

**KWAME NKRUMAH UNIVERSITY OF SCIENCE AND TECHNOLOGY,
KUMASI, GHANA COLLEGE OF HEALTH SCIENCES SCHOOL OF PUBLIC
HEALTH DEPARTMENT OF POPULATION, FAMILY AND REPRODUCTIVE
HEALTH**

KNUST

**SPATIAL ANALYSIS OF UNDER-5 MALARIA IN GHANA (2008 GDHS) FOR
PUBLIC HEALTH INTERVENTION EVALUATION**

BY

ATINUKE OLUSOLA ADEBANJI

JULY, 2016

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ATINUKE O. ADEBANJI (PhD STATISTICS)

**A THESIS SUBMITTED TO THE DEPARTMENT OF POPULATION AND
REPRODUCTIVE HEALTH, COLLEGE OF HEALTH SCIENCES, SCHOOL OF
PUBLIC HEALTH, IN PARTIAL FULFILMENT OF THE REQUIREMENTS
FOR
THE DEGREE OF MASTER OF PUBLIC HEALTH IN POPULATION, FAMILY
AND REPRODUCTIVE HEALTH**

JULY, 2016

DECLARATION

I, the undersigned student do hereby declare that, the findings of this study compiled in this script are genuine information which has not been presented to any person or group of persons elsewhere for another Masters in Public Health, however due recognition has been given to authors whose works have been cited.

Submitted by

KNUST

ADEBANJI Atinuke Olusola
(PG2390714)

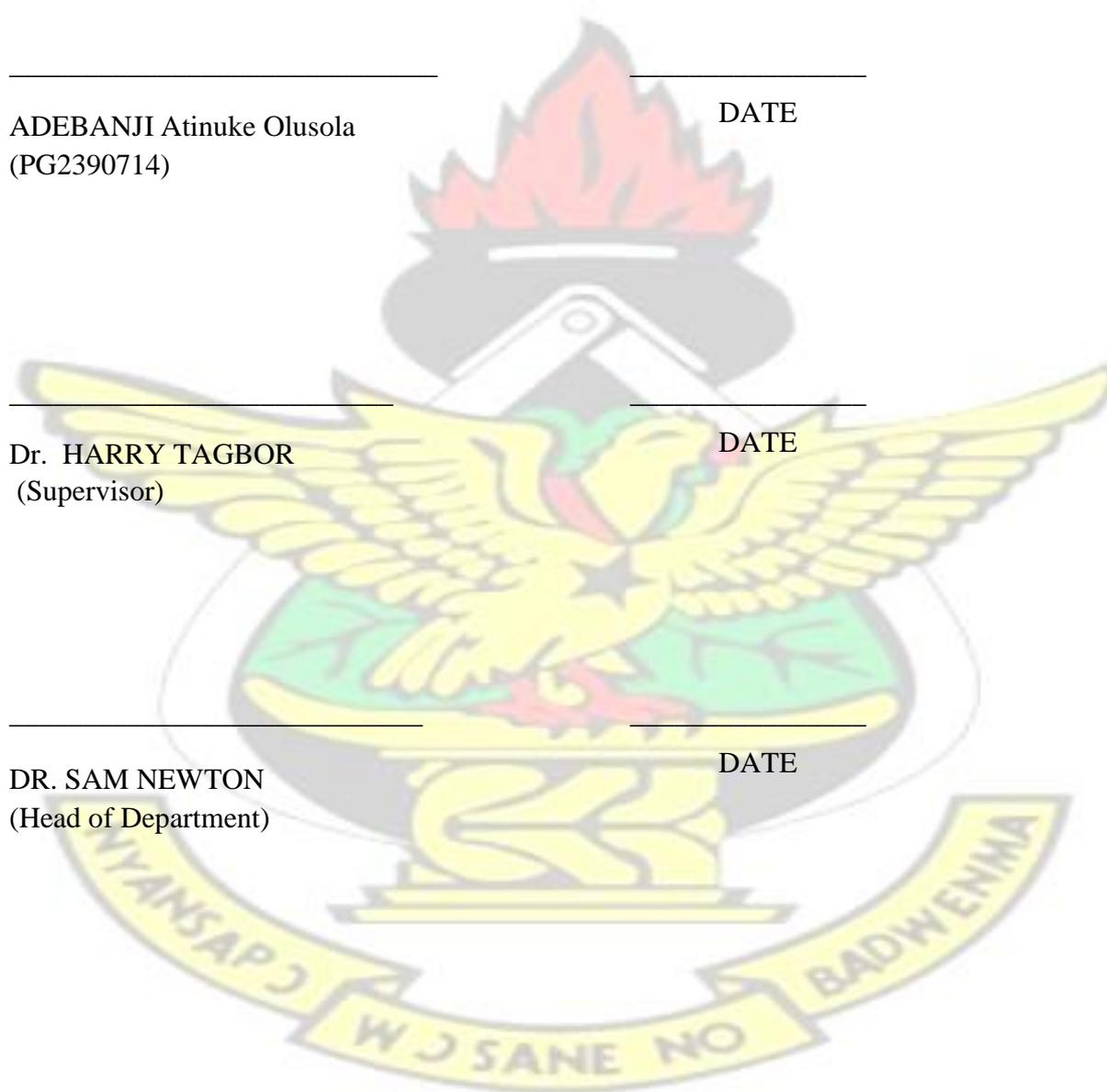
DATE

Dr. HARRY TAGBOR
(Supervisor)

DATE

DR. SAM NEWTON
(Head of Department)

DATE



DEDICATION

To *Lani, Toni* and *Eriife*.

For your loving support and giving me a reason to aspire to greater heights.

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ACKNOWLEDGEMENT

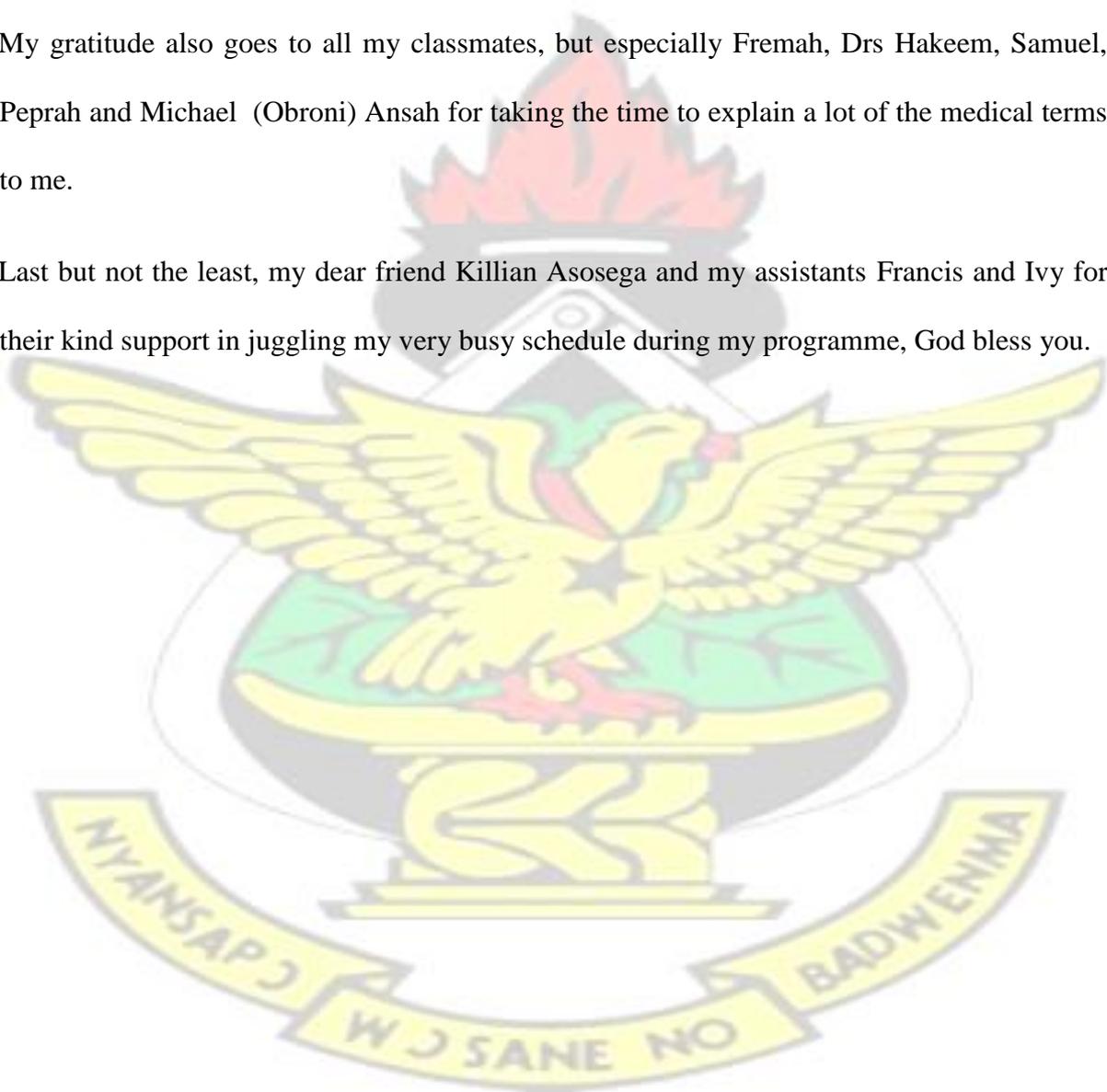
I am grateful to the Father of light, in whom I live and move and have my being.

I owe a world of gratitude to my supervisor, Harry Tagbor for his patience in teaching me the Public Health language and for helping birth this thesis.

To my lecturers at the School of Public Health for opening a whole new world to me, thank you.

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Last but not the least, my dear friend Killian Asosega and my assistants Francis and Ivy for their kind support in juggling my very busy schedule during my programme, God bless you.



DEFINITION OF TERMS

Under-5: A child aged between 6-59 months

Spatial dependence: the spatial relationship of variable values (for themes defined over space) or locations (for themes defined as objects, such as cities)

Autocorrelation: the cross-correlation of a signal or observation with itself at different Points in time



ACRONYMS



ACT	- Artemisinin-based Combination Therapy
AIDS	- Acquired Immune Deficiency Syndrome
BCC	- Behaviour Change Communication
CHRPE	- Committee on Health Research Publications and Ethics
DHS	- Demographic and Health Survey
GDHS	- Ghana Demographic Health Survey
GHS	- Ghana Health Service
GSS	- Ghana Statistical Service
HIV	- Human Immunodeficiency Virus
IRS	- Indoor Residual Spraying
ITN	- Insecticide Treated Net
LISA	- Local Indicator of Spatial Autocorrelation
LLIN	- Long Lasting Insecticide Net
MAP	- Malaria Atlas Project
M & E	- Monitoring and Evaluation
MDG	- Millennium Development Goals
MICS	- Multiple Indicator Cluster Survey
NMCP	- National Malaria Control Programme
RBM	- Roll Back Malaria
RDT	- Rapid Diagnostic Test
UN	- United Nations
USAID	- United States Agency for International Development
WHO	- World Health Organization

ABSTRACT

Introduction: Malaria control programmes adopt national strategies without recourse to individual, social and location factors that affect the dynamics of the infection transmission. Spatial relationships between locations are often unaccounted for with the number of cases assumed to be randomly occurring. This renders inappropriate a one-size-fits all intervention approach for a parsimonious allocation of limited resources for the design, implementation and evaluation of malaria control programmes. To accomplish the desired outcomes, interventions must reach the subgroups of the populations where malaria prevalence is at its highest. This can only be achieved if malaria control interventions take into cognisance factors that ensure equity in program design, implementation, monitoring and evaluation. Impact assessment requires nationally representative data that are often prohibitively expensive. To circumvent this, nationally representative routine data can easily be adopted

Methods: This study utilizes the GDHS 2008 data for the identification of disease patterns for under-5 malaria using individual child, maternal and household socio-economic and geographic variables as predictor variables. These variables were used to model the likelihood of U-5 malaria and to develop the risk/prevalence maps to explain the risk and spatial dependencies of the incidence of malaria between households. The chi-square test of independence, binary logistic regression and spatial statistics analytical tools were utilized.

Results: Logistic regression model showed age group 5, anaemia, type of residence and epidemiological zones as significant ($p < .05$) with odds ratios less than 1 of the incidence of

U-5 malaria. Model overall percentage performance was 74.7%. Moran's index for nonrandomness in occurrence was significant ($p < .02$) and LISA cluster maps showed significant clustering between 45 clusters with most of them in the southern part of Ghana.

The malaria risk maps showed 4 dense clustering of low prevalence centres clustered around hot spots in Northern, Ashanti, Western and Greater Accra regions. Identifying these high prevalence foci is important to the success of any public health intervention or vector control. These are important conduits for malaria transmission. The SEM was found to give a better fit than the SLM based on the AIC and Schwarz criteria.

Conclusion: The use of statistical models for predicting probability of under-5 malaria could be adopted as a household risk index for children's exposure to malaria. The spatial clustering and risk maps have been utilized to depict distribution of the observed pattern of under-5 malaria prevalence and demonstrated as an efficient tool for quick identification hot and cold spots of disease prevalence. This can provide valuable insight into the underlying mechanisms driving incidence and transmission of malaria in children.

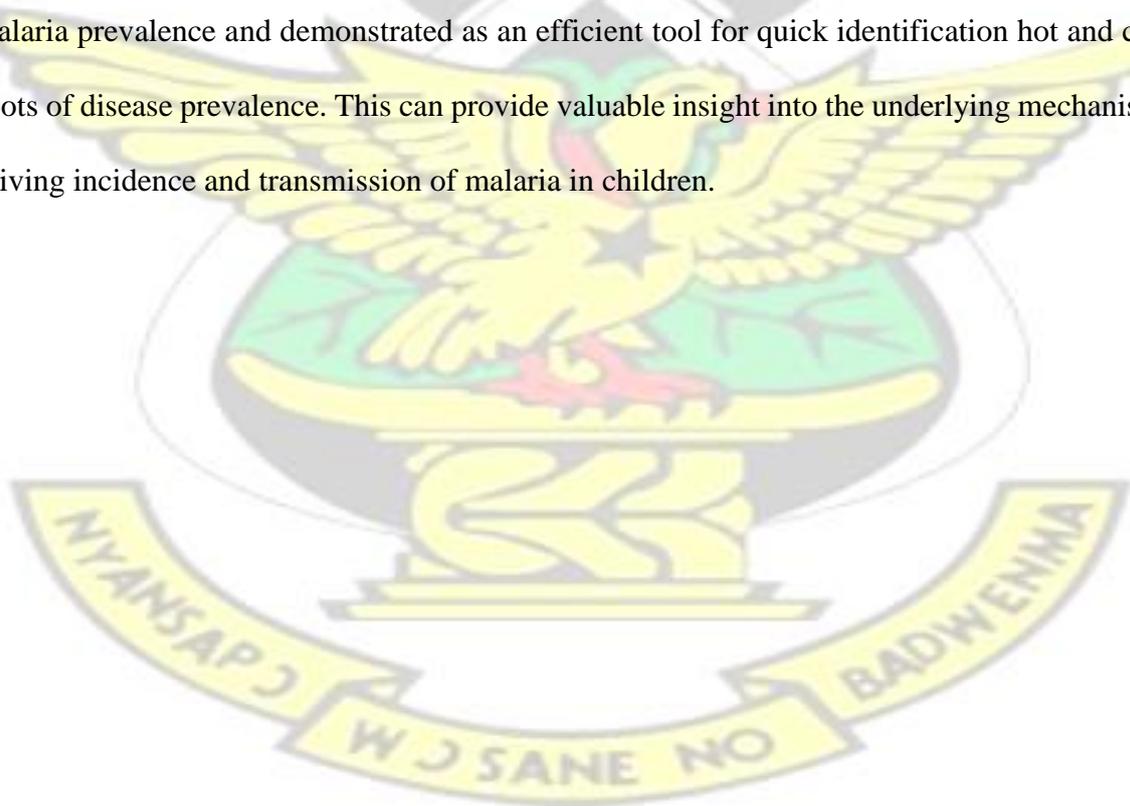


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CHAPTER ONE

INTRODUCTION

1.1 Background of the study

Malaria is an ancient scourge of humanity with almost half the world's population dwelling in malaria endemic regions and it extracts a heavy toll of life and health. Most recent estimates in December 2014 gives the number of malaria cases in 2013 to be about 198 million (with estimation error of 124 million to 283 million) and an estimated 584 000 deaths (with an estimation error of 367 000 to 755 000). A 47% decline in malaria mortality rates have been observed globally since 2000 (WHO 2015).

In Sub-Saharan Africa (where the bulk of the disease burden is borne), malaria is a leading cause of morbidity and mortality accounting for 90% of the world's 300-500 million annual cases and the same proportion of deaths annually (WHO 2013). Malaria is understood to be a disease of poverty and a cause of poverty (Bi and Tong 2014), constituting 9% of the disease burden in SSA and 25% of all deaths below the ages of 5 years. The direct and indirect costs of malaria in Africa exceed US\$2 billion a year (Sodzi-Tettey 2011).

The geographic location of Ghana makes the climate suitable for malaria transmission. Although the seasonality, intensity, and duration of the malaria transmission season is heterogeneous across the ecological strata, Ghana can be grouped into three malaria endemic zones based on the endemicity that prevails within the zones: the northern savannah is the first, followed by the tropical rainforest; and the third is the coastal savannah/mangrove swamps (PMI 2015).

The four parasite species of *Plasmodium* that cause malaria in humans are the *Plasmodium falciparum*, *Plasmodium vivax*, *Plasmodium malariae* and *Plasmodium ovale*. *Plasmodium*

falciparum and *Plasmodium vivax* are the most common of which *Plasmodium falciparum* is the most deadly. Malaria due to *Plasmodium falciparum* (accounts for 85-90%) is most dangerous; if not treated quickly and completely, complicated and severe malaria can result.

The malaria diagnosis is based on clinical diagnosis which is supplemented by microscopy to detect parasites in the blood. The most common symptom of malaria is fever (especially in young children), although other illnesses also present with a fever. In Ghana, the recommended first-line treatment is artemisinin-based combination therapy (ACT) for uncomplicated malaria.

The 2014 GDHS report gives a malaria prevalence rate of 36% in children age 6-59 months as measured by RDT or 27 percent as measured by analysis of blood smears via microscopy. This is a decrease from 48% (as measured by RDT) observed in the 2011 MICS survey. The estimates of prevalence as measured by analysis of blood smears via microscopy recorded only a 1% drop to 27% in 2014 from 28% in 2011. A microscopy results prevalence rates was most prevalent among children living in rural areas especially of the Northern, Western, and Central regions. This was also observed among children in the two lowest wealth quintiles.

Efforts at controlling malaria in Ghana started in the early 1950s with interventions such as residual insecticide application, mass chemoprophylaxis, medicated salt and improved drainage system. Other interventions have been introduced with different degrees of success. The Roll Back Malaria (RBM) initiative was developed in 1999 with the set goal of reducing malaria specific morbidity and mortality by 50% by the year 2010. The National Malaria Control Programme (NMCP) was subsequently implemented in line with the attainment of the Millennium Development Goals (MDG-6). The goal generally aimed at reducing malaria disease and death by 75% by the year 2015.

Under the auspices of the RBM, the use of insecticide-treated mosquito nets as a primary health intervention to stem malaria transmission in Ghana was introduced in 2003 with public awareness programmes and large scale distribution. Since the late 2012, the focus changed from mass campaigns for LLIN to support for regular distribution of ITNs. Increased communications that promote increase in ITN usage has also been adopted.

Indoor Residual Spraying (IRS) model introduced by AngloGold in Obuasi has been rapidly scaled up in some districts in the Northern regions although there have been questions raised on the most efficient and appropriate deployment of this measure in Ghana. The scale up is actively pursued with several M&E activities in the sprayed districts to determine the most favourable conditions under which IRS can achieve its greatest impact. The protocol for management of malaria cases was also revised to include testing, prior to treatment and follow-up after treatment.

The evaluation of these respective programmes to determine their effects on reduction of malaria burden is an essential indicator of their contribution to public health improvement. Quantitative evaluation of the effect of these measures under varying environmental and socio-economic factors (especially at household and community levels) is important for cost effective health care resource allocation and for effective programming of malaria control. Putting such a system in place will reduce the greatest disease burden among the populace especially women and children under 5-years.

1.2 Problem Statement

A growing body of evidence has demonstrated that many public health interventions fall short of reaching their intended target. In the field of malaria control, a number of studies have shown

significant differences in the use of malaria prevention services among segments of the population. Furthermore, malaria control programmes adopt national strategies without recourse to individual, social and location factors that affect the dynamics of the infection transmission. Spatial relationships between locations are unaccounted for with the number of cases assumed to be randomly occurring. This renders the one-size-fits all intervention approach inappropriate for a parsimonious allocation of limited resources for the design, implementation and evaluation of malaria control programmes.

If malaria control interventions are to achieve their desired outcome, they must reach the most vulnerable segments of the populations where malaria prevalence is at its highest. This can only be achieved if malaria control efforts begin to factor in approaches relevant to equitable program design, implementation, monitoring and evaluation.

This study analyses a nationally representative data (from 2008 GDHS survey) to elucidate the contributions of other factors to the disparities in under-5 malaria prevalence across regions in Ghana. The contributions of sex and age of child, maternal age, parity, marital status and education, household socio-economic variables and geographical information of household, are employed to determine location specific expected number of cases is investigated. The data is also explored for information that helps in identification of under-five malaria clusters in Ghana and their spatial patterns. The characterization of malaria heterogeneity allows the identification of localized malaria clusters (hot spots) which may allow prioritization of risk areas and focused control interventions.

1.3 Rationale of Study

Malaria incidence is influenced by individual, vector, environmental and household socioeconomic factors which vary over space and time. The spatial statistical methods proposed

in this study assume the presence of a certain degree of interdependence between the values of under-five malaria at various geographic locations and identifies factors that account for it. When these covariates are employed in developing risk maps to describe the incidence variation in space and time (it allows for a proper description of public burden of disease). It also allows for easy identification of high risk areas for health policy Implementation and resource allocation for treatment. These maps are very efficient not only for predicting the risk/incidence at an un-sampled/unobserved location using the fitted spatial model, but more importantly for malaria control intervention evaluation. When these maps are developed before and after introducing control measures, they serve as invaluable tools for assessing the impact of the intervention activities which will inform resource allocation decisions geared towards reducing the greatest illness burden among the populace.

This study utilizes the 2008 GDHS data for the identification of diseases patterns for under-5 malaria using individual child, maternal factors and household socio-economic and geographic variables as predictor variables. These variables were used to develop the risk/prevalence maps to provide knowledge of the spatial variations in risk and spatial dependencies of the incidence of malaria between households as well as construct a model that predicts the likelihood of malaria in a household with at least one under-five child.

1.4 Hypothesis/Conceptual Framework

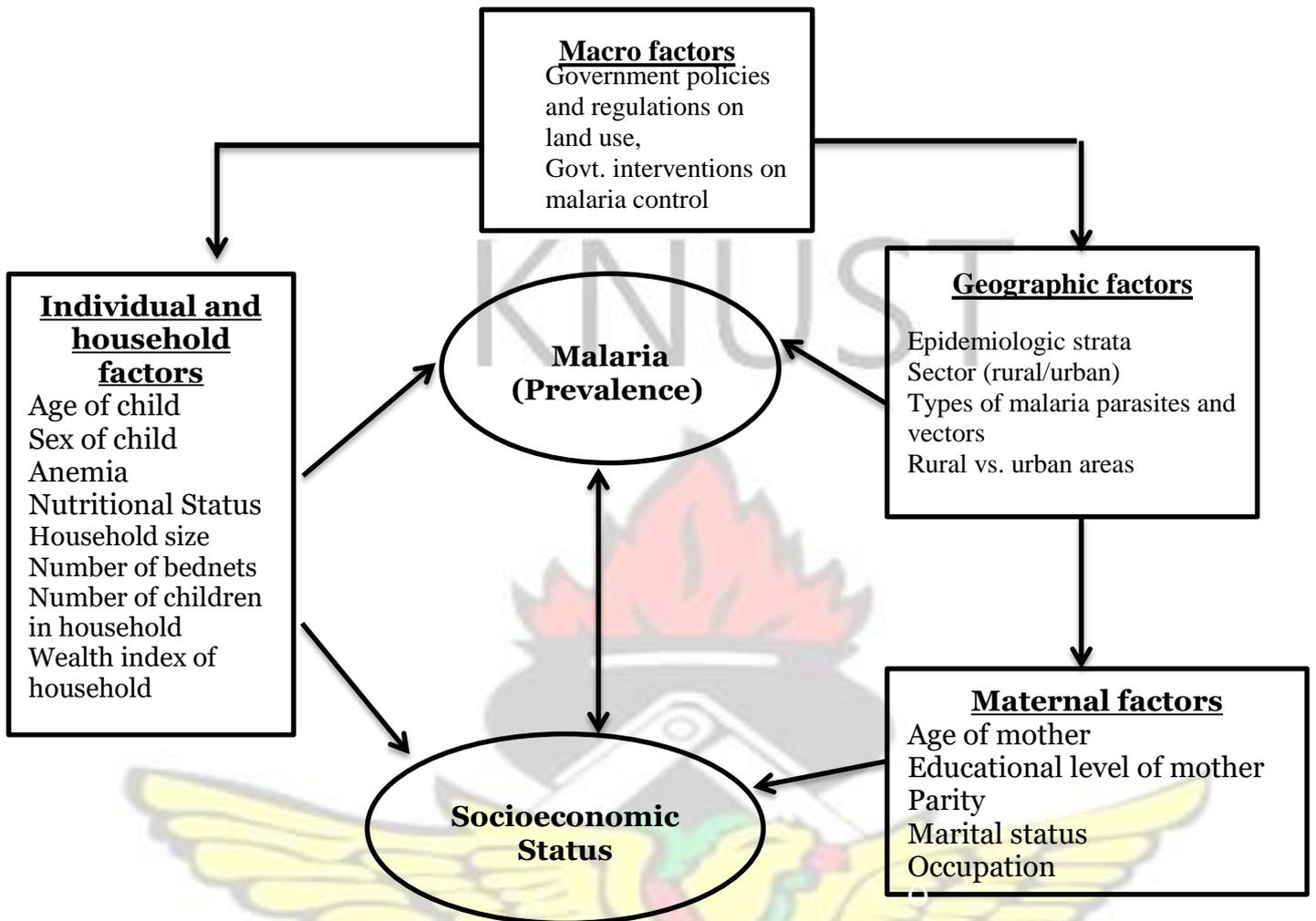


Figure 1.1: Conceptual Framework

1.5 Research Questions

The study sought to address the following questions:

1. What is the risk of malaria at cluster level within regions?
2. What is the pattern of spatial dependency of under-5 malaria between clusters?
3. What individual, socio-economic and demographic factors are significant indicators for modelling the incidence of under-five malaria?

1.6 Objectives of the study

The general and specific objectives of the study are stated in this subsection of the thesis.

1.6.1 General Objectives

The main objective of the present study was to determine the contributions of individual child, maternal and household factors that influence location specific under-5 malaria explain heterogeneity of incidence across space.

1.6.2 Specific Objectives

The study specifically sought to:

1. To determine individual, maternal and household factors which influence the incidence of under-5 malaria in malaria in Ghana.
2. To identify clusters of under-5 malaria in Ghana and their spatial patterns using 2008 DHS data.
3. To explore linkages between DHS determinants of under-5 malaria in Ghana and spatial variables.
4. To model the spatial relationship between incidence of under-5 malaria and household exposure factors.

1.7 Scope of Study

This study analysed the 2008 GDHS data from the National-level population and health surveys conducted in Ghana as part of the global Demographic and Health survey (conducted by Ghana Statistical Services (GSS) in collaboration with Ghana Health Service (GHS)). Household Questionnaires was used for data acquisition from each selected household and a total of 12,323 households were interviewed. Data collection took place over a three-month period, from early September to late November 2008.

The DHS survey obtained detailed information on several demographic and health variables such as fertility, marriage, sexual activity, breastfeeding practices, nutritional status of women and young children, childhood mortality, maternal and child health, awareness and behaviour regarding HIV/AIDS, and other sexually transmitted infections. In addition, the 2008 GDHS collected malaria and use of mosquito nets. The total number of households with under- 5 children was 5336 of which 2992 were included in the malaria survey.

The main study variables considered were derived from the objectives, conceptual framework and literature review of this study.

1.8 Profile of Ghana

1.8.1 Geography of Ghana

Ghana is situated in West Africa, lies just above the equator between latitude four degrees 45 minutes and 11 degrees 11 minutes North and extends from Longitude one degree 14 minutes east to three degrees 17 minutes west. Ghana shares common boundaries with Togo in the east, Burkina Faso in the north and Cote d'Ivoire in the West. The Atlantic Ocean is in the south. It covers a total area of 238,533 sq km (227,533 sq km of land and 11,000 sq km of water (Mundi Index 2014). The country is divided into 10 administrative regions with Accra as the country's capital. Ghana has a tropical climate with temperatures and rainfall varying according to distance from the coast and elevation. The average annual temperature is about 26°C (79°F). There are two distinct rainy seasons, April to June and September to November. In the north, however, the rainy season begins in March and lasts until September. The climate is tropical with temperatures ranging between 21 and 32 degrees Celsius. It is usually breezy and sunny. The South of Ghana has two rainy seasons, from March to July and from September to October. There is only one rainy season in the north, from July to September (GDHS report 2014).

GHANA



Figure 1.2 Map of Ghana

1.8.2 Demographics

The 2014 projected population for Ghana is 25,758,108 using the 2010 census figures. Ghana is demographically young with a median age of 20 and 38.6% of the population at or below 14 years and 15-24 years making up 18.7%. Ghana is a rapidly urbanizing country with 51.9% of the total population living in the urban centres.

1.8.3 Under-5 Malaria prevalence profile

Malaria surveillance in Ghana is inadequate to allow for a robust subnational delineation. The Multiple Indicator Cluster Survey (MICS) with Malaria Biomarker Survey provides a rough impression of the regional (and zonal) disparities in malaria prevalence. Figure 1.3 provides a map of regional malaria prevalence using MICS 2011.

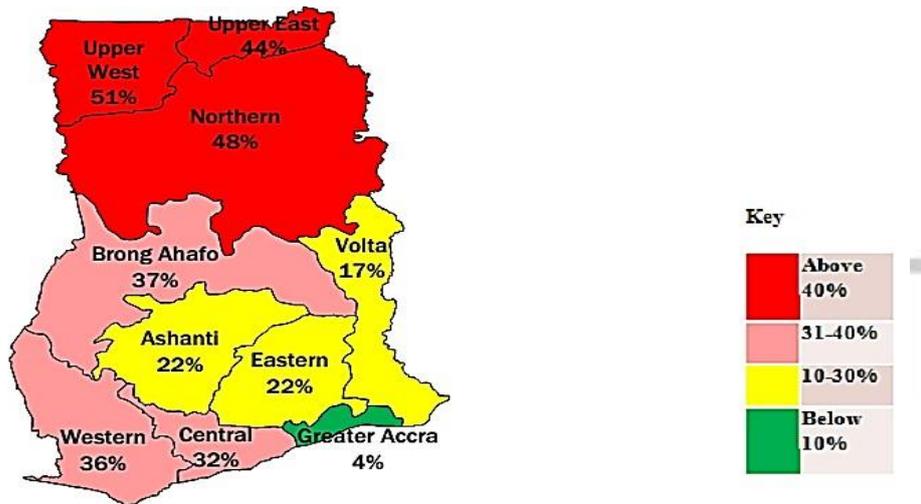


Figure 1.3: Malaria Prevalence in Children 6-59months, by Region.
Source: 2011 MICS.

Ghana has three malaria epidemiologic strata for under-5 malaria with boundaries are not clearly defined. The rapid urbanization further dulls the epidemiologic demarcation (with 51% of Ghanaians living in urban areas). The epidemiologic stratification of under-5 malaria is presented in figure 1.4 below.

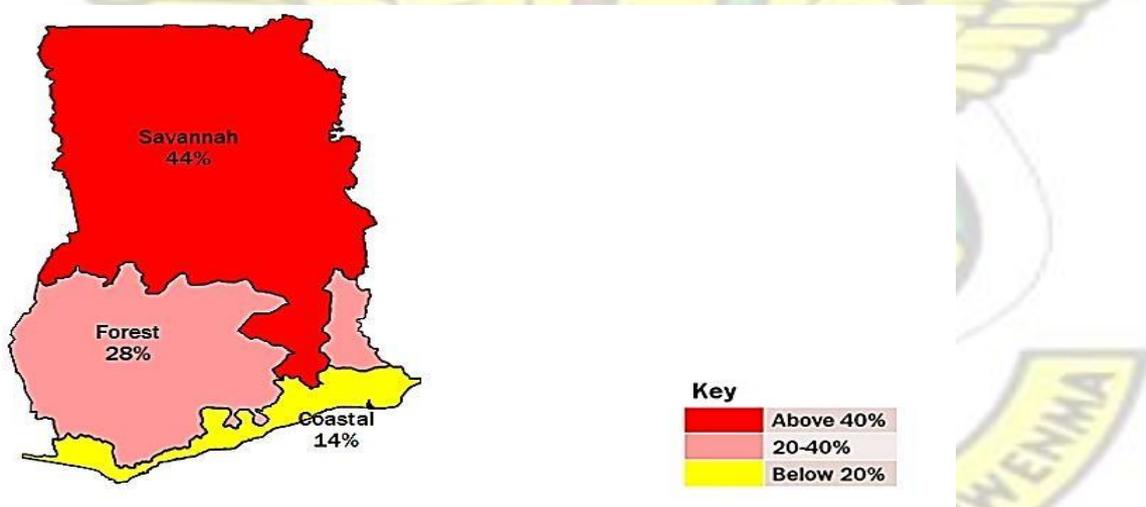


Figure 1.4: Malaria Prevalence in Children 6-59months, by Ecologic Zones. Source: 2011 MICS.

This study adopted the regional malaria prevalence stratification because it provides clearer boundaries for easy interpretation.

1.8.4 Main drivers of Under-5 Malaria prevalence

The main drivers of endemic malaria prevalence are interactions of vectors (abundance in a suitable climate for vector sustainability), specie of plasmodium parasites, host immunological vulnerability, and low socio-economic status.

Most malaria cases are caused by the *falciparum* specie of plasmodium and it is the cause of 90% of malaria cases in Ghana. Studies in Tanzania and Gambia have shown that sustainably higher prevalence of malaria was observed among poor people who are at increased risk of repeated malaria infection. Child mortality rates from malaria were also found to be higher in poorer households.

The prevalence rate of Under-5 malaria in Ghana has declined steadily since 2012 principally due to gains made in breaking the vector-host link through the universal distribution of long lasting insecticide treated nets targeted to the most vulnerable groups and aggressive vector control measures.

1.9 Organization of the Report

This thesis is organized into six main chapters. The first is the introductory chapter which consists of background of the study, research problem, research objective, and justification, profile of study area, scope and limitation of the study. The second chapter is a review of literature on previous works on spatial epidemiology and spatial statistical analysis. Chapter three outlines the study methods and design, data collection, ethical consideration, limitations of the study and assumptions. The fourth chapter presents the results of identifying predictive variables for under-5 malaria using logistic regression and results of the spatial regression analysis. Chapter five is a discussion of the findings in chapter four with respect to our study

objectives and literature review. The sixth chapter is the concluding section. It focuses on conclusions and recommendations from this study.

CHAPTER TWO

LITERATURE REVIEW

In this chapter some salient issues related to malaria transmission, the interdependent relationship between malaria incidence and poverty, and the disease burden are discussed with a focus on under-5 year olds. Measures and strategies adopted for malaria control in Ghana are also discussed. This chapter concludes with a review of the emergence of spatial epidemiology for developing malaria risk maps and its use for decision making on resource allocation and intervention evaluation.

2.1 Malaria morbidity in children

Malaria deaths in children make up most of the 1-3 million annual mortality figures from Africa. In children under-5years, malaria poses greater threat because it is atypical and more severe than in older children where the pattern is similar to that of adults. Maternal antibodies provide passive immunity in the first two months of life, but this give way to increased parasite rate as the child gets older. The rates increase from 0 to 10% in the first three months of life to 80 to 90% by age one. Highest threat of mortality is during the first two years of life. By school age, the degree of immunity in the child would have increased considerably and asymptomatic parasitemia can be as high as 75% in primary school children.

In Africa, about 1 in 20 child deaths is attributable to malaria, and its related diseases. This could be as high as 1 in 5 or 6 in the worst affected areas. (Malaria site 2015). Lower immunity is observed in areas of low endemicity, as a result of which severe infection occurs in all age

groups including adults. Such areas of low endemicity tend to record higher morbidity and mortality due to malaria in children.

Higher susceptibility to severe falciparum malaria has not been observed in malnourished children. It has actually been observed that well-nourished children are more likely to develop severe malaria than those with malnutrition. However, malnourished children have a higher morbidity and mortality when severe malaria does occur because of a prevailing poor state of health.

Congenital malaria and malarial parasitemia in newborns are very rare in spite of significant maternal parasitemia and sequestration of the parasites in the placenta of newborns, While the reasons for this are not fully understood, it is suspected that passive immunity due to maternal antibodies, retarded growth of the parasites in erythrocytes containing Haemoglobin F and resistance for parasite growth in old red cells with HbF may be the causes.

Less fatal infections have been observed in children with heterozygous sickle cell trait than in normal children. This reason for this is not fully understood but the Thalassemias may confer some protection as well as the higher levels of HbF. Homozygous sickle cell disease however does not provide such protection.

The commonest cause of death in neonates and toddlers in malaria endemic regions is severe *falciparum* malaria. There is a rapid increase in parasite counts which results in complications and increased mortality is not quickly diagnosed and completely treated (Malaria Site 2015 and UNICEF 2007).

2.2 Malaria Control Measures in Ghana

Malaria control measures are usually targeted at vector control, breaking the vector-host link and early detection and treatment of cases. The efforts of malaria control in Ghana dates back

to pre-independence period and this has consistently been high on the agenda of different governments. Accelerated malaria control (through vector control) coupled with rapid case management was the main thrust until when the “Roll Back Malaria” initiative was adopted in 1998 as a combination to serve preventive and curative purposes. The Roll Back Malaria programme in Ghana has been multipronged with several initiatives introduced for the control of malaria. Notable among these are the introduction of insecticide treated nets in collaboration with Global Health Initiative and President’s Malaria Initiative (NMCP 2014).

2.2.1 Use of Insecticide-Treated Nets

The introduction of ITNs in the control of malaria has brought significant gains to the fight against malaria. The proper use of bed nets especially ITNs as a means of reducing malaria transmission and mortality by at least 25% has been confirmed in studies. (Sagoe-Moses 2005 cited in Agomo & Oyibo 2013).

Sodzie-Tettey (2011) in a study on the efficacy of ITNs as a malaria control measure in Northern Ghana reported a reduction in parasitemia among children under-5 and pregnant women when the number of children under-5 sleeping under the net increased from 26.7% to 81.1% and also 7% to 39.5% for pregnant women. This was following a free distribution of ITNs and house to house visits to ensure correct installation and use of ITNs.

While the RBM and NMCP have focused extensively on mass distribution of ITNs principally to pregnant women (through ANCs) and children under-5 years (through CWCs); to measure progress toward intervention coverage goals (and eventual malaria eradication), it is important to accurately measure mosquito net ownership and use.

Several studies have shown the relationship between individual characteristics of household members and the likelihood that they will use mosquito nets (Macintyre *et al.*, 2002 cited in

De Castro & Fisher (2012). The most likely groups to have slept under a mosquito net the night prior to the DHS survey were found to be children under-5years and women of reproductive age. The number of nets and household size are important determinant in use of ITNs and the chances of sleeping under a mosquito net increases with increase in ratio of nets: household size. Studies have also shown the association of several individual and household level characteristics and mosquito net use. Individual characteristics age and gender are related to mosquito net use within households. Their findings are consistent with the DHS 2014 reports on use of ITNs in Ghana.

There are however some challenges in the fight against malaria through the distribution of ITNS. Some of the issues cited by James Frimpong, (Programmes Manager for NMCP) are abuse of malaria commodities that are given out free of charge, beneficiaries of free insecticides treated bed net failing to use their bed nets and some schools were engaged in illegalities of charging pupils to pay varied amounts for the nets that were supposed to be given out free of charge. This attitude hindered underprivileged ones from getting access to the bed nets for protection against mosquitoes (Frimpong 2014).

2.2.2 Global Health Initiative (GHI)

The Government of United States of America is a major supporter of global interventions and measures of malaria prevention and control. In May 2009, President Barack Obama announced a global community and family focused comprehensive effort to reduce the burden of disease and promote healthy living (tagged Global Health Initiative (GHI)) was announced by. Through this initiative, the United States will provide financial and technical support to partner countries in improving health outcomes, with a particular focus on improving the health of women, newborns and children (PMI 2014).

The GHI as a global invest is committed to ensuring healthy and productive lives, (building upon and expanding the USG's successes in ameliorating the menace of specific diseases and issues) aims to maximize the impact the United States achieves for every health dollar it invests, in a sustainable way. At the core of the GHI model is to implement a woman- and girl-centred approach; increase efficacy and impact through coordination that is strategic and programmatic integration; leveraging and strengthening key partnerships between multilateral organizations, and private contributions; encouraging country ownership and investing in country-led plans and health systems; improving metrics, monitoring and evaluation; and promoting research and innovation (Kramer & Lesser 2015).

2.2.3 President's Malaria Initiative (PMI)

Ghana became a President's Malaria Initiative (PMI) country in December 2007. The 5-year USD 1.2 billion was launched as a core component of the GHI. PMI's mandate is rapid scaling up of malaria prevention and treatment interventions and reduction in malaria-related mortality by 50% in 15 high-burden countries in sub-Saharan Africa. This has been revised to reduce malaria mortality by 70% when funding for PMI was extended through FY 2014 in the original 15 countries by the end of 2015. The strategy is the continuing scale up in coverage of the most vulnerable groups – children under five years of age and pregnant women. The introduction of intermittent preventive treatment of pregnant women (IPTp) using Artemisinin-based Combination Therapies (ACTs), free distribution of ITNs, and indoor residual spraying (IRS) are the main intervention strategies being adopted.

The GHS in 2008 commenced large scale up of implementations of IPTp and has progressed rapidly with the scale up of interventions with support from PMI and other partners. Artemisinin-based combination therapies and IPTp are now available and being used in most public and private health facilities nationwide.

The activities of distributing LLINs are being coordinated by the NMCP with support for ownership and use. These activities are run concurrently with Indoor Residual Spraying (IRS) to cover one third of Ghana's 170 districts (NMCP 2014).

2.3 Spatial epidemiology of malaria

From the late 1990s, malaria research groups have attempted to map the burden of malaria in Africa geographically using new geospatial analysis techniques. The re-emergence of malaria risk maps an important tool for appropriately targeting the limited resources available for malaria control has been a notable development especially in Sub-Saharan Africa where available resources are usually stretched thin (Omumbo *et al.* 2005). These maps make estimates based on environmental factors as well as population data on malaria suitability of transmission and in some cases actual incidence.

In 2007, the first map to estimate prevalence of malaria parasites in Sub-Saharan countries was produced by Malaria Atlas Project (MAP).

The change in focus of malaria control programmes towards elimination necessitates the identification of transmission foci, and directing of attack measures at high-risk areas are now high priority especially with limited resources to address a disease that varies seasonally and over space. The measures for different locations would differ according to the dynamics of individual localities which are often an intricate intertwine of climatic, vector abundance and individual host characteristics and health seeking habits.

The important role of good maps of malaria risk cannot be over emphasized and its usefulness has been recognized in effective malaria control. These maps are produced from models based on information from sampled locations and then used to estimate the risks at unobserved locations.

Modelling to predict malaria risk for unobserved locations using information from observed limited locations is the basis of malaria risk maps. Accurate prediction requires knowledge of factors that affect the environment and climate and that are related to malaria transmission.

This otherwise simple procedure is complicated by local variation of risks which cannot be explained by known covariates. A further complication is when malaria risks are not evenly or randomly distributed across locations. Such modelling of risk has to take into consideration the spatial autocorrelation among observed data points and this renders most traditional methods inappropriate.

The use of generalized linear models in spatial analysis of small-Area malaria incidence rates in Kwazulu Natal was studied by Kleinschmidt *et al.* (2000). Spatial smoothed risk maps for malaria were produced for the northernmost districts in Kwazulu Natal. The model adjusted for autocorrelation was found to outperform the ordinary regression models that assumed independence of observations.

Risk maps for malaria were developed for seven villages in north-central Sri-Lanka in 2003 by Hoerk *et al.* using the house location relative to vector breeding sites. Proximity to vector breeding site (within 750 m) presented higher risk of malaria with adjusted odds of 5.93 (95% CI: 3.50 – 8.91). Poor housing construction was an independent risk factor for malaria in the villages studied.

Omumbo *et al.* (2005) produced malaria risk maps for East Africa (Kenya, Tanzania and Uganda) using high spatial resolution environmental data. They achieved a high degree of predictive accuracy for *p. falciparum* parasite prevalence.

Hui *et al.* (2009) studied the spatio-temporal distribution pattern of malaria in Yunnan Province, China using a geographic information system technique. The spatial autocorrelation analysis indicated that malaria incidence was not randomly dispersed in the province. Spatial

clustering was observed in the high risk areas and obvious associations between *P. vivax* and *P. falciparum* malaria incidences and climatic factors with a clear 1-month lagged effect was found to exist especially in cluster areas. These were proposed as a source of useful information on where and when malaria prevention and control measures would be applied.

Their findings suggested directing countermeasures at high risk areas at suitable times especially during seasons of transmission peaks.

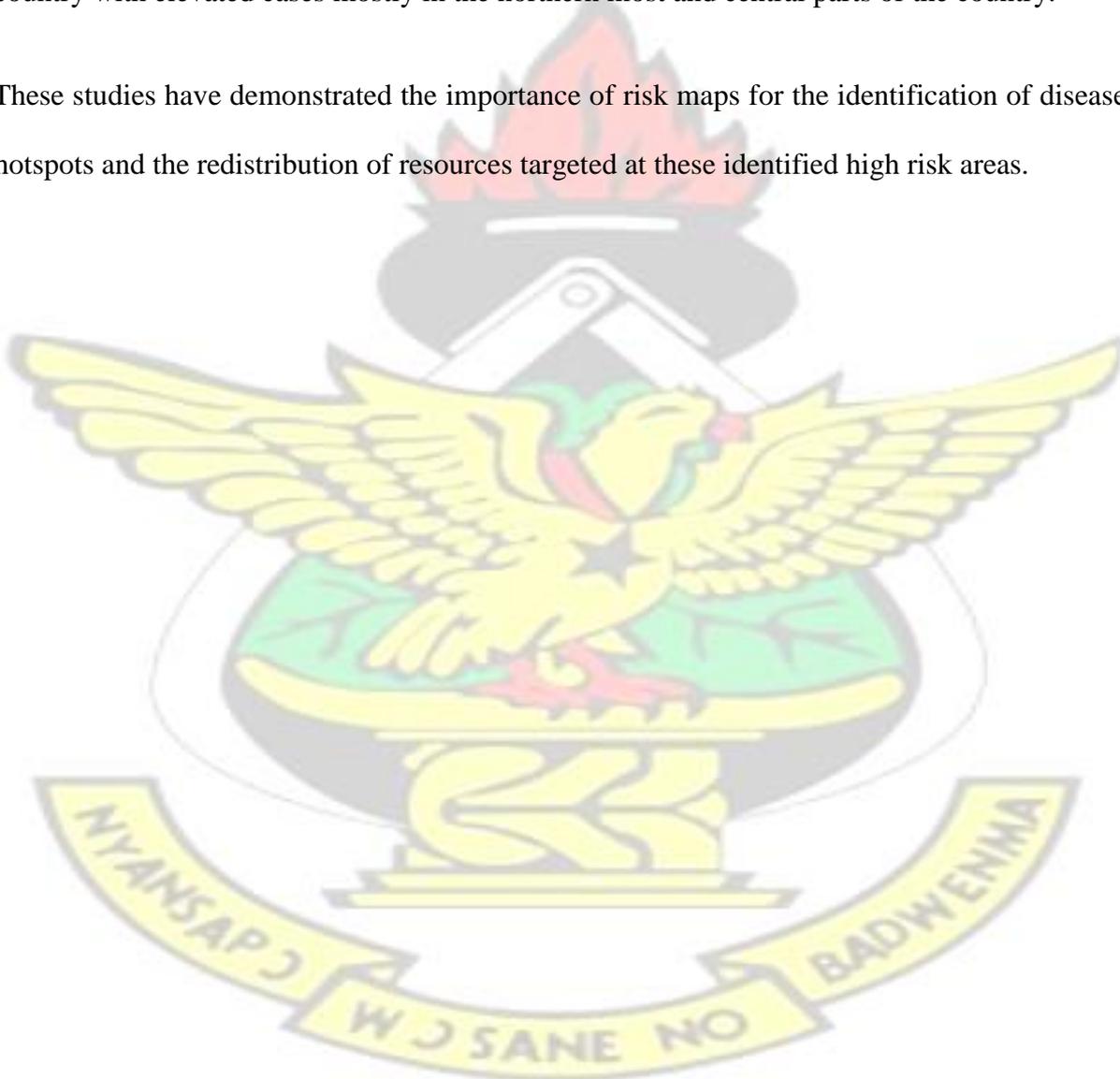
In a similar study by Reid *et al.* (2010), Bayesian geostatistical logistic regression models with environmental covariates were used to predict *P. falciparum* prevalence for 2- to 10-year-old children in Bangladesh. Their model validation statistics showed that the final Bayesian geostatistical model was found to have good predictive ability. Risk maps generated from the model showed non-random patterns of malaria prevalence across the endemic regions.

Kleinschmidt *et al.* (2014) in their study to model the risk of malaria in children under 10 years in Mali, adopted a two-stage modelling approach. Logistic regression was used to determine approximate risk on a larger scale using ecological predictors in the first instance and this was followed by geo-statistical analysis to account for spatial dependence of the model residuals and make improved predictions at the local level. Their final logistic found environmental variables as good predictors and it explained about 65% of the variance in children under-10 years of age.

Tatem *et al.* (2014) studied the integrating rapid risk mapping and mobile phone call record data for strategic malaria elimination planning in Namibia. The GPS information of the households of malaria reported cases were obtained from their mobile phones and this was used as a tool for active surveillance to determine the prevalence for developing risk maps.

Appiah *et al.* (2011) conducted spatial temporal analysis of malaria incidence in Ghana. In order to produce evidence-based monthly maps and illustrating the patterns of malaria risk over space and time. Monthly morbidity cases reported on malaria from public health facilities at district level and population data for the period 1998-2010 was used to compute the malaria incidence rates, being the number of reported cases per unit resident population of 10,000. Their results indicated non-random spatial and temporal distributions of the disease across the country with elevated cases mostly in the northern most and central parts of the country.

These studies have demonstrated the importance of risk maps for the identification of disease hotspots and the redistribution of resources targeted at these identified high risk areas.



CHAPTER THREE

METHODOLOGY

This chapter focuses on the theoretical and conceptual frame work of the data acquisition, management and analysis. The research design, study population and area, data handling procedure and statistical tools adopted for the analysis are discussed.

3.1 Source of data

This study analyses a national representative routine data (DHS 2008) with records for 12,323 households selected in a two-stage sampling procedure. Descriptive statistical methods were employed to give summary views of data distribution and graphical statistical tools were used for pictorial representation of proportions and group classifications by individual and household characteristics. Association between these characteristics and the incidence of u-five malaria was tested for significance and the significant variables were used as predictors in the multivariate logistic regression. Malaria risk maps were developed using spatial statistical analysis.

3.2 2008 GDHS coverage area

Ghana is situated in West Africa, lies just above the equator between latitude four degrees 45 minutes and 11 degrees 11 minutes North and extends from Longitude one degree 14 minutes east to three degrees 17 minutes west. Ghana shares common boundaries with Togo in the east, Burkina Faso in the north and Cote d'Ivoire in the West. The Atlantic Ocean is in the south. It covers a total area of 238,533 sq km (227,533 sq km of land and 11,000 sq km of water (Mundi Index 2014). The country is divided into 10 administrative regions with Accra as the country's capital. Ghana's climate isa tropical climate with temperatures and rainfall varying according to distance from the coast and elevation. The average annual temperature is about 26°C (79°F).

There are two distinct rainy seasons, April to June and September to November. In the north, however, the rainy season begins in March and lasts until September.

The climate is tropical with temperatures ranging between 21 and 32 degrees Celsius (2014 GDHS Report).

3.3 GDHS population

The survey population included all households with at least one child under-five years and their mothers aged between 15 and 49 years who were captured in the GDHS – phase V survey conducted in the 2008 and also included in the malaria survey. There were 5336 households with children under-five of which 2992 were included in the malaria and anaemia prevalence survey. From the initial number of 12,232 households in the data, only households with at least one child under – five and included in the malaria and anaemia survey were considered for the purpose of this study.

3.4 2008 GDHS Data Collection Techniques and Tools

The GDHS 2008 is the fifth in the series of National-level population and health surveys conducted in Ghana as part of the global Demographic and Health Surveys (DHS) programme to provide information on population and health. The survey was (conducted by Ghana Statistical Services (GSS) in collaboration with Ghana Health Service (GHS)).

The data collection tool was a set of questionnaires (translated from English into three major local languages, namely Akan, Ga, and Ewe). Data collection took place over a three-month period, from 08 September to 25 November 2008. The total number of clusters interviewed was 411 of the 412 earmarked, and each household had a cluster identification number.

The survey obtained detailed information on several demographic and health variables such as fertility, marriage, sexual activity, breastfeeding practices, nutritional status of women and

young children, childhood mortality, maternal and child health, awareness and behaviour regarding HIV/AIDS, and other sexually transmitted infections. In addition, the 2008 GDHS collected data on malaria in children and use of mosquito nets.

3.4.1 Inclusion/Exclusion Criteria

Households with at least one child aged 6-59 months along with their mothers aged between 15 to 49 years and included in the malaria and anaemia prevalence survey were included in the study. Households without at least a child 6-59 months or with at least one child under five but that did not participate in the anaemia and malaria prevalence survey were excluded.

3.5 Data analysis variables

The characteristics of individual children, their mothers and household demographics were extracted from the GDHS data and explored to investigate the incidence of malaria at household levels. The table below presents the variables used in the study.

Table 3 1: List of study variables

Variable	Operational definition/indicator	Scale of measurement
Malaria incidence	Incidence of fever (with or without cough or catarrh) within two weeks prior to or at the time of survey and if fever was treated with an antimalarial.	Nominal (yes/no)
Age of Child	The age of child in months	Ratio
Sex of child	Sex of child	Nominal
Anaemia	Haemoglobin concentration level measured in g/dl <ul style="list-style-type: none"> • Not anaemic: > 10g/dl • Mild: 10.0-10.9 g/dL • Moderate: 7.0-9.9 g/dL • Severe: less than 7.0 g/dL 	Ordinal
Birth order	Birth order of the child for the mother and not for the household	Ordinal
Use of bed net	If child slept under a net the night before the household was surveyed	Nominal

Under-5 in households	Total number of children 6-59 months de jure in the households	Ratio
Household size	Total number of de jure household residents	Ratio
Wealth Index of Households	Wealth category or quintile of Households measured as: Lowest, second, middle, fourth and highest.	Ordinal
Maternal Educational	The completed level of formal education by mothers of the children. No education and primary – 0 Secondary and higher – 1	Ordinal
Zones	Regional groupings into malaria prevalence zones using MICS 2011 classifications. Zone 1: > 40% (UE, UW, N) Zone 2: 31 – 40% (BA, W, C) Zone 3: 10 – 30% (As, E) Zone 4: < 10% (GA)	Nominal
Type of Residence	Urban or Rural	Nominal
Household Size	Number of people living in a household	Ratio
Household size/nets	Ratio of persons in the household to number of nets	Ratio
Maternal age	Age of mother	Interval
Parity	Number of children ever born	Ratio
Maternal Education	Highest educational level of mother No education- primary – 0 Secondary and Tertiary – 1	Ordinal
Marital status	The marital status of the mother. Married/living together = 1 All other categories = 0	Nominal
Longitude	Cluster longitude	Interval
Latitude	Cluster latitude	Interval

3.6 The GDHS Sampling Procedure

The GDHS 2008 survey utilised a two-stage sampling design. The first stage involved selecting clusters or sample points from the 2000 Ghana Population and Housing census sampling frame using systematic sampling proportional to size. The second stage involved the selection of households.

At the first stage, sample points or clusters were selected in the first stage using the 2000 Ghana Population and Housing Census. A total of 412 clusters were selected systematically with probability proportional to size. Data were not collected from one cluster for security reason. A complete household listing was conducted from June to July 2008 in all the selected clusters to construct a sampling frame for the second stage selection of households. In the second stage of sampling, the systematic sampling of 30 of the households listed in each cluster was carried out to ensure adequate numbers of completed individual interviews to provide estimates for key indicators with acceptable precision. A total of 12,323 households were selected with a response rate of 97%.

The questionnaires were pre- tested in July 2008 before its final implementation. Lessons learnt from the pre – test were used to finalize the survey instruments as well as logistics arrangements for the actual survey which kick started in September 2008.

3.7 Data handling

Data on household with at least one child aged 6 – 59 months were extracted from the DHS 2008 data and the data was cleaned and checked for completeness. The DHS GIS data was obtained as shape files. The child related data was converted to excel csv files and merged with the shape files in GeoDa 1.6.2 for spatial analysis while the child data was exported to Stata 12 for descriptive analysis and logistic regression.

3.8 Data processing and Analysis

Individual, maternal and household data was obtained on under-5 children aged 6 – 59 months along with the GIS coordinates of the cluster they fall into. The GIS file and child data were obtained in different SPSS files but the unique household identification numbers and the cluster numbers were used to merge the files. The earlier defined variables were extracted into

Microsoft Excel CSV files and merged with the GIS files. The descriptive analysis, tests of significance and logistic regression were done in Stata 12 while the spatial statistical regression analysis was done in GeoDa 1.6.2 and the risk maps were drawn in ArcGIS 10.2.1 for desktop.

The incidence of under-5 malaria in a household was measured using the variables on child illness with fever in the last two weeks (with/without catarrh and cough) and treated with antimalarial. The number of cases per cluster was divided by total number of under-5 in the respective clusters to determine the proportion of cases per cluster. The normalized values were used to construct intensity thresholds.

Z scores ≤ 0 , low

Z scores ≤ 0 , average

Z scores between 0.0001 and 2.000, high

Z scores between 2.0001 and 3.000, very high

Z scores ≥ 3 , extremely high

The cluster level medians of maternal age, child age, parity and household wealth index were obtained and along with number of U-five per cluster, were merged with GIS file containing the coordinates of 411 clusters to model the risk per cluster and develop the risk maps.

The analyses were carried out to address the specific objectives of the study. Empirical results are presented in the first instance, followed by tests of association between individual explanatory variables and incidence of malaria in u-fives. The variables that were found to be significant are included in the stepwise multiple logistic regression to determine their contributions to the outcome of interest.

The Moran's I test for existence of clustering patterns was utilized to test for spatial dependency of malaria prevalence across clusters. The Ordinary least squares, Spatial Error

Model and Spatial Lag Model are used for the spatial regression and the Akaike Information Criterion and Likelihood ratio tests were used for model comparison and final model

selection.

The LISA maps for test of strength of spatial dependencies are produced along with the malaria risk maps (using GIS). The hot spots were identified as well as the cold spots.

3.8.1 Empirical Analysis

These are descriptive results using summary statistics, tables, and charts.

3.8.2 Tests of association between predictor variables and under-5 malaria cases

To determine individual, maternal and household factors which influence the incidence of under-5 malaria in Ghana, the predictor variables in this study are examined for association with the under-5 malaria incidence using the chi-square test for independence in the first instance, and the variables are also considered as possible predictors for the probability of the incidence of under-5 malaria at household level.

3.8.2.1 Chi square test of independence

The chi square test has the null hypothesis is that of independence between two or categorical variables under consideration in the contingency table. The test statistic compares the observed cell frequencies of the contingency table to the expected frequencies under independence and follows an approximate chi-square χ^2 with $(r-1)(c-1)$ degrees of freedom.

A rejection of the null hypothesis of independence does not provide any information on the strength and nature of the association between the variables. To determine this, further tests such as Phi coefficient (for 2 by 2 contingency tables) and Cramer's V statistic (for tables of higher dimensions) are required.

3.8.2.2 Binary logistic regression

To predict the odds of the incidence of under-5 malaria in a household, the binary logistic regression model is employed. It is one of the models in a large family of Generalized Linear models for modelling outcome variables that do not conform to the traditional continuous normally distributed forms. In this instance, the response variable is the likelihood of occurrence or non-occurrence of under-5 malaria, being determined by the predictor variables under consideration. The interest is to determine how well the variables are able to predict the outcome.

The model transforms the odds into a linear function of the explanatory variables by taking the natural log transform of the odds. This transformation allows us to compute a number, called $\text{logit}P(X)$, for an individual with independent variables given by X , which is a probability of the individual experiencing the outcome of interest. For this study, the outcome of interest is location specific incidence of under-5 malaria.

3.8.4 Spatial regression analysis

To test the existence of spatial dependencies in under-5 malaria between neighbouring observations which we expect (logically) to be more similar than those far apart, we utilized the Moran's I statistic. For each pair of observations x_i, x_j we assign a weight, w_{ij} (measure of neighbourliness) sometimes referred to as **neighbouring functions**.

Interpretation of Moran's scatter plot.

The four different quadrants of the scatter plot identify four types of spatial associations.

- (HH) a high attribute cluster with high attribute neighbours (quadrant I);
- (LH) a low attribute cluster surrounded by high attribute neighbours (quadrant II);

- (LL) a low attribute cluster surrounded by a low attribute neighbours (quadrant III) and
- (HL) a high attribute cluster surrounded by low attribute neighbours.

A major limitation of Moran's I is its being a global measure of global autocorrelation and thus unable to identify the specific locations of spatial patterns. Anselin's Local Indicator of Spatial Autocorrelation (LISA) provides a remedy for the shortfall in I statistic. LISAs are simple local disaggregation of global measures of spatial autocorrelations (Anselin 1995).

Spatial Regression models are used as a Confirmatory Spatial Data Analysis after ESDA. Two of the common spatial regression models (Anselin 1999) are; Spatial Lag Model (SLM) and Spatial Error Model (SEM). Ordinary Least Square (OLS) model is often used as a null model for comparative analysis. Parameter estimation of spatial autoregressive model can be done using the Maximum Likelihood Estimation, Bayesian Estimation and Generalized Method of Moments (Anselin 2003).

3.9 Ethical considerations

Ethical clearance to conduct the study was obtained from KNUST's Committee on Human Research, Publications and Ethics (CHRPE).

3.10 Limitations of using DHS data

Using the DHS data for statistical analyses has advantages of convenience of collection, broad temporal and spatial coverage and other attendant benefits of using secondary data; it is however bedevilled with the problem of not being readily amenable for modelling or other statistical analyses other than the purpose for which the data was obtained.

Coupled with this is the case definition for malaria in the GDHS V malaria module. It is not defined as confirmed malaria but rather as illness with a fever (in the last two weeks).

Questions on loss of appetite, whether or not the child had a running nose, faster breathing, difficulty in breathing and cough were asked as well as questions on the source and type of medication administered as treatment of the child's fever/illness. A wide range of antimalarial drugs (Fansidar, Malafan, Chloroquine, Camoquine, Quinine, Artesunate with Amodiaquine, Artemisinin, Artemether/Lumefantrine and other Antimalarial) were considered in the data. Questions are also asked on Antibiotics administered and analgesics (GDHS 2008 Report, pg 419 – 425).

For our case definition, we consider cases of illness with fever (with or without catarrh or cough) treated with antimalarial as suspected cases of malaria. We are not unaware of the subjectivity of this case definition, but these are the most feasible proxy variables for measuring malaria incidence from the available data.

A further limitation of the DHS data is that the GPS coordinates for the clusters are scrambled to within 4 kilometres radius to protect the identity of the respondents. This will limit the accuracy of the clusters on the spatial maps to within 4km radius.

Also in this study, we are unable to demonstrate the utilization of the risk maps for malaria intervention analysis due to the unavailability of the GDHS 2014 data. We had requested for the 2008 and 2014 data sets because it is expedient to have risk maps at a minimum of two time points to evaluate the impact of the intervention. These limitations however do not devalue the merit of this study.

CHAPTER FOUR

RESULTS OF THE STUDY

In this chapter, we present results data analysis on the prevalence of malaria among children under-5 in Ghana. The results and analysis presented are for households with at least one child

under five years in which the child had a fever within two weeks or at the time of survey (with or without cough or catarrh), treated with antimalarial and included in the anaemia and malaria survey.

4.1 Empirical Analysis

Table 4.1 presents the categorization of some of the variables used in the analysis. The empirical results show that most households in Ghana are poor with a cumulative percentage of 54.45 % comprising 32.52 % of the poorest class and 21.93 % of the poorer class. On the other hand, the richest and the rich together constitute a mere 28.7% of households in the country.

For the purposes of this study, suspected malaria case of a child is recorded in a household if the child had fever within two weeks to (or at time of) enumeration with or without other symptoms such as cough, catarrh, headache, running nose and if s/he was treated with antimalarial and if the child was included in the anaemia survey. Malaria prevalence was 28.04 % (about one in four of the children in the survey). There were about as many males as females covered with only a 2% excess of males over females and 63.2% of all the children were aged between 6-35 months. Only 8.1% of them were severely anaemic with 80% being moderately or mildly anaemic. About nine in ten children under-5 had one form of anaemia. The usage of any type of bed net the night before the survey was 44.9% with more than half of the children reported no bed net use.

On maternal education, the data shows that 61.97 % of the women had no form of formal education or had primary education. Only 38% had secondary or higher forms of education. The highest parity observed was 14 children recorded for two women.

Epidzone 3 (Volta, Ashanti and Eastern regions) recorded the highest frequencies for women with 1-3 children. For women with 4-9 children, it was more predominant in Zone 1 (Upper

East, Upper West and Northern regions). The pattern for higher number of children appeared random.

On the rural-urban dichotomy, there were more children from the rural sector (66.58%) among the respondents than from the urban sector (33.42%).

Table 4.1 Frequency Distribution of Variables

Variables	Frequency	Percentage (%)
Child related variables		
Malaria cases		
No	2153	71.96
Yes	839	28.04
Sex of Child		
Male	1526	51.00
Female	1466	49.00
Age category of Child		
1 (6 to 11 months)	640	23.85
2 (12 to 23 months)	562	20.95
3 (24 to 35 months)	494	18.41
4 (36 to 47 months)	464	17.29
5 (48 to 59 months)	523	19.49
Total	2683	100
Anaemia		
Not anaemic: > 10g/dl	176	8.13
Mild: 10.0-10.9 g/dL	1091	58.49
Moderate: 7.0-9.9 g/dL	467	21.56
Severe: less than 7.0 g/dL	432	11.82

Table 4.1 Continued

Slept under net		
Child did not sleep under net	1482	55.09
Child slept under net	1208	44.91
Maternal related variables		
Maternal Educational Level		

No education	1854	61.97
Secondary and higher	1138	38.03
Maternal Agegroup		
1 = "15 - 19"	119	3.98
2 = "20 - 24"	583	19.49
3 = "25 - 29"	824	27.54
4 = "30 - 34"	603	20.15
5 = "35 - 39"	520	17.38
6 = "40 - 44"	242	8.09
7 = "45 - 49"	101	3.38
Parity		
1 - 3	1639	54.78
4 -7	1135	37.93
8 -14	218	7.29
Household related variables		
Wealth Index of Household		
Poorer	973	32.52
Poorest	656	21.93
Middle	504	16.84
Richer	502	16.78
Richest	357	11.93
Type of Place of Residence		
Rural	1000	33.42
Urban	1992	66.58
Epidemiological zones		
Zone 1: > 40% (UE, UW, N)	1005	33.59
Zone 2: 31 - 40% (BA, W, C)	763	25.50
Zone 3: 10 - 30% (As, E)	945	31.58
Zone 4: < 10% (GA)	279	9.32

*Cases with missing observations were excluded from in this table. Source: 2008 GDHS

* Eidemiological zones is hereafter also referred to as epidzones

The pie charts of four variables that are considered key variables (age of child, anaemia, household wealth index and epidemiological zones) are presented in figure 4.1 as a matrix of pie charts. The first pie chart shows the percentage distribution of the children by age, the second chart shows the wealth index distribution with 32% of the children coming from the

poorest quintile. Overall, 92 percent of children age 6-59 months in the data had some level of anaemia, including 54% percent of children who are mildly anaemic, 30% percent who are moderately anaemic, and 18%ercent of children with severe anaemia. The chart for epidzones shows the distribution of children across epidemiological zones.

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4.2 Malaria prevalence by regions and epidemiological zones

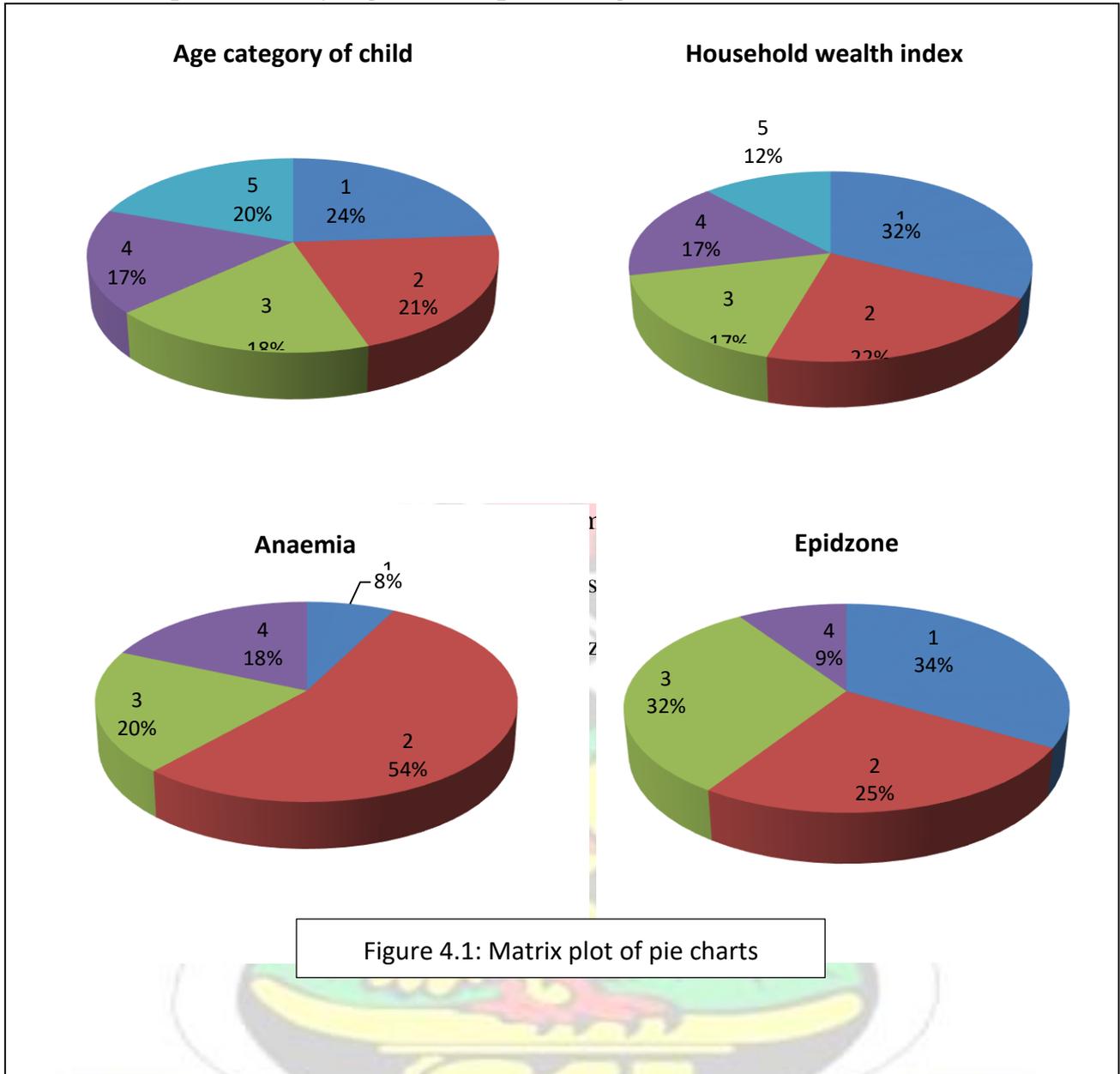


Table 4.2: Malaria cases and prevalence by epidemiological zones

Epidemiological Zones	Malaria Cases			Prevalence
	No	Yes	Percentage of total cases	
1	712	293	34.92	29.15
2	553	210	25.03	27.52

3	674	271	32.30	28.68
4	214	65	7.75	23.30
Total	2153	839	100	
Pearson χ^2 of association between Epidzones and malaria	$\chi^2_{(3)} = 4.0195$		$pr = 0.259$	

Zone 1 recorded the highest number of cases (34.92%) followed by Zone 3 (32.3%), Zone 2 (25.03%) and Zone 4 (7.75%). This pattern was the same for malaria prevalence within epidzones. Zone 1 had a prevalence of 29.15%, Zone 3 had 28.68% and Zones 2 and 4 had prevalence of 27.52% and 23.30% respectively. The prevalence in zone 4 (greater Accra) was particularly much higher than expected. Prevalence was calculated as a ratio of number of malaria cases to total number of under- fives within the zone.

The test of association between epidzones and malaria cases did not show a significant association at 10% level of significance.

The regional distribution of malaria cases is analysed and the prevalence for each region is determined along with the test of association of suspected malaria cases and region of residence. Results (presented in Table 4.3) show Northern region topping the list of number of malaria cases with 18.29% of total cases followed by Ashanti region with 17.99% of the total cases. Volta, Upper East and Eastern regions had similar percentages and Western region recorded the lowest with a percentage of 4.88%. When the prevalence was calculated by region, Brong Ahafo region had the highest of 36.84%, followed closely by Ashanti region with 34.40%. Western region recorded the lowest prevalence of 15.19%. Details of percentages and prevalence are presented in Table 4.3 below.

The Pearson's test of association gave $\chi^2_{(18)} = 52.497$ with p-value <0.0001 and Cramer's V

was .137. This shows a significant association between region and number of malaria cases at 1% level of significance.

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Table 4.3 Regional distribution of malaria cases and prevalence

Region	Malaria cases	Percentage	Prevalence
Western	41	4.88	15.19
Central	73	8.69	32.16
Greater Accra	50	5.95	17.92
Volta	67	7.93	27.35
Eastern	61	7.32	23.37
Ashanti	151	17.99	34.4
Brong Ahafo	98	11.74	36.84
Northern	153	18.29	31.94
Upper East	67	7.93	29.52
Upper West	78	9.3	26.09
Total	839	100.00	
Pearson χ^2 of association between Regions and malaria	$\chi_{(218)} = 52.497$	$pr < 0.0001$	
Cramer's V	.137	$pr < 0.0001$	
Contingency Coefficient	.136	$pr < 0.0001$	

4.3 Determining association between study predictor variables and occurrence of under-5 malaria

In this section, the results for the tests of independence between the child, maternal, socioeconomic and demographic factors and occurrence of under-5 malaria are presented in Table 4.4. Some of the variables did not show significant association with the incidence of under-5 malaria at household level.

Table 4.4 Chi square test of association between malaria and other risk factors

Factor	Pearson Chi ²	Pvalue	Cramer's V/Phi
Agecategory (child)	31.7364	.000***	.110
Anaemia	32.9049	.000***	.111
Sex of child	1.3154	.251	.021
Birth order of child	7.3705	.882	.05
Slept under net	5.434	.02*	.045
Maternal education	4.151	.246	.037
Maternal age group	7.1397	.308	.049
Parity	18.7561	.131	.079
Marital status	3.0432	.081*	.032
Household size	21.4342	.313	.085
Number of under 5 in household	47.2140	.000***	.126
Wealth index	5.3770	.251	.042
Epidemiological Zone	4.0195	.259	.037
Type of residence (Ur/Ru)	1.3739	.241	.021
Level of significance for test of independence is 10%.			
Source: GDHS 2008 data			

Significant associations were observed between age category, anaemia, slept under net, marital status, number of children under 5 in household and the incidence of malaria. However for the modelling stage, all variables showing significance at 20% will be explored as possible explanatory variables for the incidence of malaria.

4.4 Identifying predictor variables for the incidence of under-5 malaria

Further analyses to determine how well the variables perform in predicting the odds of under5 malaria was done using the univariate binary logistic regression model. The purpose was

exploratory and the identified variables were used in different model constructs of multivariate logistic regression model. The Chi² and Likelihood Ratio tests were used for identifying the most parsimonious model.

4.4.1 Using binary Logistic Regression to predict the incidence of under-5 malaria

All the study variables were examined as possible determinants of malaria incidence in under-5 children using univariate logistic regression and the emphasis was on variables that had shown significant association with malaria in section 4.3. The results are presented in Table 4.5

Table 4.5 Univariate logistic regression

<u>Malaria</u>	<u>Odds Ratio</u>	<u>P>Chi²</u>	<u>[95% Conf. Interval]</u>	
Age	.971	.314	.917	1.028
Anaemia	.845	.001	.763	.935
Sex of child	.911	.251	.776	1.068
Birth order	.991	.626	.955	1.027
Slept under net	1.202	.029	1.019	1.416
Maternal Educ	.972	.730	.824	1.145
Maternal age grp	1.016	.562	.962	1.074
Parity	.964	.054	.931	1.006
Marital Status	.791	.085	.608	1.029
Household size	1.018	.222	.989	1.047
Wealth index	1.002	.938	.947	1.061
No. under-5 in hh	1.057	.177	.976	1.145
Epid zone	.948	.197	.876	1.028
Type of Res.	.905	.242	.765	1.069

*test of significance is at 10% level of significance for exploratory purposes

The preliminary test of significance was at 10% level of significance. The significant variables are anaemia, slept under net, parity and marital status. These variables along with those found

to be significantly associated with malaria in 4.3 are included in the multivariate logistic regression using the likelihood ratio test for the final model selection. The final model is presented in Table 4.6 below.

Table 4.6 Multivariate Logistic regression model

Malaria	Odds Ratio	P>Z	[95% Conf. Interval]	
Agegroup	.859	.000	.801	.921
Anaemia	.873	.013	.785	.972
2.typeofresidence	.741	.006	.599	.916
Epizone				
2	.776	.039	.610	.987
3	.861	.196	.687	1.079
4	.629	.017	.429	.922
Cons	1.563	.026	1.055	2.313

LR chi² statistic = 41.98 Prob > Chi² = .0000 Pseudo R² = .0153 Log Likelihood = -1348.5112 Overall Percentage Performance = 74.7%

From Table 4.6, the results show a reduction in incidence of malaria in older children who were not experiencing severe anaemia and living in the urban sector. Malaria cases were also fewer among children in epidemiological zones 2 and 4 relative to those in epidemiological zone 1. For instance, for a child in age group 5, the odds of having malaria is reduced by 15% when compared with a child in age group 1. Increase in haemoglobin level by a unit reduces the odds of malaria by 13% and the odds of malaria for children in the urban residence is reduced by 13% when compared to children residing in rural areas.

The model test for multicollinearity was the standard errors of the coefficients. None of the standard errors was >2 which implies that there is no problem of multicollinearity in the explanatory variables. The observed standard errors were between .03 and .12.

4.5 Spatial Analysis and under-5 malaria incidence risk maps

In this section, the focus is on the pattern of the occurrence of under-5 malaria across Ghana. The data is investigated for clustered patterns as opposed to randomness in the pattern of occurrence. Risk

maps were also developed to depict the associated risks of under-5 malaria at cluster level across Ghana.

4.5.1 Test of spatial dependence in occurrence of under-5 malaria

The Moran's index is used to test the hypothesis that the incidence of under-5 malaria is randomly occurring across Ghana against an alternative of non-random spatial pattern in occurrence. Moran's I can be conceived as the correlation between a variable and the spatial lagged form of the variable. The scatter diagram plots the average of the neighbouring values of the variable of interest on the vertical axis and the actual observed values on the horizontal axis.

The Moran's Index was obtained as 0.106944 with a p-value of .002. Implying that clusters with high proportion of under-5 malaria cases tend to be near or close to clusters with similar high proportions likewise those with low proportions clustered together showing spatial dependence in under- 5 malaria incidence among some clusters across the entire country.

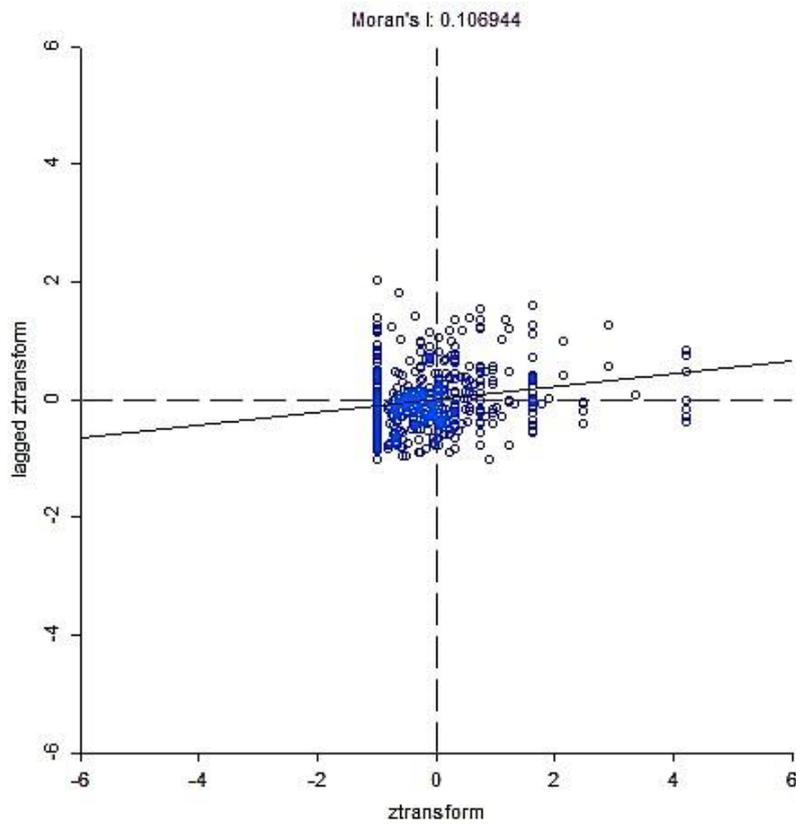


Fig 4.2 Moran's I scatter plot

Table 4.7 Test of significance for Moran's I Statistic

Estimate	E(I)	Standard Error	Z-value	Sig.
0.1069	-0.0024	0.00322	3.3183	0.002

The Morans I statistic does not give any indication of the locations of the clusters. Using the threshold values given in section 3.9, the risk map for malaria is produced and this shows the nature of spatial dependency exhibited by the data.

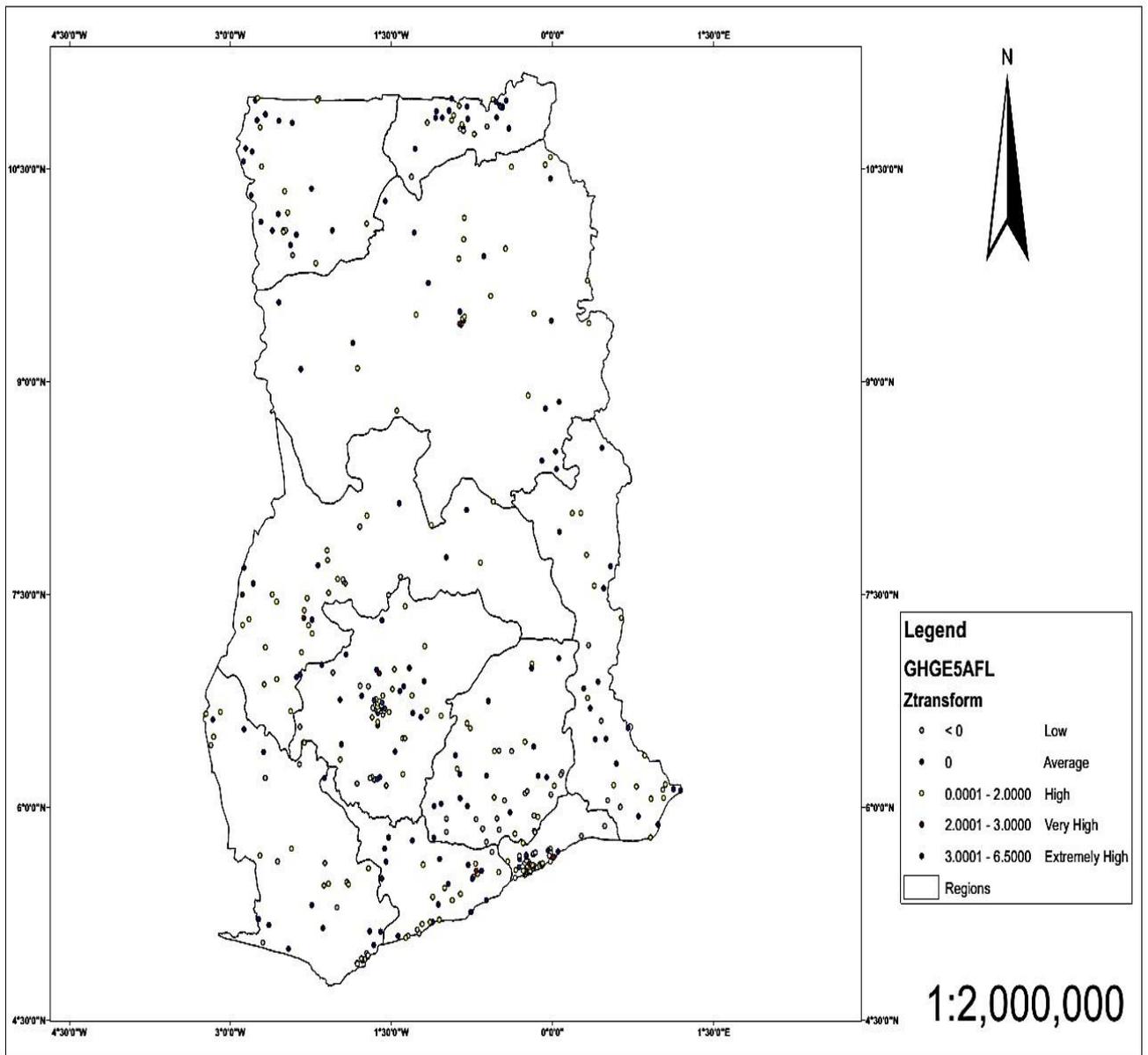


Figure 4.3 Malaria risk map for clusters

The map shows some clustering of low to average risk clusters around some hot spots. These hotspots should be the focal points for resource allocation as they are most likely the breeding spots or malaria exporting clusters. There are two hot spots in the Upper East and the other in the Upper West Region. While the hotspot in the Upper East is solitary, the one in the Upper West has a dense clustering of low prevalence clusters around it. Regions with predominantly low risk could be studied for the best practices of malaria control being adopted there.

4.5.2 Local Indicator of Spatial Autocorrelation (LISA)

The LISA plot explores the local spatial dependence structure in the malaria risk values of specific smaller geographical areas. The plot shows a non-random pattern of occurrence (clustering) between clusters is in the southern belt of the country covering Ashanti, Eastern, Greater Accra and a few clusters around Volta region. There was no indication of spatial clustering in the northern savanna zone of the country.

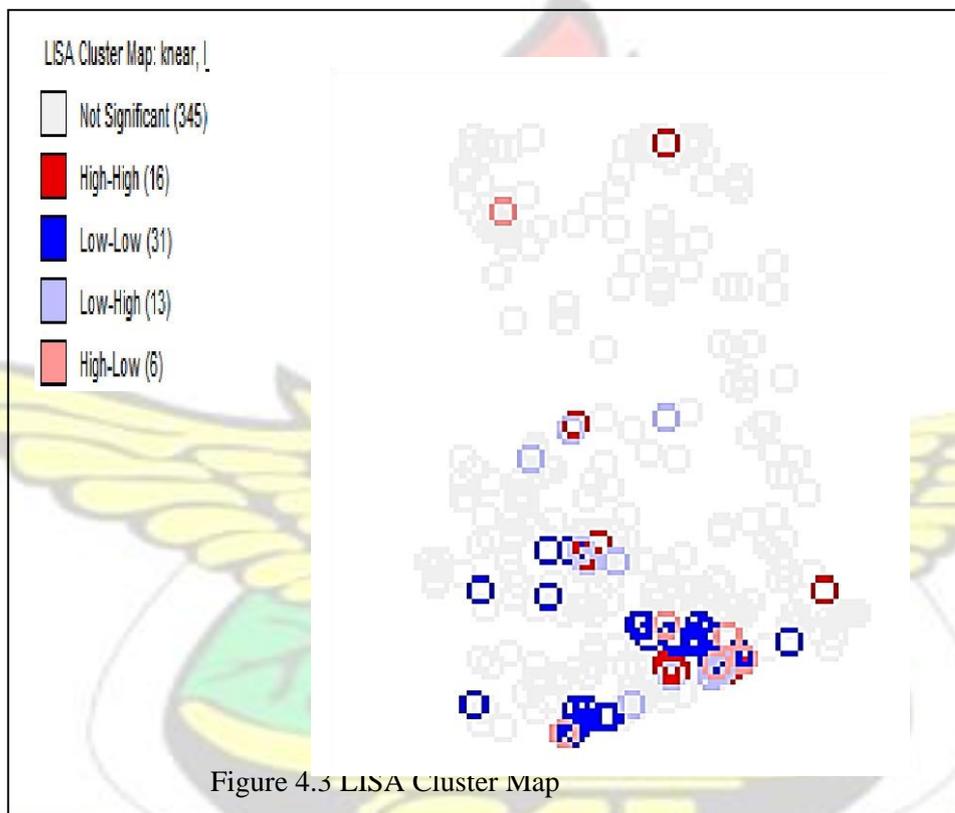
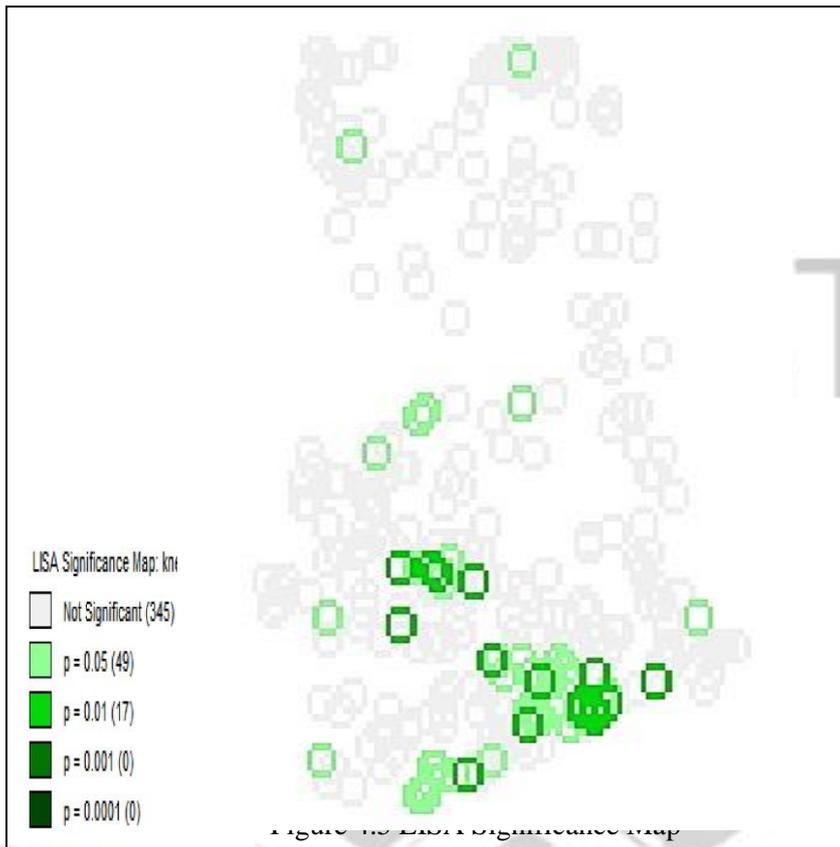


Figure 4.3 LISA Cluster Map

Figure 4.4 LISA Cluster Map



The significance map tests autocorrelation between the clusters for significant clustering. That is, if the frequencies of under-5 malaria at location say A, is influenced by the frequencies observed at neighbouring locations say B, C and D. Where closer neighbours exert more influence than farther ones.

4.5.3 Determining the variables that describe the spatial distribution of under-5 malaria prevalence

When observed values of a phenomenon have been found to be location dependent, it becomes imperative to use models that take into account the contribution of location factor to describe the occurrence or distribution of such phenomenon across the specified spatial boundaries. We consider the SLM and SEM as discussed in subsection 3.9.4 and used the AIC Schwarz criterion for the model selection.

4.5.3.1 Spatial Lag Model (SLM)

This model is mostly proposed and preferred over the Spatial Error Model when the dependence in the variable of interest is due to sources other than the random errors which might not have been captured by explanatory variables. The result of the SLM analysis for prevalence of malaria cases within clusters using median parity, number of under-5s in households, median maternal age, median child age, and median wealth score per cluster as the explanatory variables is presented in Table 4.8.

Table 4.8 Spatial Lag Model estimation

Log likelihood : 110.11

Akaike info criterion : -206.22

Schwarz criterion : -178.09

Variable	Coefficient	Std. Error	Sig.
Constant	0.1249	0.0603	0.0382
W_proportion	0.1804	0.0758	0.0174
Median Parity	0.0182	0.0084	0.0291
Number of U-5	-0.0035	0.0009	0.0002
Median Mage	0.0038	0.0024	0.1079
Median Child Age	0.00099	0.0009	0.2769
Median Wealth	-1.68×10^{-7}	1.193×10^{-7}	0.1595

From the SLM results in Table 4.8, the significant variables in describing the spatial distribution of under-5 malaria are Proportion of cases in neighbouring clusters, Median parity of mothers per clusters and the number of under – 5 in a cluster. Whilst maternal age, child age in months and wealth of the clusters did not make significant contribution to the proportion of cases recorded in a particular cluster.

4.5.3.2 Spatial Error Model (SEM)

SEM is appropriate when the concern is with correcting for the potentially biasing influence of the auto-correlation, due to the use of spatial data (irrespective of whether the model is spatial or not) (Anselin, 1999). Also, unlike SLM, if we believe that the proportion of cases (say Y) in a particular cluster (say I) is not influenced by the value of Y among neighbours, but rather that there is some spatially clustered feature that influences the value of Y for I and its neighbours but is omitted from the specification, then we may consider SEM with spatially correlated errors.

Table 4.9 Spatial Error Model estimation

Log likelihood: 109.914

Akaike info criterion : -207.827

Schwarz criterion: -183.716

Variable	Coefficient	Std. Error	Sig.
LAMBDA	0.1769	0.0776	0.0228
Constant	0.1649	0.0582	0.0046
Median Parity	-0.0179	0.0083	0.0309
Number of U-5	-0.0036	0.0009	0.0002
Median Mage	0.0036	0.0023	0.1255
Median Child Age	0.00101	0.0009	0.2682
Median Wealth	-1.598×10^{-7}	1.261×10^{-7}	0.2052

Table 4.9 for the SEM presented above also shows that, the same variables as in the SLM are significant. The Lambda term takes care of the dependences in the proportion of under-5 malaria cases in the model.

From the two models fitted, the best model for the data is selected based on the one with minimum AIC and Schwarz criterion values. On the basis of this, the SEM provides a goodfit to the dataset and is preferred to the SLM.

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CHAPTER FIVE

DISCUSSION OF THE RESULTS

This chapter of the study discusses the results of the study and links the results of the study to the research objectives. These are discussed with relevant literature as reviewed in chapter two of this thesis.

The main objectives of this study was to determine the individual, maternal and household factors that influence the incidence of under-5 malaria and use this to identify malaria clusters, describe the spatial dependencies and develop risk maps of malaria in Ghana. To achieve this, we sought to do the following:

1. To determine individual, maternal and household factors which influence the incidence of under-5 malaria in malaria in Ghana.
2. To identify clusters of under-5 malaria in Ghana and their spatial patterns using 2008 DHS data.
3. To explore linkages between DHS determinants of under-5 malaria in Ghana and spatial variables.
4. To model the spatial relationship between prevalence of under-5 malaria and household exposure factors using Spatial Durbin or Spatial Lag regression models.

5.1 Individual, maternal and household factors which influence the incidence of under-5 malaria in malaria in Ghana

Sections 4.1 and 4.2 of the analysis focused on identification of individual, maternal and household factors that influence the incidence of under-5 malaria in Ghana. The results of these sections are discussed here.

5.1.1 Malaria prevalence and risk factors

The empirical results gave the distributions of the study variables. It showed that most households in Ghana are poor with a cumulative percentage of 54.45 % comprising 32.52 % of the poorest class and 21.93 % of the poorer class while the richest and the rich together constitute a mere 28.7% of households in the country. This distribution agrees with the distribution reported in GDHS (2008) that about 7 in 10 Ghanaians were living below poverty level. Malaria prevalence was observed as 28.04 % (about one in four of the children in the survey). This is slightly higher than the GDHS figure of 20% because of difference in case definitions. While they had defined malaria as fever within two weeks prior to the study, we have included children with fever at time of study in our case definition. This has resulted in our having more cases than the GDHS survey had observed.

Anaemia prevalence was high 88% and consistent with reports in Ghana and other malaria endemic African countries (Schellenberg *et al.* 2003 cited in Owusu-Agyei *et al.* 2009 (a)). It is the commonest complication of malaria in children and the rate at which a child develops anaemia and the degree of anaemia depends on the severity and duration of malaria (Fact sheet 2014). While children with anaemia are not at a higher risk of malaria, they do stand a higher chance of developing complicated malaria and much more rapidly too (malaria site 2015).

The high prevalence of anaemia could also be as a result of other factors such as poor and inadequate nutrition, worm infection or homozygous sickle cell disease. However, the contribution of these illnesses to anaemia in a malaria endemic region has been found to be minimal compared to malaria (Owusu-Agyei *et al.* 2009 (b)).

The usage of any type of bed net the night before the survey was 44.9% with more than half of the children reported no bed net use. NMCP report (2014) emphasized on the importance of

ownership and usage of ITNs. The report put the national figure for usage at 47% but the figures are higher for pregnant women, under-5 and rural households.

The parity reported is consistent with regional fertility rates in Ghana. Epidzone 3 (Volta, Ashanti and Eastern regions) recorded the highest frequencies for women with 1-3 children. For women with 4-9 children, it was more predominant in Zone 1 (Upper East, Upper West and Northern regions). The pattern for higher number of children appeared random (GDHS 2008).

To determine the prevalence of malaria by epidemiological zones, we have adopted the MICS (2011) malaria epidemiological classification. Zone 1, comprising of Upper East, Upper West and Northern regions, Zone 2 has Brong Ahafo, Western and Central regions, in Zone 3 are Volta, Ashanti and Eastern regions. Zone 4 has only Greater Accra. The malaria prevalence rates used by MICS 2011 were > 40%, 31-40%, 10-30% and <10% for Zones 1, 2, 3 and 4 respectively. In our study, Zone 1 recorded the highest number of cases (34.92%) followed by Zone 3 (32.3%), Zone 2 (25.03%) and Zone 4 (7.75%). This pattern was the same for malaria prevalence within epidemiological zones. Zone 1 had a prevalence of 29.15%, Zone 3 had 28.68% and Zones 2 and 4 had prevalence of 27.52% and 23.30% respectively. Prevalence was calculated as a ratio of number of malaria cases to total number of under- fives within the zone. The prevalence within epidemiological zones was at variance with MICS (2011) for Zones 2 and 3. No significant association was observed between zones and malaria cases using the Pearson Chi² test of independence at 10%. This suggested the malaria prevalence was distributed about uniformly across zones.

The distribution of malaria cases by region showed Northern region topping the list with 18.29% of total cases followed by Ashanti region with 17.99% of the total cases. Volta, Upper East and Eastern regions had similar percentages and Western region recorded the lowest with

a percentage of 4.88%. The prevalence however showed Brong Ahafo region with the highest (36.84%), followed closely by Ashanti region (34.40%). Western region recorded the lowest prevalence of 15.19%. These regional figures are in synch with the GDHS (2008) report.

The Pearson's test of association gave $\chi^2_{(18)} = 52.497$ with p-value = .000 and Carmer's V was .137. This shows a significant association between region and number of malaria cases at 1% level of significance. That is, the prevalence is not uniform across regions and this should inform resource allocation for control measures.

Studies have shown the effect of socio-economic and environmental factors (type of vegetation and proximity to mosquito breeding grounds) as contributory factors that account for regional disparity of malaria prevalence in endemic regions. Krefis *et al.* (2011), Chukwuocha and Dozie (2011), Yadav *et al.* (2014) and Kramer & Lesser (2015) have reported causal effects of socio-economic and environmental factors on the transmission, prevalence and control of malaria.

When the study variables were examined for association with malaria incidence, age of child, anaemia, sleeping under a net, maternal marital status and number of under 5 in households showed significant associations. These results buttress the strong association between age of Under-5 and malaria incidence. Malaria site (2015) describes the rapid progression in parasite counts from six months to school age. By school age the immunity level of the child would have been developed considerably and asymptomatic parasitemia can be as high as 75% in school children. Children are at their most vulnerable to malaria related mortality in the first two years of life and interventions targeted and children should focus on the stages in early childhood.

Anaemia could also be a consequence of malnutrition. Susceptibility to severe falciparum malaria is not higher in malnourished children. It has actually been observed that wellnourished

children are more likely to develop severe malaria than those with malnutrition. However, malnourished children have a higher morbidity and mortality when severe malaria does occur.

No association was shown between wealth index and malaria although studies have shown a strong association between poverty and malaria. Calcas de Castro and Fisher (2012) showed that malaria worsened the burden of poverty in Tanzania but could not establish a reverse causal relationship between poverty and malaria. Their study suggested that poorer households tend to live in neighbourhoods with poor vector control measures and as such would have higher exposure to parasitemia.

Also, use of bed nets was strongly associated with malaria cases. ITNs are distributed on a one for every two household member basis. Households with higher number of under-5 might not have sufficient nets for every under-5 child in the household to sleep under a net. Thus, households with more children should be targeted for more ITNs.

5.1.2 Logistic regression analysis of malaria incidence

Logistic regression is a member of the family of generalized linear models. It predicts the probability of a categorical outcome using a linear combination of explanatory variables. In answering our second study question of our first objective, we considered all the study variables as univariate predictors of the incidence of malaria. Anaemia was again found to be significant (p-value .001) along with slept under net (p-value .029, Parity (p-value .054)) and marital status (p-value .085). We have again used 10% level of significance because we are exploring for possible risk factors.

The variables included in the multiple logistic regressions are age, sex of child, anaemia, slept under a net, marital status, maternal education, parity, wealth index, number of under-5 in households, epidzones and type of residence. The Chi² test and Likelihood Ratio test was

used for model comparison and the final model was determined to be

$$\text{(odds of malaria} \pm \text{CI)} \exp \{.4465 + .1517X_1 - .1348X_2 - .299X_3 - .2533X_{4,2} - .464X_{4,4}\}$$

Alternatively,

$$\log(\text{odds of malaria} \pm \text{CI}) = 1.563 + .859X_1 - .873X_2 - .741X_3 - .776X_{4,2} - .629X_{4,4}$$

Where X_1 = Agecategory, X_2 = Anaemia, X_3 = Type of residence, X_4 = Epidemiological zones 2 and 4.

These variables all had odds ratios less than 1 which shows they are protective and reduce the risk of under-5 malaria. The age category 5 had an odds ratio .859 (p-value .000) which shows a .15 reduction in the odds of malaria in children in age interval 48 – 59 months relative to children below 12 months. The odds ratio for anaemia was .873 (p-value .013) which implies a .13 reduction in odds of malaria for a unit increase in haemoglobin level. The introduction of iron supplements could also serve the dual purpose of malaria prevention and reduce the high malaria morbidity and mortality associated with malaria in malnourished children (Hui *et al.* 2009, Vale and Lima 2014, Caldas de Castro and Fisher, Reid *et al.* 2010).

The type of residence had odds ratio .741 (p-value .006). That is, the odds of malaria among children in urban dwellings were .26 less than that of children in rural dwellings. This confirms the disparity in malaria prevalence between urban and rural dwellers as shown by several studies (GDHS 2008, Bi & Tong 2014, Kramer & Leisser 2015).

Epidemiological zones 2 and 4 were significant with odds ratios .776 (p-value .039) and .629 (p-value .026). Odds of malaria is reduced by .23 for children in zone 2 relative to those in zone 1, while the odds is reduced by .38 for children in zone 4 relative to those in zone 1.

Zone 1 has Upper East Upper West and Northern regions, Zone 2 has Brong Ahafo, Western and Central regions, while Zone 4 has only Greater Accra. Appiah *et al.* (2011), Klienschmidt *et al.* (2000) and Dery *et al.* (2010) all reported similar findings.

The model had Prob > Chi² = .0000, LR Chi² statistic 41.98, Log Likelihood -1348.5112 and an overall percentage performance of 74.7%.

5.2 Spatial Analysis and risk maps

The data was examined for spatial dependency and spatial regression model was proposed for predicting malaria prevalence within clusters. Malaria Risk maps are also developed.

5.2.1 Spatial dependency

Moran's I statistic for spatial dependency gave an index of .1069 (sig .002) which showed a significant spatial dependency in the malaria prevalence between neighbouring clusters although it does not indicate where these clusters exist.

The LISA cluster map was used for showing where the clusters exist and what pattern of clustering existed. The clusters in the northern parts did not show significant spatial dependency except for 2 clusters in the Upper East and Upper West which showed clustering of high prevalence clusters being surrounded by high prevalence clusters. There were also high-high and low-high clustering observed in Brong Ahafo region. The southern part of the country showed higher number of clusters and these were high-high, high-low and low-low. Western, Central, and Greater Accra regions showed dense clustering.

Information on the pattern of clustering is important for vector control and other interventions such as distribution of ITNs. The high-high should be targeted for aggressive control measures and the high-low form an important transmission conduit to neighboring clusters.

Hoek *et al.* (2003) and Chuckwuoka and Dozie (2011) show similar results in the transmission of malaria. Tonui *et al.* (2013) found transmission patterns from areas of high malaria prevalence to malaria-free areas in the Kenyan highlands.

LISA significance map was used for testing significance of the clusters. At .05 level of sig. 45 clusters showed significant clustering, 17 showed significance at 1% level of significance. No other significant clustering was observed.

5.2.2 Malaria Risk Map

The spatial distribution of disease depicts the observed pattern of incidence or prevalence and this can provide valuable insight in to the underlying mechanisms driving disease incidence, transmission and progression which informs the design and implementation of public health responses (Waller 2015). Risk maps are an essential tool in spatial epidemiology and can be used for intervention evaluation when developed at different time points over the intervention period. This informs resource allocation and programme design for interventions.

The gains in malaria control have informed a re-orientation towards elimination of malaria. This makes information on transmission foci and high risk areas high priorities in resource limited regions (Tatem *et al.* 2014) especially in Sub-Saharan Africa where malaria is hyperendemic.

The risk map was developed using ArcGIS and areas of very high prevalence (hotspots) were identified. Some of these hotspots are clustered around by areas of low prevalence. In effective disease control, these hot spots are areas of high priority.

5.3 Spatial regression model

The SLM and SEM were considered for modeling the cluster level prevalence of under-5 malaria. Both models found the same variables significant (median parity, Number of under5, median maternal age and median child age), the SEM provided a better fit using the AIC and Schwarz criterion. Appiah *et al.* (2011) discuss the importance of spatial regression model for predicting malaria prevalence in unobserved clusters.



CHAPTER SIX

CONCLUSIONS AND RECOMMENDATIONS

In this chapter, we summarize the key findings, draw relevant inference and make appropriate segmented and targeted recommendations to specific stakeholders and interested parties.

6.1 Conclusion

This study employed the GDHS 2008 data set with information on 12,323 households drawn from 412 clusters in Ghana with a response rate of 97%. Data was collected over a three month period from September to November 2008. Our target population were households with children under-5, and there were 5336 households of which 2992 met our inclusion criteria. Ethical approval for the study was obtained from Committee on Human Research, Publications and Ethics, KNUST.

For the purpose of the study we defined malaria as fever within two weeks to enumeration or at time of enumeration (with or without cough and catarrh) and having antimalarial administered.

These children also had their haemoglobin level measured and their mothers were in the age interval 15 to 49. In our study data, 88% of the children had one form of anemia or the other and the number of males and females were quite balanced. The distribution across age groups was also about equal. More than half (54%) of the children were from households in the very poor and poorest wealth index and 66% of the sample was drawn from the rural sector.

Our study sought to identify child, maternal and household characteristics that are risk factors for under-5 malaria, determine spatial dependency in malaria prevalence patterns across Ghana and use these characteristics to model the cluster level prevalence using spatial information in

the GHDS data set. We also produced risk maps to indicate hot spots and develop spatial regression models for predicting prevalence for unobserved locations.

Preliminary data analysis showed the frequency distributions of study variables and the distribution of the outcome variable across regions and epidemiological zones. The zones were adapted from MICS (2011), and there was no significant disparity observed across zones. There was however a strong association between regions and malaria. The test of association between other study variables and malaria incidence showed the significance of age of child, anaemia, use of bed net, marital status of mother and number of under-five in the household. The test of association of wealth index and malaria prevalence did not show a significant association.

The entire set of study variables were examined as possible univariate predictors of probability of malaria incidence. Four variables (anaemia, use of bed net, parity and marital status) were found to be significant predictors.

Multiple logistic regression analysis was carried out to find a parsimonious model that could be used for the prediction of under-5 malaria in the household. The age group 5, anaemia, type of residence and epidemiological zones were found to be significant in a stepwise process. All the variables had odds ratios less than 1 which indicated their protective effects against the probability of under-5 malaria. The final obtained model was $\log(\text{odds of malaria}) = 1.563 - .859X_1 - .873X_2 - .741X_3 - .776X_{4,2} - .629X_{4,4}$ with an overall percentage performance of 74.7%.

The spatial analysis showed between cluster spatial dependencies in malaria prevalence. The Moran's Index was .1069 (sig .002) and the LISA cluster maps showed that most of the clustering were in the southern part of the country. It also showed the type and location of the spatially dependent clusters. The LISA significance map was used for testing the significance

of the spatial clustering. Significant clustering was found to exist between 45 clusters (17 clusters showed significance at 1% level of significance). No other significant clustering was observed.

The malaria risk map developed using ArcGIS showed 4 dense clustering of low prevalence centres clustered around hot spots in Northern, Ashanti, Western and Greater Accra regions. Identifying these high prevalence foci is important to the success of any public health intervention or vector control. These are important conduits for malaria transmission. The reemergence of spatial epidemiology attests to the importance of visual depiction of spatial distribution of disease in intervention planning and implementation as well as resource allocation.

The SEM was found to give a better fit than the SLM based on the AIC and Schwarz criteria. The regression variables found to be significant for modeling under-5 malaria prevalence at cluster level were the median parity, number of under-5 within cluster, median child age, and median wealth. Median wealth had a negative sign which shows an inverse relationship to malaria prevalence at cluster level. The model serves as a predictive tool for determining the under-5 malaria prevalence within a cluster.

6.2 Recommendations

This study has identified the important determinants in predicting under-5 malaria and these risk factors (especially anaemia and use of net) should be taken into consideration when developing malaria intervention programmes for children.

The use of statistical models for predicting probability of under-5 malaria could be adopted as a household risk index for children's exposure to malaria.

The spatial clustering and risk maps have been utilized to depict distribution of the observed pattern of under-5 malaria prevalence and this can provide valuable insight in to the underlying mechanisms driving incidence and transmission of malaria in children. This should inform the design and implementation of public health responses.

The risk map has also been demonstrated as an efficient tool for quick identification hot and cold spots of disease prevalence. This is an essential tool in spatial epidemiology and can be used for intervention evaluation when developed at different time points over the intervention period. This is very important for efficient resource allocation and programme design for interventions.

The gains in malaria control have informed a re-orientation towards elimination of malaria. This makes information on transmission foci and high risk areas high priorities in resource limited regions (Tatem *et al.* 2014) especially in Sub-Saharan Africa where malaria is hyperendemic.

6.3 Further research

Areas of further study would be a comparison of spatial analysis results of 2008 GDHS data to the 2014 GDHS data when it becomes available to determine changes in spatial distribution of under-5 malaria and for evaluation the effect of malaria control interventions.

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APPENDIX



KWAME NKURUMAH UNIVERSITY OF SCIENCE AND TECHNOLOGY
COLLEGE OF HEALTH SCIENCES

SCHOOL OF MEDICAL SCIENCES / KOMFO ANOKYE TEACHING HOSPITAL
COMMITTEE ON HUMAN RESEARCH, PUBLICATION AND ETHICS



Our Ref: CHRPE/AP/315/15

26th August, 2015

Dr. Atinuke Olusola Adebajji
Department of Population
and Reproductive Health
School of Public Health
KNUST.

Dear Madam,

LETTER OF APPROVAL

Protocol Title: "Spatial Analysis of U-5 Malaria in Ghana (DHS 2008) for Public Health Intervention Evaluation."

Sponsor: *Principal Investigator.*

Your submission to the Committee on Human Research, Publications and Ethics on the above named protocol refers.

The Committee reviewed the following documents:

- A Completed CHRPE Application Form.

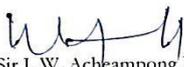
The Committee has considered the ethical merit of your submission and approved the protocol. The approval is for a fixed period of one year, renewable annually thereafter. The Committee may however, suspend or withdraw ethical approval at anytime if your study is found to contravene the approved protocol.

Data gathered for the study should be used for the approved purposes only. Permission should be sought from the Committee if any amendment to the protocol or use, other than submitted, is made of your research data.

The Committee should be notified of the actual start date of the project and would expect a report on your study, annually or at the close of the project, whichever one comes first. It should also be informed of any publication arising from the study.

Thank you Madam, for your application.

Yours faithfully,


Osomfuor Prof. Sir J. W. Acheampong MD, FWACP
Chairman