	1	1	1	15	0	1
0	0	0.17	0	1	6	0	0
0	0	3	0	1	3	0	0
0	0	2	0	1	2	1	1
0	0	1	0	1	10	1	0
0	0	6	1	1	9	1	0
0	0	14	0	1	3	1	0
0	0	10	1	1	12	0	0

KNUST

0	0	3	0	1	2	1	0
0	0	3	1	1	3	1	0
0	0	6	1	1	14	1	1
0	0	3	0	1	5	0	0
1	1	7	0	1	3	0	1
0	0	4	0	1	2	1	0
0	0	3	1	1	3	1	0
0	0	4	1	1	3	0	0
0	0	6	1	1	4	1	0
0	1	2	1	1	3	0	1
0	0	7	1	1	3	0	0
0	0	3	0	1	3	0	0
0	0	0.67	1	1	4	0	0
0	0	3	1	1	4	0	0
0	0	6	1	1	4	0	1
0	0	2	1	1	3	0	1
0	0	3.25	1	1	2	1	1
1	0	1	0	1	2	0	0
0	0	5	0	1	3	1	0
0	0	1	0	1	2	0	1
0	0	3	1	1	4	0	0
0	0	5	0	1	2	1	1
1	1	2	1	1	2	1	0
0	0	7	0	1	3	0	1
0	0	0.5	1	1	4	0	1
0	0	9	1	1	3	0	1
0	0	4	0	1	3	0	1
0	1	1	1	1	2	1	1
0	0	2	1	1	2	0	1
0	0	1.17	1	1	2	0	1
0	1	6	0	1	3	1	0
0	0	2	1	1	6	1	0
1	1	0.42	1	1	1	1	0
0	0	2	1	1	3	1	0
0	0	1	0	1	2	1	1
0	1	1	0	1	6	1	1
0	0	2	1	1	3	1	1
0	1	3	1	1	6	1	0
0	0	0.67	1	1	13	0	1
0	0	3	0	1	3	0	1
0	1	3	1	1	6	1	0

KNUST
NYANSAPOW JSANE NO BADWENMA

0	0	3	1	1	4	1	1
0	0	2	0	1	5	0	1
0	0	4	0	1	2	0	1
0	0	3	1	1	6	0	0
0	0	3	0	1	4	0	0
0	0	5	0	1	4	0	0
0	0	13	1	1	8	0	0
0	0	6	0	1	3	0	1
0	0	7	1	1	3	0	1
0	0	3	1	1	2	1	0
0	0	2	1	1	3	0	1
0	0	5	1	1	4	0	1
0	0	3	0	1	4	0	1
0	1	4	0	1	21	1	0
0	0	1.5	1	1	4	0	0
0	0	2	1	1	4	0	0
0	0	2	0	1	4	0	1
0	0	3	0	1	2	0	1
0	0	4	0	1	1	0	1
0	0	3	1	1	3	0	0
0	0	3	1	1	4	1	0
0	1	3	1	1	5	1	0
0	0	5	0	1	2	0	1
0	1	2	0	1	4	1	0
0	0	11	0	1	2	0	1
0	0	2	1	1	16	0	1
0	0	8	1	1	2	0	1
0	0	10	0	1	20	0	0
0	0	2	0	1	7	0	1
0	0	10	1	1	2	0	1
0	0	1.5	1	1	2	1	1
0	0	8	0	1	2	0	0
0	0	12	1	1	16	1	0
0	0	7	1	1	3	0	0
0	0	1.5	0	1	3	1	0
0	0	4	1	1	2	0	1
0	0	2	1	1	5	0	0
0	0	0.33	1	1	2	0	1
0	0	4	1	1	4	0	0
0	0	3	1	1	16	0	0
0	0	1	1	1	26	0	0

KNUST
NYANSAPƆW ƆSANE NO BADWENMA

APPENDIX B

Table 4.8 Outcome of Administered Malaria Patient

	Frequency	Percent
Alive	2182	95.2
Dead	111	4.8
Total	2293	100.0

KNUST

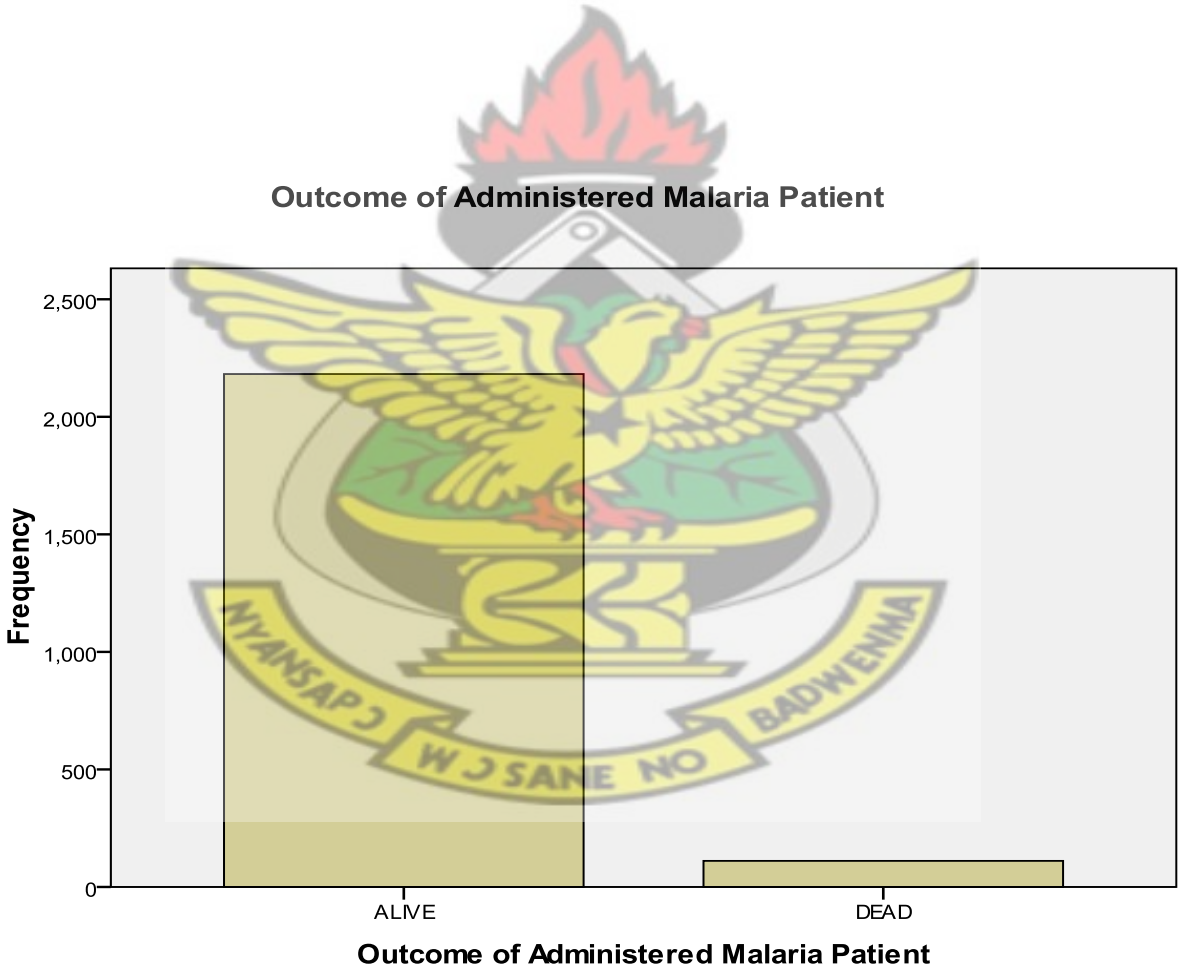

Fig. 4.3 The outcome of administered malaria patients

Table 4.9 Referral Status of Patients

	Frequency	Percent
Non Referral	2157	94.1
Referral	136	5.9
Total	2293	100.0

KNUST

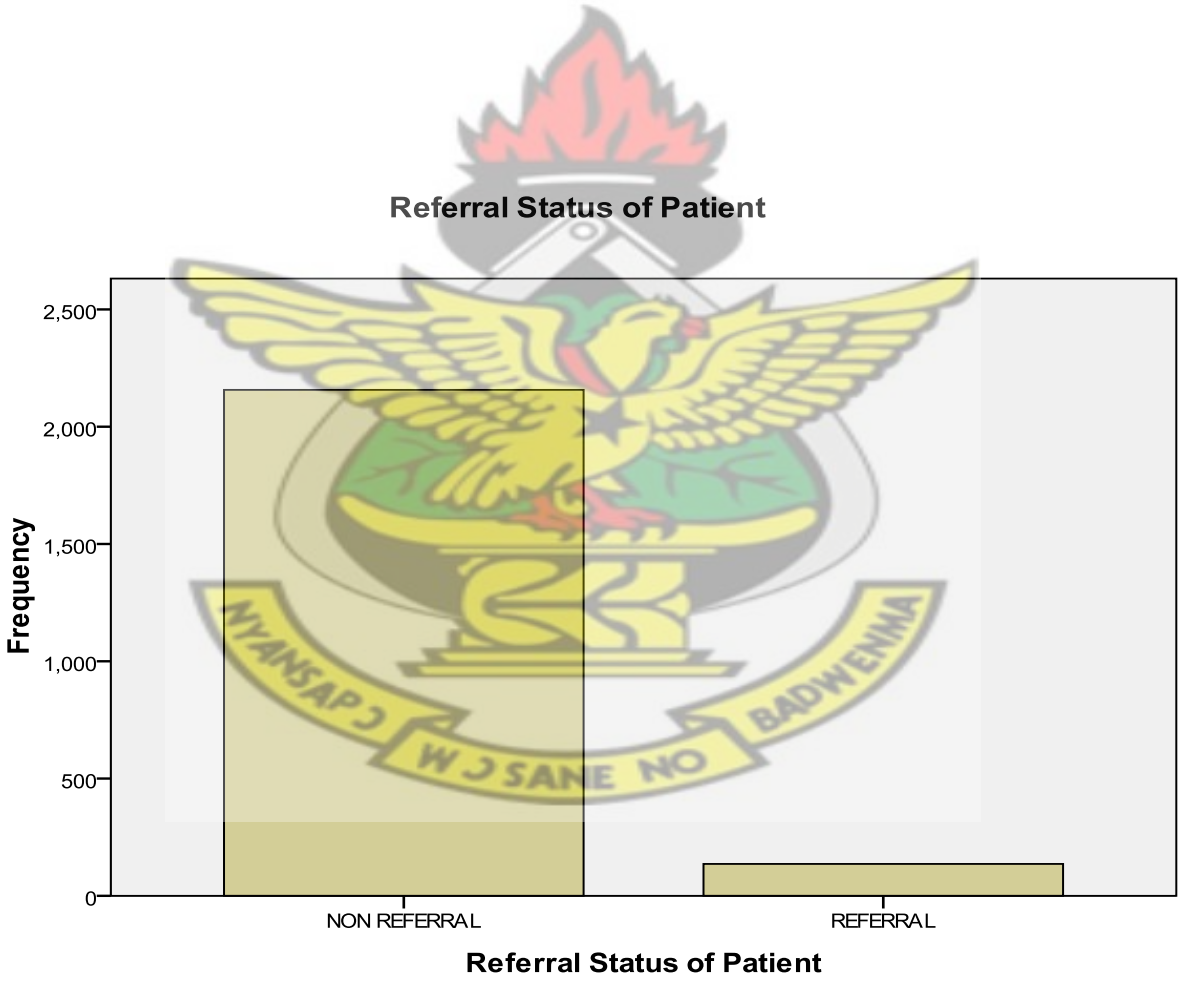

Fig. 4.4 The referral status of administered malaria patients

Table 4.10 Distribution of Sex of Patients

	Frequency	Percent
Female	946	41.3
Male	1347	58.7
Total	2293	100.0

KNUST

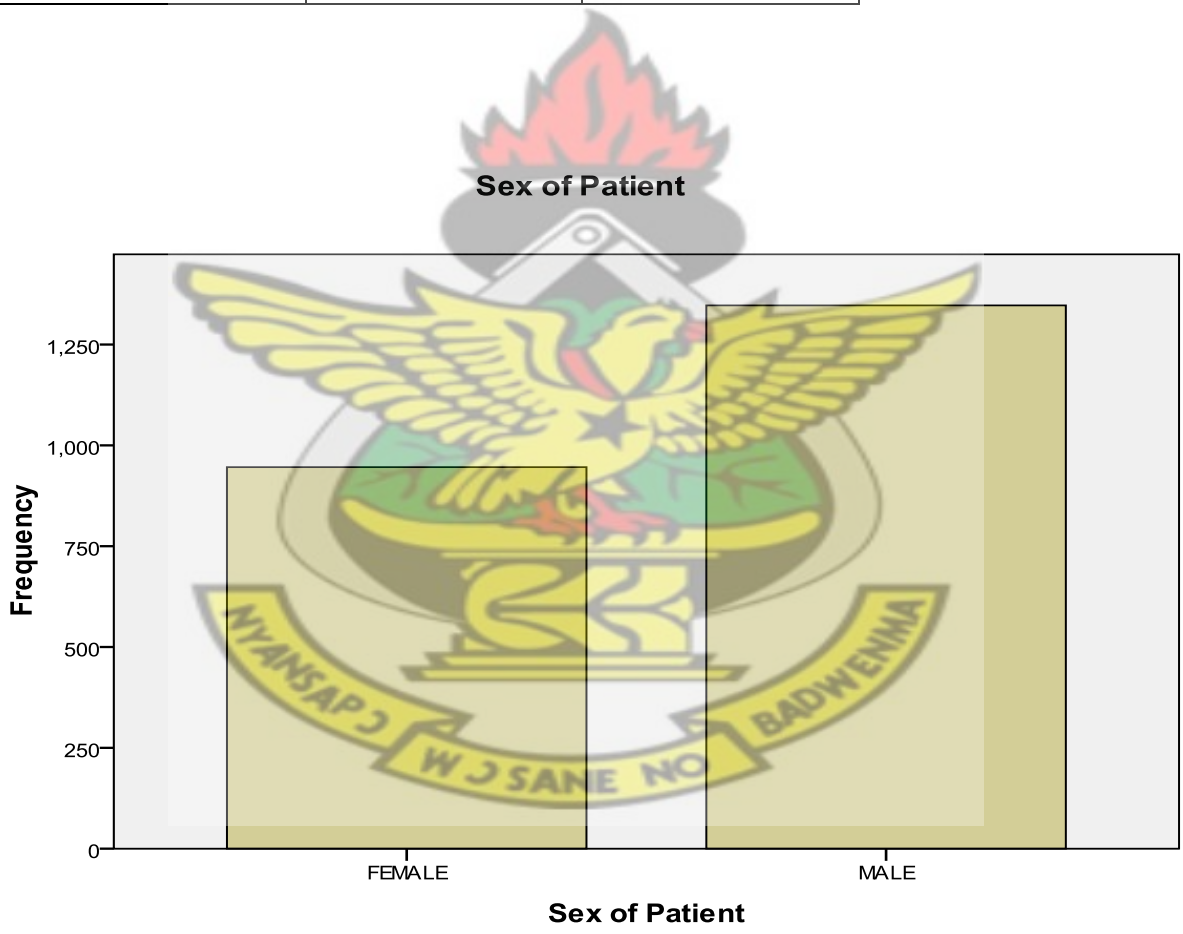

Fig. 4.5 The sex of administered malaria patients

Table 4.11 Season of Admission

	Frequency	Percent
Dry	1306	57.0
Wet	987	43.0
Total	2293	100.0

KNUST

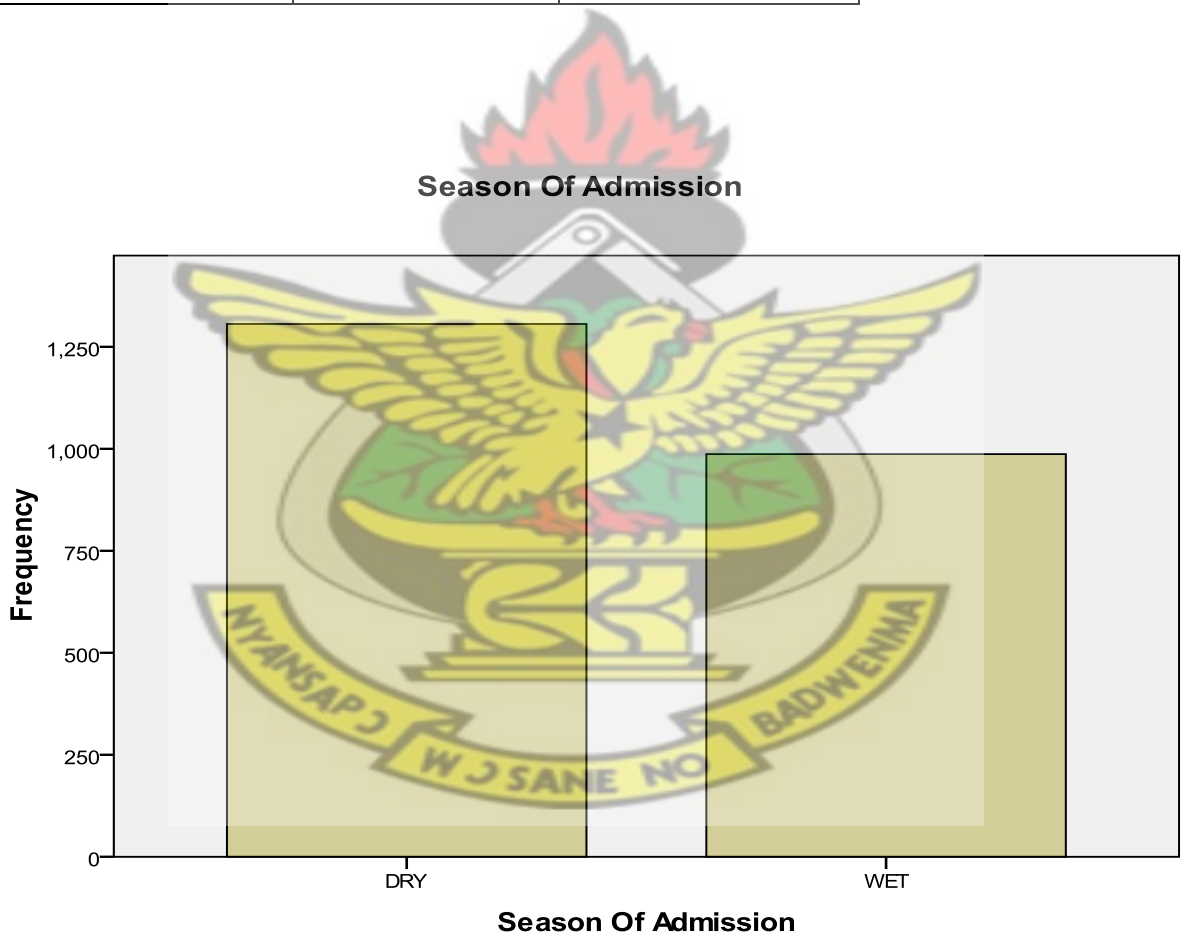

Fig. 4.6 Season of admission of administered malaria patients

Table 4.12 Distances to Hospital

	Frequency	Percent
Less than 5Km	1784	77.8
Greater than or equal to 5KM	509	22.2
Total	2293	100.0

KNUST

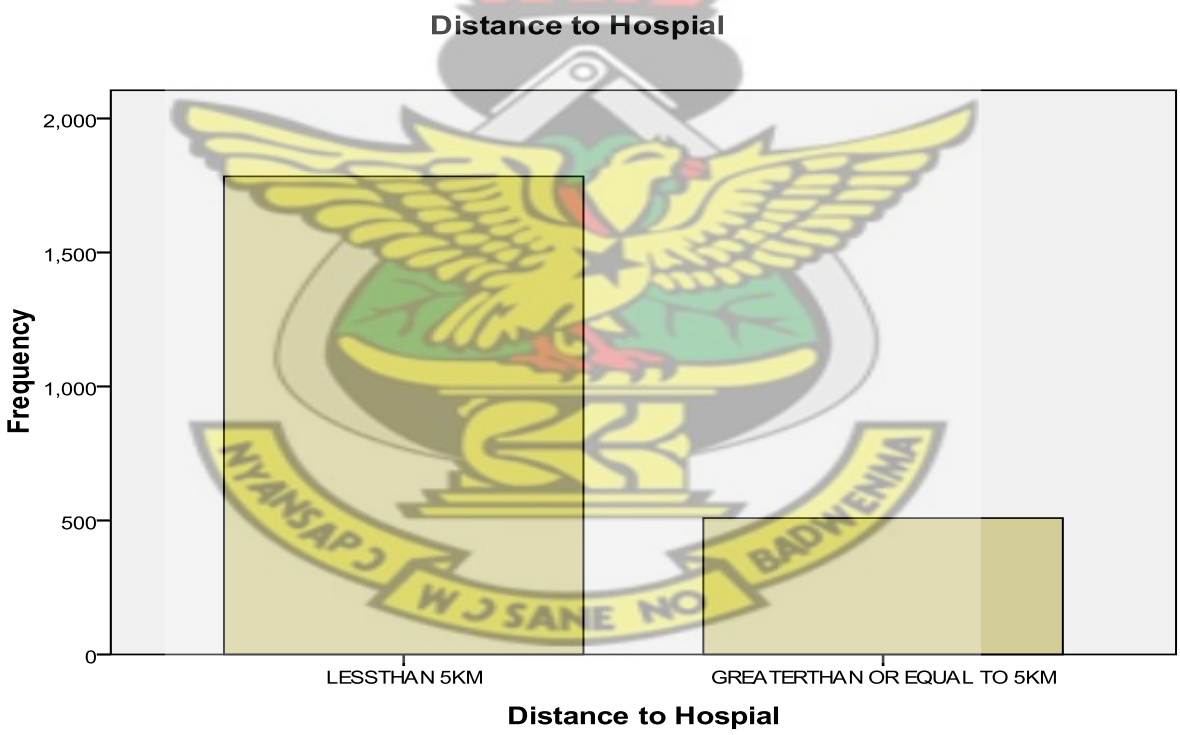

Fig. 4.7 Distance to hospital of administered malaria patients

Table 4.13 Treatment Type Given to Patients

	Frequency	Percent
Artesunate Ammodiaquine	775	33.8
Quinnine	1518	66.2
Total	2293	100.0

KNUST

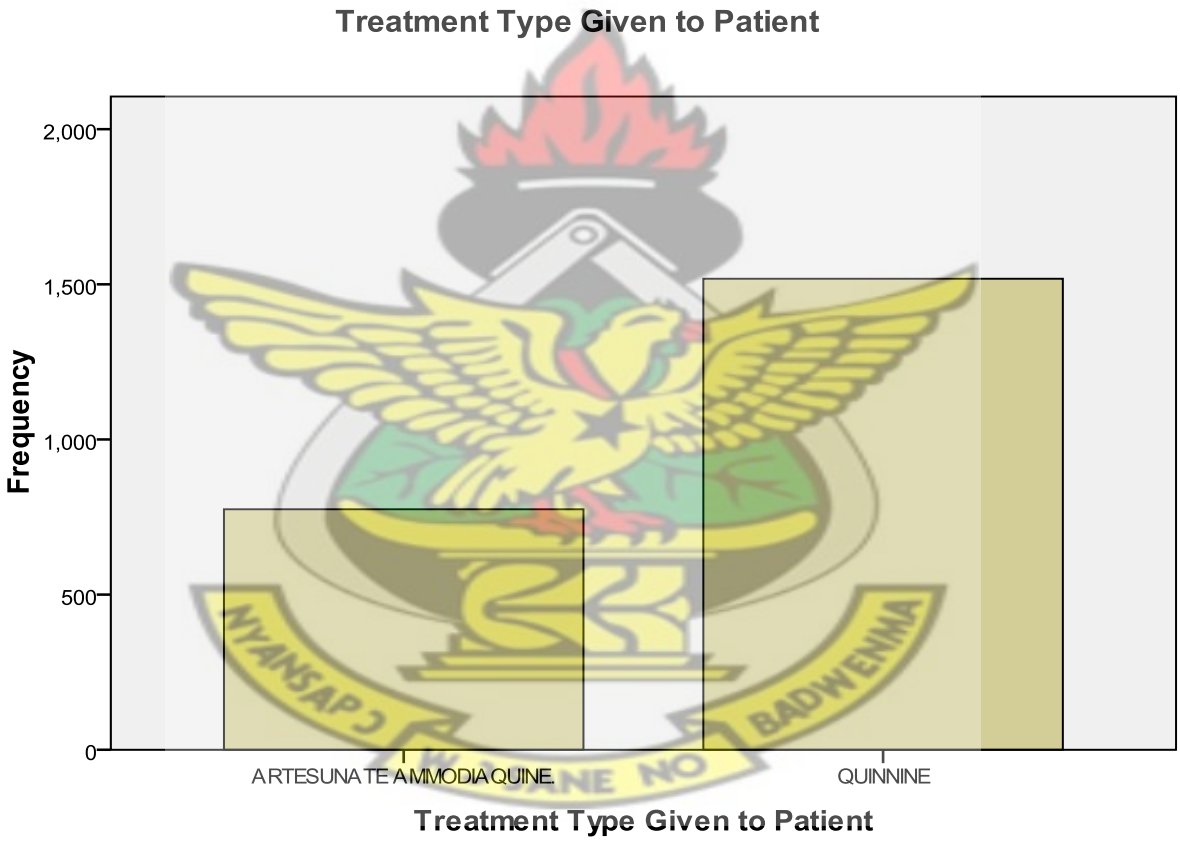

Fig. 4.8 The treatment type given to administered malaria patients

Table 4.14 Classification Table

Observed		Predicted		
		Outcome of Administered Malaria Patient		Percentage Correct
		Alive	Dead	
Outcome of Malaria Patient:	Alive	2155	25	98.9
	Dead	72	39	35.1
Overall Percentage				95.8

KNUST