SPATIAL ANALYSIS OF MALARIA EPIDEMIOLOGY IN THE AMANSE WEST DISTRICT.

By

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ABSTRACT

Malaria has become a major global health problem. It affects 3.5-5.0 billion people worldwide with environmental factors contributing about 70-90% of the disease risk. The World Health Organization has estimated that over one million cases of Malaria are reported each year, with more than 80% of these found in Sub-Saharan Africa. The malaria situation in Ghana is typical of sub-Saharan Africa, presenting a serious health problem in Ghana. It is hyper endemic with a crude parasite rate ranging from 10 – 70% with Plasmodium falciparum dominating.

Disease Risk mapping has long been effective in disease modeling, monitoring, evaluation and providing major intervention for areas at risk.

The spatial dependency of the malaria risk was explored using Poisson variograms and the risk was used to create surface maps from 2004 to 2009 to identify areas at high risk. Bayesian geostatitical approach was then used to correlate the relationship between the elevation and the disease risk. Geographic Information System (GIS) was used to create the risk surfaces and overlays in the study. A buffered distances of 500m, 1000m, 1500 and 2000m was used to overlay the disease risk map with forest, rivers/streams to find out its effects with the disease prevalence.

The risk map created in this study, which integrates Poisson statistical methods showed areas at risk, especially in the central portions of the district capital. It also showed an average of 20% rise yearly from 2004 to 2009. The results in the semi-variogram analysis with an average range of 2000m showed that the disease incidence was local and not global. The local nature of the disease occurrence gives credence to the fact that the covariates used which were rivers/streams,

forest, temperature, rainfall and elevation had different and independent influence on the malaria prevalence. Areas which were more than 2km away from the water source (rivers/streams) recorded relatively higher cases except for some few within 1km of the Offin and Oda rivers. There was a varied effect of elevation with the disease prevalence as evidenced in the Bayesian regression model. There was a general trend of high disease incidence between 1-3 km from the forest edge.

The study also showed that rainfall had an effect on the yearly disease incidence. However, there was no trend as far as the temperature over the disease prevalence was concerned.

DEDICATION

Dedicated to my lovely father and mother

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LIST OF ABREVIATIONS

Abbreviation	Full Meaning
CDC	Center for Disease Control
DDT	Dichlorodiphenyltrichloroethane
DEM	Digital Elevation Model
GHS	Ghana Health Service
GIS	Geographic Information System
GPS	Global Positioning System
IPTI	Intermittent Prevention Treatment in Infants
IRS	Indoor Residual Spraying
ITNs	Insecticide Treated Nets
LLIN	Long-Lasting Insecticide Nets
MCMC	Markov chain Monte Carlo
MOH	Ministry of Health
MSAT	Mass Screening and Treatment
NASA	National Aeronautic and Space Administration
PMI	President Malaria Initiative
RBM	Roll Back Malaria
SP	Sulfadoxine-Pyrimethamine
UNICEF	United Nations Children's Fund
WHO	World Health Organisation

CHAPTER ONE

INTRODUCTION

1.0 BACKGROUND

Malaria has been a long life-threatening parasitic disease transmitted by female anopheles mosquitoes. This has contributed child morbidity in the world. It threatens 2.4 billion people, or about 40% of the world's population living in the world's poorest countries and more than one million deaths are attributable to the disease annually (WHO, 2000).

It is a major public health problem in Africa with over 200 million clinical episodes and nearly one million deaths occurring annually (WHO/UNICEF, 2005). In semi-arid and highland regions of Africa, malaria is unstable and epidemic malaria is a common problem causing deaths annually (Worall et al, 2004). However, the risks of morbidity and mortality associated with malaria, particularly in semi-arid and highland regions, vary spatially and temporally (Snow and Marsh,2002). Most malaria infections, particularly in sub-Saharan Africa, are caused by Plasmodium falciparum. Malaria presents a major socio-economic challenge to African countries since it is the region most affected. This challenge cannot be allowed to go unnoticed since good health is not only a basic human need but also a fundamental human right and a prerequisite for economic growth (UN, 2003).

Malaria is caused by a parasite that is transmitted from one person to another through the bite of the Anopheline mosquito (a female Anopheles mosquito). Humans get malaria from the bite of the malaria-infected mosquito. When the mosquito bites an infected person, it ingests microscopic malaria parasites found in the person's blood. The malaria parasite must grow in the mosquito for a week or more before infection can be passed to another person. Thereafter, if the

mosquito bites another person, the parasites go from the mosquito's mouth into the person's blood.

They feed on the blood cells, multiply inside the liver and thereby destroying the red blood cells causing a cut off in blood circulation which could lead to premature death. (WHO, 2000). Symptoms of malaria include fever, shivering, pains in the joint, vomiting, anaemia, hemoglobinuria, retinal damage, and convulsions. The classic symptom of malaria is cyclical occurrence of sudden coldness followed by rigor then fever and sweating lasting four to six hours. This occurs every two days in plasmodium vivax (*P. vivax)* and plasmodium Ovale (*P. ovale*) infections, while every three days for plasmodium malariae (P. *malariae*) (Nyika, 2009).

Malaria can be prevented by the use of mosquito coils and repellants, spraying the insides of houses (where most *Anopheles* species feed and rest) with insecticides (indoor residual spraying, IRS) and by sleeping under bed nets that have been treated with long-lasting insecticides (long-lasting insecticide nets, LLINs). Mass screening and treatment (MSAT) with effective antimalarial drugs can also reduce malaria transmission (Griffin et al., 2010).

However, the levels of malaria risk and transmission intensity exhibit significant spatial and temporal variability related to variations in climate, altitude, topography, and human settlement pattern (Abeku et al, 2003).

The malaria situation in Ghana is typical of sub-Saharan Africa making its transmission in southern Ghana an all- year -round affair and seasonal variation in the northern parts (Afari *et al*. 1995). It is the major cause of morbidity and mortality, directly contributing to poverty, low productivity, and reduced school attendance.

The Ministry of Health (MOH, 2009) records that between 3-3.5 million cases of malaria are reported each year, over 900,000 of which are children under five years. Malaria according to the President Malaria Initiative (PMI) is said to account for 61% of under-five hospital admissions and 8% of admissions of pregnant women. The country can be stratified into three malaria epidemiologic zones: the northern savanna; the tropical rainforest; and the coastal savanna and mangrove swamps (PMI, 2009).

Four species of the malaria parasites exist, Plasmodium falciparum, Plasmodium vivax, Plasmodium ovale and Plasmodium Malariae. Epidemiological study in Ghana shows that only three species of the Plasmodium are present; Plasmodium falciparum, Plasmodium malariae and Plasmodium ovale .The Plasmodium falciparum is thus the predominant parasite species carried by a combination of vectors (MOH, 1991).

Climatic factors, particularly rainfall, temperature and relative humidity have a strong influence on the biology of mosquitoes. In malaria endemic countries, climate factors reportedly contribute to the increased number of mosquitoes and thus make transmission favorable. Once adult mosquitoes have emerged, the ambient temperature, humidity, and rains will determine their chances of survival. Warmer ambient temperatures shorten the duration of the extrinsic cycle, thus increasing the chances of transmission (Jackson, 2010). Geographic Information Systems (GIS) can be used to investigate associations between these climatic variables and the distribution of the different species responsible for malaria transmission (Sweeney, 1997).

GIS is a computerized systems utilized to process and manage spatial data. A GIS is capable of integrating topographical maps, satellite images, and aerial photos with attribute data such as demographic and socioeconomic characteristics and disease incidence. The systems have been

used widely to produce maps of disease distribution and for analyzing spatial patterns in disease distribution (Cattani et al., 2001). These maps have been used as tools for developing control and intervention strategies. GIS has been used as a tool to strengthen the analytical, management, monitoring and decision-making capacity in public health, as well as a tool for advocacy and communication between technical personnel, policy makers and the general public. It can be used in the management of geographical dimensions, integrating health-related data from various sources, helping to discover and visualize new patterns and geographical relations in data that would otherwise be difficult to identify, and displaying these on maps that constitute a more expressive and visual representation (Epidemiological Bulletin, 2004).

GIS mapping provide powerful tools for management and analysis of malaria control programs. The use of this technology can be tailored to suit a wide range of applications. These include: practical operational maps to assist with resource allocation; analytical tools to facilitate program monitoring and evaluation as well as sophisticated research projects to investigate various spatial aspects of malaria epidemiology (Connor et al, 1997).

In recent times, GIS and spatial analysis have proved equal to the task of improving mosquito monitoring as far as vector-borne diseases are concerned. It has therefore aided health professionals in their control and implementation strategies as far as malaria control is concerned (Griffith, 2005).

Various work has been done in recent time using GIS, remote sensing and geostatistical modelling to predict the spatial and temporal distribution of malaria and *Anopheles* vectors. Bayesian statistical approaches have been combined with GIS in this venture. It allows fitting of complex models in quite a flexible way as compared with other methods such as, Markov chain Monte Carlo (MCMC) simulation. Its computational advantages cannot be over emphasized

(Diggle et al, 2002). These techniques allow the use of spatial analysis of environmental factors that contribute to the spread of vector-borne diseases, by identifying hot spots, monitoring disease patterns, and defining areas (locations) that need attention in disease control planning. The integration of those climate parameters with malaria incidence has become relevant for most scientists in the world.

Topography or elevation variables have spatial variability which when analysed geostatistically could be used to determine the potential distribution of the vector and malaria risk areas. Poisson kriging offers more flexibility in modelling the spatial structure of disease risk and generates less smoothing, reducing the likelihood of missing areas of high risk as compared to other statistical methods as it inculcates the population size in computing the disease rates.

This thesis would therefore use Poisson kriging to create risk maps and corelate the malaria risk with topographic and climatic covariates as well as the forest cover in the area to explore the spatial variability of the disease with these factors.

1.1 PROBLEM STATEMENT

Malaria continues to be an economic burden and a great threat globally and almost impossible to eradicate for the past six decades. It is a mosquito-borne disease causing 1.5 to 2.7 million people to die annually (Breman and Alilio 2004).Malaria vectors have become more resistant to insecticides and the parasites that cause the disease are becoming resistant to chloroquine and other anti-malarial drugs, making prevention and treatment increasingly more difficult and costly. About 40% of the world's population live in regions where malaria transmission is endemic, mainly within the tropical and sub-tropical regions. (Aultman, 2002).

Malaria is by far the leading cause of death in Ghana. Twenty five (25%) of children who die before their fifth birthday are killed by the disease, and it claims the lives of many pregnant women too. (Asante and Asenso-Okyere, 2003)

Malaria and mosquito control challenges operate at a wide spatial scale. Prevalence of Malaria is also known at a limited number of specific sample locations. The pattern and variation of risk cannot be accounted for by only the known covariates. Data points of measured malaria prevalence are not evenly or randomly spread across the area to be mapped and must be interpolated spatially. Elevations have mostly influenced the rate of mosquito replication at different spatial scales.

GIS risk maps with geo-statistical capability would be used to account for the local variation in the climatic covariates, forest, rivers and streams. Bayesian approach would be used to explore the effect of topography on the malaria rates in the study area.

1.2 JUSTIFICATION

Malaria has become a great concern globally and has impacted negatively on the economies of developing nations. Health workers generally are unable to identify high or risk areas in the areas they operate so as to tailor interventions and do effective health monitoring. Research conducted so far by medical and climate professionals have either lacked knowledge or showed less concern for the variation of the climate conditions that accompany the transmission of malaria.

The geographical distribution of any major disease forms an important basis for locating appropriate interventions for its control and a means to monitoring their effectiveness. It also provides a possibility for identifying ecological factors with which the disease may be associated.

The link between climate and medical data has not been well defined, and health information systems have been weak due to the lack of case detection, irregularity in reporting, under reporting and poor coordination (Dziedzom, 2009). There is a need for a risk map to draw attention to hot spots and areas where intervention measures can be tailored to improve the monitoring of the occurrences, distribution and control of malaria in different geographical areas and time periods. Spatial statistical modelling is also necessary to correlate the factors that are associated with these spatial and temporal heterogeneity of malaria transmission at the different geographic locations.

1.3 RESEARCH QUESTIONS

1. What are the associated patterns in the malaria cases?

2. Can we link the disease incidence to climatic, forest and topographic variables operating in the area?

3. What is the spatial variability of these covariates?

4. Which areas in the map have hot spots in the disease prevalence?

1.4 AIM

The aim of this study is to use GIS and spatial statistical methods such as Poisson and Bayessian approach to create malaria risk map and examine the association which relates the risk factors, forest, rivers/streams, topography and the prevalence of malaria in the study area.

1.5 RESEARCH OBJECTIVE

- To create a Poisson risk map of malaria prevalence
- Investigate the effect of topography, forest cover, rainfall and temperature on the malaria Poisson risk

1.6 STRUCTURE OF THE THESIS

The thesis is generally structured under five chapters as outlined below

- Chapter Two is the literature review of previous work done on the disease and how Geographic Information Systems with geostatistics has been used in the disease application.
- Chapter Three outlines Material and Methods used in this thesis.
- Chapter Four discusses the results which are the outcome of materials applied in the thesis.
- Chapter Five deals with Conclusion and Recommendation of the thesis.

CHAPTER TWO

LITERATURE REVIEW

2.0 DEFINITION OF MALARIA

Malaria is caused by a parasite called Plasmodium, which is transmitted through the bites of infected female anopheles mosquitoes. In the human body, the parasites multiply in the liver, and then infect red blood cells. There are four of this different species causing the human malaria disease: Plasmodium falciparum, Plasmodium vivax, Plasmodium ovale and Plasmodium malaria. (WHO, 2010)

2.1 MALARIA SITUATION

Malaria is a vector-borne disease that is widespread in the tropical and subtropical areas of the world. This has become a serious challenge for most developing countries where between 300 and 500 million people are infected annually. The disease is a leading cause of infant and child mortality in sub-Saharan Africa (WHO, 2003).

The disease accounts for more than 44% of reported outpatient visits and an estimated 22% of under-five mortality in Ghana. Reported malaria cases represent only a small proportion of the actual number of episodes as majority of people with symptomatic infections are treated at home and are, therefore, not reported (WHO, 2005)

There have been several efforts by government of Ghana and other development partners in the health sector to eradicate malaria in the country but its prevalence rate is still on the increase. This has prompted the question why the malaria cases are still on the increase despite these efforts. The continuous increase in malaria cases is of great concern to many people because high

level of malaria worsens the poverty situation in the country, because many man-hours are lost to malaria and the annual economic burden is estimated to be 1 to 2 per cent of the Gross Domestic Product in Ghana (UNICEF, 2007). The country is still at the control stage of Malaria programme, which is the first step in the fight against the disease. The second stage is the elimination of the disease which must be supported by a functioning health system, while the third stage is the eradication which is usually global and undertaken when vaccines exist. (GNA, 2010)

2.1.1 *SOCIO-ECONOMIC BURDEN OF MALARIA*

It has been known that malaria and underdevelopment are closely linked. As a general rule of thumb, where malaria prospers most, human societies have prospered least (Gallup. & Sachs 2001). The disease causes widespread premature death and suffering, imposing financial hardship on poor households, and holds back economic growth and improvements in living standards. Malaria flourishes in situations of social and environmental crisis, weak health systems and disadvantaged communities (WHO, 2000)

Developing countries are still having a chunk of their national budget being used for malaria eradication. Studies according have established the fact that malaria affects mostly the poor impacting negatively on their socio-economic development. The burden of malaria is therefore greatest among the world's poorest countries (Worrall, 2003).

The disease in Ghana has impoverished most of the poor communities. The adult population is mostly affected reducing working hours and lowering productivity and economic livelihood impacting substantially on the national gross domestic product. (Asante and Asenso-Okyere, 2003)

2.2 HISTORY OF MALARIA

History of malaria and its terrible effects is as ancient as the history of civilization. Malaria is seen to have probably originated in Africa. Fossils of mosquitoes ranging 30 millions years old show that the vector for malaria was present well before the earliest history of man. Early travelers might have likely brought strains of *Plasmodium* from Africa to the other parts of the world, a phenomenon that continues to this day as tourists bring malaria home from areas in which the disease is endemic. (Newton and White, 1999)

2.3 BIOLOGY OF THE DISEASE

Understanding the biological basis of the disease aids in unveiling the nature, causes and implication of the disease control and monitoring process.

2.3.1 VECTOR BIOLOGY

Adult females of many mosquito species will bite humans, using the blood meals for egg production. However, only about 60 species of the genus Anopheles can transmit malaria. Anophelines generally bite at night and usually rest on a surface (such as the wall of a house) before or after feeding. As with all mosquitoes, the immature stages are aquatic, and they prefer slow-moving or still water in which they can stay close to the water surface with their breathing orifices open to the air (Kathleen, 2002).

2.3.2 SYMPTOMS OF MALARIA

Symptoms of malaria world wide include fever, headache, and vomiting, and usually appear between 10 and 15 days after the mosquito bite. If not treated, malaria can quickly become life-

threatening by disrupting the blood supply to vital organs (WHO, 2010). The symptoms of clinical malaria in Ghana according to Asenso-Okyere (1994) are yellowish eyeball, chills and shivering, headache, a bitter taste, body weakness and yellowish urine.

2.3.3 THE PARASITE: PLASMODIUM

Fig 2.1: Malaria Parasite

The protozoan Plasmodium from the malaria parasite in Fig 2.1 is transmitted to humans by mosquitoes of the genus Anopheles. The mosquito picks up the parasite during a blood feeding from an animal with parasitaemia. Plasmodium falciparum causes a large majority of the clinical cases and mortalities. (Bozdech et al., 2003).

2.34 LIFE CYCLE OF THE MALARIA PARASITE

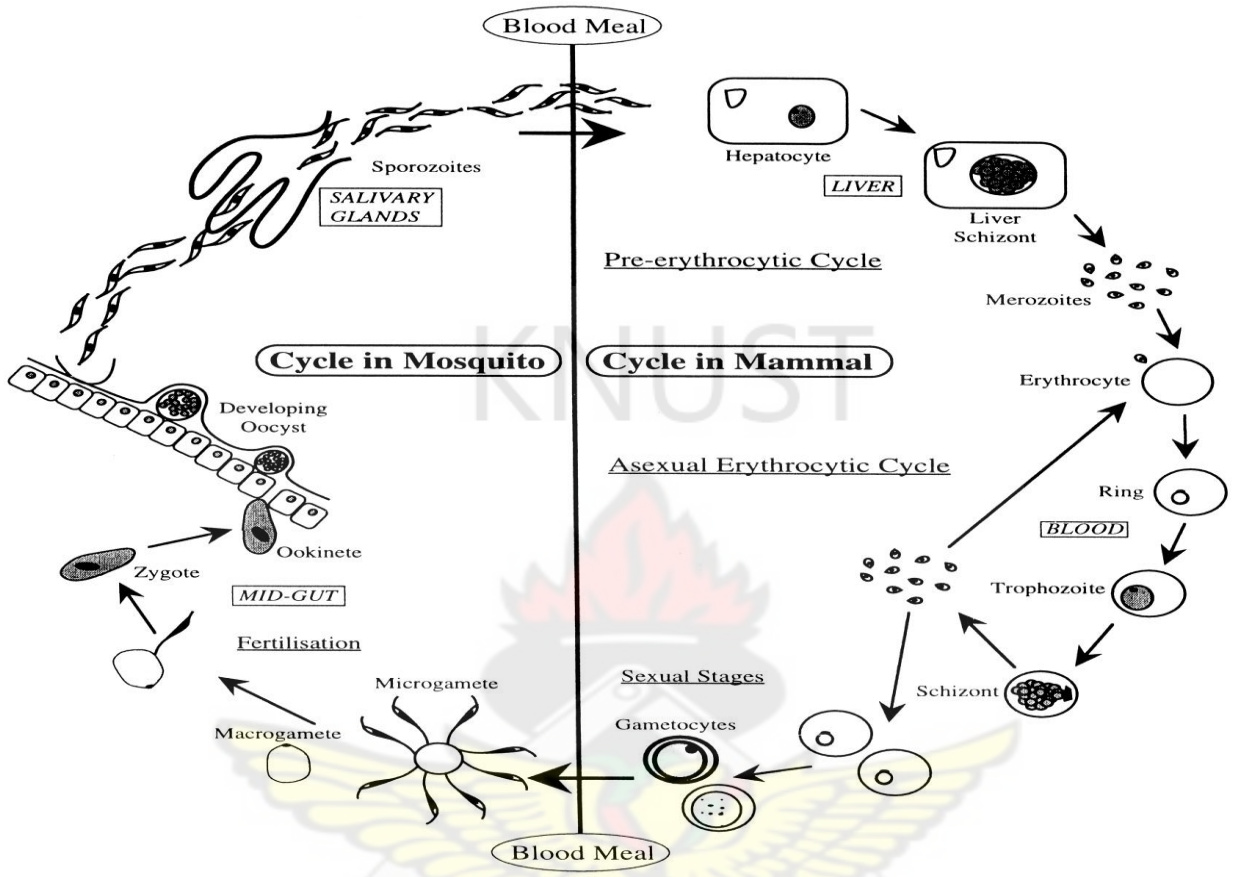

Fig 2.2: Life Cycle of Malaria

(Mendis et al., 2001)

The life cycle of the malaria parasite shown above in Fig 2.2 is as follows:

- A female Anopheles mosquito carrying malaria-causing parasites feeds on a human and injects the parasites in the form of sporozoites into the bloodstream. The sporozoites travel to the liver and invade liver cells.

- Over 5-16 days, the sporozoites grow, divide, and produce tens of thousands of haploid forms, called merozoites, per liver cell. Some malaria parasite species remain dormant for extended periods in the liver, causing relapses weeks or months later.
- The merozoites exit the liver cells and re-enter the bloodstream, beginning a cycle of invasion of red blood cells, asexual replication, and release of newly formed merozoites from the red blood cells repeatedly over 1-3 days. This multiplication can result in thousands of parasite-infected cells in the host bloodstream, leading to illness and complications of malaria that can last for months if not treated.
- Some of the merozoite-infected blood cells leave the cycle of asexual multiplication. Instead of replicating, the merozoites in these cells develop into sexual forms of the parasite, called male and female gametocytes, that circulate in the bloodstream.
- When a mosquito bites an infected human, it ingests the gametocytes. In the mosquito gut, the infected human blood cells burst, releasing the gametocytes, which develop further into mature sex cells called gametes. Male and female gametes fuse to form diploid zygotes, which develop into actively moving ookinetes that burrow into the mosquito midgut wall and form oocysts.

Growth and division of each oocyst produces thousands of active haploid forms called sporozoites. After 8-15 days, the oocyst bursts, releasing sporozoites into the body cavity of the mosquito, from which they travel to and invade the mosquito salivary glands. The cycle of human infection re-starts when the mosquito takes a blood meal, injecting the sporozoites from its salivary glands into the human bloodstream

2.4 TREATMENT AND CONTROL

Malaria vectors have become more resistant to insecticides and the parasites that cause malaria are becoming resistant to chloroquine and possibly other anti-malarial drugs, making prevention and treatment increasingly more difficult and costly than ever (Sharma, 1996).

Combination therapy has been shown to increase the efficacy of combining drugs Whitty and Allan (2004) acknowledged the wide spread situation of drug-resistant malaria in Africa. Chloroquine resistant malaria is now almost universal and resistant to successor drug, sulfadoxine-pyrimethamine (SP) which is growing rapidly (Whitty and Allan, 2004).

Self prescription or medication is a widespread phenomenon in Ghana. Majority of the malaria victims only seek medical examination and treatment from health facilities when the initial attempts have failed resulting in late presentation. (Asenso-Okyere and Dzator, 1995).

2.4.1 INSECTICIDE TREATED NETS

Insecticide-treated bed nets (ITNs), including long-lasting insecticidal nets (LLINs), play a primary role in global campaigns to roll back malaria in tropical Africa. Effectiveness of treated nets depends on direct impacts on individual mosquitoes including killing and excite-repellency, which vary considerably among vector species due to variations in host-seeking behaviours. While monitoring and evaluation programmes of ITNs have focused on morbidity and all-cause mortality in humans, local entomological context receives little attention. Without knowing the dynamics of local vector species and their responses to treated nets, it is difficult to predict clinical outcomes when ITN applications are scaled up across the African continent. Sound model frameworks incorporating intricate interactions between mosquitoes and treated nets are

needed to develop the predictive capacity for scale-up applications of ITNs (Weidong Gu et al, 2009).

2.5 MALARIA IN GHANA

In Ghana, malaria is the number one cause of morbidity accounting for 40-60% of out patient reports (Asante and Asenso -Okyere, 2003). Reported malaria cases represent only a small proportion of the actual number of episodes as majority of people with symptomatic infections are treated at home and are, therefore, not reported (World Malaria Report, 2005).

In a recent study in Northern Ghana, it was found out that the cost of malaria care is just 1% of the income of the rich households, and 34% of the income of the poor. Usually malaria attacks are associated with poor social, economic and environmental conditions. The main victims are the poor who are often forced to live on marginal lands. Malaria endemic communities are therefore caught in a vicious circle of disease and poverty. (Akazili, 2002). In Ghana the vulnerability of the disease is about 50% making Ghanaians to spend considerable amount of money on mosquito control products such as fly proof nets and mosquito repellent (GHS , 2004).

2.5.1 PROGRESS OF MALARIA CONTROL

Ghana has stepped up progress ever since malaria became endemic in the country. Through various donor agencies and seminars, there has been a concerted effort by the government and the Ghana Health Service (GHS) to make the country a malaria free state. Since the 1950 - 1960's: the World Health Organization (WHO) has supported indoor residual spraying using Dichlorodiphenyltrichloroethane (DDT) in many households. Chloroquine drug was used extensively and intensified at all health facilities in Ghana between the 1970's and 1980's.

Furthermore, Ghana approved the WHO program of accelerated malaria control in 30 pilot districts that emphasized chloroquine usage and building health workers' capacity to recognize malaria symptoms and properly deliver treatment from 1996-1997. The Roll Back Malaria Partnership program (RBM) began in 1999 and Ghana adopted the following from RBM's Global Strategy, improving case management through capacity building for health practitioners and caregivers at home known as home based care which adopted multi preventive strategies, including ITN and environmental management. About $8.8 million was received from the Global Fund in 2003 to Fight AIDS, TB and Malaria. There was an increasing resistance to chloroquine that kicked off child health campaign to provide all children under two with nets in 2006 and therefore became one of the 15 focused countries under the U.S. President's Malaria Initiative in 2007 (Ghana Malaria Alert, 2007) .

2.6 ENVIRONMENTAL RISK FACTORS OF MALARIA

2.6.1 RAINFALL

Malaria is greatly influenced by rainfall in the tropics. It creates an opportunity for *anopheles* mosquitoes to lay eggs, which can reach adulthood within nine to twelve (9-12) days that are necessary for the mosquito life cycle. Rainfall as one of the climatic variables that aid in the multiplication of mosquito breeding places and increasing humidity, which improves mosquito survival rates. The rainy season is a fertile period for the breeding sites, which are numerous. These species have the highest population density during the rainy season and these account for the high incidence of malaria at this period of the year (Reid, 2000).

Studies have established complex relationship between malaria and rainfall because water is very vital for larval development. A prolonged dry season can decrease mosquito numbers by

reducing breeding sites and also reduce malaria incidence whiles higher rainfall during the wet season may flush mosquito larvae away (Patz, 2001).

Lindsay *et al.* (2000) identified a reduction in the infection of malaria in Tanzania as associated with El Niño. It was found out that heavy rainfall may have flushed out Anopheline mosquitoes from their breeding sites thereby increasing the mosquito population. Smith et al (1995) in their study also showed a positive association between the abundance of Anopheles gambiae and rainfall. Increased malaria mortality in the Punjab correlated with high rainfall of the previous month (Smith et al, 1995).

In a study of a web-based climate information resources for malaria control in Africa, the results showed that rainfall is largely responsible for creating the conditions that allow sufficient surface water for mosquito breeding sites and is therefore recognized as one of the major factors influencing malaria transmission (Grover-Kopec et al., 2005).

2.6.2 TOPOGRAPHY

Topography generally has a great influence on mosquito replication and thus affect the rate of malaria cases. Higher topographies results in cooler temperatures which limits the rate at which the parasite reproduces. Higher elevations therefore result in low rise malaria cases as result of the cooler temperatures as you go through higher altitudes thereby elongating the life cycle of the malaria parasite.

Entomologic studies in eight villages to investigate the patterns of malaria transmission in different ecologic zones in Eritrea showed a positive relationship between the malaria cases and topography. Mosquito collections conducted for 24 months showed that the biting rates in the

higher elevations as a result of the lower temperatures were twice as high as the lowlands (Shillu et al., 2003). The complexity of topography and landscape in the highlands contributes to the spatial heterogeneity of vector abundance and malaria transmission intensity. It has implications for the survival of the vector for different altitudes (Minakawa et al., 2002).

Malaria has been observed to be a growing problem in African highlands because at high altitudes in the highlands and on hilltops, where malaria transmission intensity is low, human populations have poorly developed immunity to malaria because exposures are infrequent. Balls et al (2004) investigated whether the risk of infection with malaria parasites was related to topography in the Usambara Mountains, Tanzania. Clinical surveys were carried out in seven villages, situated at altitudes from 300m to 1650m. Each village was mapped and incorporated into a Digital Terrain Model. Univariate analysis showed that the risk declined with increasing topography and the fact that such elevations washed away water when it rained therefore decreasing potential for water to accumulate. This therefore prevents stagnation of the water that could result in the breeding of mosquitoes.

Lindsay et al (2000), discussing the effect of the 1997-98 El Niño on highland malaria in Tanzania, discovered quite an opposing results of the malaria incidence with the associated highlands. The study showed that the level of malaria infection was rather following this event than in the previous year, suggesting that heavy rainfall may have washed away mosquito breeding sites

Cohen et al (2008) in their study of topography-derived wetness indices and household-level malaria risk in two communities in the western Kenyan highlands and tried to show the effect of topography on the malaria incidence. They found that the transmission of *Plasmodium*

falciparum generally decreases with increasing topography. Knowledge of these local topographic effects may have permitted prediction of regions at high risk of malaria within the highlands at small spatial scales. The results indicated that high wetness indices are not merely proxies for valley bottoms, and that hydrologic flow models may prove valuable for predicting areas of high malaria risk in highland regions.

2.6.3 TEMPERATURE

Malaria incidence is closely linked with temperature. It affects malaria transmission in several ways among which we can account for two reasons: either the minimum temperature is so low that it prevents parasite and vector development or the temperature is too high resulting in increased mortality of the vector. A minimum temperature of 16 degrees celsius restricts parasite development and also prevents the development of the vector in its aquatic stages. At 17 degrees celsius parasites develop but not rapidly enough to cause an epidemic (Lindsay and Martens, 1998).

Temperature also plays a fundamental role in the rate of multiplication of the parasite in mosquitoes and directly influences the mosquito development, gonotrophic cycle and longevity, as well as the duration of the extrinsic cycle of the Plasmodium parasite. In warmer temperatures the mosquitoes develop more rapidly accelerating the mosquito life cycle and replicating rapidly the parasite growth (WHO/AFRO (2001).

The optimum temperature for the malaria parasite extrinsic incubation period is about 20º-27ºC whiles the maximum temperature for both vectors and parasites is 40°C. (MARA/ARMA, 1998). Malaria transmission in areas colder than 20°C can still occur because Anophelines often live in houses, which tend to be warmer than external temperatures. Larval development of the

mosquito also depends on temperature. Higher temperatures increase the number of blood meals taken and the number of times eggs are laid by the mosquitoes. (Martens et al, 1995).

Broker et al. (2002), studied to see the spatial distributions of Helminth (one type of parasites) in Cameroon. They collected epidemiological and population data. Land surface temperature was derived from NOAA-AVHRR. They used a Logistic regression model to identify significant environmental variables which affect the transmission of infection. The variables used in the regression analysis were mean, minimum and maximum land surface temperature; total annual rainfall and altitude. The result revealed that maximum temperature was an important variable in determining Helminth distribution. At higher temperatures it is realized that female adult mosquitoes feed more frequently and digest blood more rapidly and the Plasmodium parasite matures more rapidly within the female mosquitoes (Githeko et al., 2000).

2.6.4 CLIMATE CHANGE

Climate change and its relation to vector borne disease review was carried out by Githeko et al., (2000) on the whole world. The study revealed that climate variability has a direct influence on vector-borne disease epidemics. A complex interaction exists between man, the parasite, the vector and the environment and this interaction determines malaria's endemicity. Climate therefore has a major impact on vector and the parasite development.

Climate is a major driving force behind malaria transmission and climate data are often used to account for the spatial, seasonal and inter- annual variation in malaria transmission. The transmission of many infectious diseases varies noticeably by season. For example, the majority of influenza outbreaks in the northern hemisphere occur in mid to late winter (WHO, 2000)

In predicting and mapping malaria under climate change scenarios, Tonnang et al (2009) sought information previously generated by entomologists, e.g. on geographical range of vectors and malaria distribution in order to build models that will enable prediction and mapping of the potential redistribution of *Anopheles* mosquitoes in Africa. GIS was utilized in this process and it enabled the setting up of an early warning and sustainable strategies for climate change and climate change adaptation for malaria vectors control programmes in Africa (Tonnang *et al.*, 2010).

2.6.5 LAND USE/LAND COVER AND FOREST

Land use and land cover changes has a significant influence on malaria transmission intensity. It affects the spatial and temporal variations in the distribution of anopheline larval habitats. In a study investigated by Munga et al (2009) the spatial and temporal variations in the distribution of anopheline larval habitats and Land use changes in western Kenya highlands over a 4-year period showed that Anopheles gambiae complex larvae were mainly confined to valley bottoms during both the dry and wet seasons. They were also located in man-made habitats where riparian forests and natural swamps had been cleared. The association between land cover type and occurrence of anopheline larvae was statistically significant.

Forest cover may double the high rate of malaria in some of the areas recording high malaria cases. The disease incidence is very high in the forest and forest fringes as compared to plains or urban areas (Sharma, 1991). Mosquitoes in the forested area according to the study were seen to live longer than those in the deforested area in both dry and rainy seasons in the highlands. Forested areas are areas with high humid conditions which favour the ecological reproduction

and transmission of the malaria parasite (Afrane et al., 2005). Proximity to forest and swamp have both been associated with increased vector density. Broker et al. (2004), established a positive relationship between forest and malaria risk. Logistic regression was used to examine the effects of distance to forest on malaria prevalence. It was found to escalate the malaria rates consistent with other studies. Proximity to forest was found to be a major risk factor for malaria.

In a study in the Brazilian Amazon, forest cover can increase malaria incidence by nearly 50%. Open spaces and partially sunlit pools of water, typical conditions of deforested landscapes, provide an ideal habitat in which the Anopheles mosquito can thrive. The study revealed that a 4 % change in forest cover was associated with a 48% increase in malaria incidence. (Hirschfeld, 2010).

2.7 APPLICATION OF GIS AND MAPS IN MALARIA STUDIES

GIS can be described as general-purpose computer-based technologies for handling geographical data in digital form in order to capture, store, manipulate, analyse and display diverse sets of spatial or geo-referenced data (Burrough and McDonnell, 1998)

GIS also open new possibilities of data analysis not limited to spatial analysis. Data generated within GIS, distances, areas, and selections based on spatial criteria, can all be used as inputs to statistical modelling. Large amounts of information are necessary for almost all aspects of malaria control programmes. GIS offers the ability to process quantities of data beyond the capacities of manual systems. Data are stored in a structured digital format, which permits rapid retrieval and use. In addition, data may be quickly compiled into documents, using techniques such as automatic mapping and direct report printouts (Bernhardsen 1992).

GIS is an efficient information management system in malaria eradication process and programme. It aids in quick retrieval of infomation and dynamic generation of maps to highlight hot spots of malaria for formulating prompt and focused malaria control strategy. GIS mapping makes it easier to update information instantly and to identify the trouble spots at given locations. This approach was utilized in the tribal state of India for national malaria control programme**.** This process aided in the identification of hot spots of malaria prevalence and spatial analysis of the disease **(**Aruna et al., 2009**)**.

GIS has contributed immensely to malaria control programs. It has become a valuable tool in the operations and implementation strategies of the programme. It has an additional capability of being an evaluation tool for providing spatially analyzed outputs generated by health information systems in graphic visual formats which can be readily understood by field workers and program managers. Financial constraints, however, limits the widespread use of the GIS technology. (New Zealand, 1998*)*

GIS and Remote Sensing have fuelled a renaissance in malaria risk mapping in Africa using climate data. Such climate and environmental data enable the stratification of the varied epidemiology of malaria across the areas of sub-Sahara Africa where the disease is endemic (Hay et al., 2004).

Some new insights on application of spatial technology in malaria research and control by Rekha et al. (2009) saw the application of GIS that has emerged as the core of spatial technology which integrates wide range of dataset available from different sources including Remote Sensing and Global Positioning System (GPS). GIS tools have contributed immensely in understanding the epidemiological processes of malaria and examples drawn have shown that GIS is now widely used for research and decision making in malaria control.

Hay et al. (2004) used GIS in the mapping process of the global distribution of malaria. This technique helps define populations at risk for appropriate resource allocation to combat the disease. They further overlayed historical maps of malaria risk to create a single global distribution map of malaria risk which illustrated range changing from 1900 to 2002.

Markus et al. (2008) used GIS for the surveillance of infectious diseases. Spatio-temporal clusters of disease detected by computer assisted cluster analysis (SaTScan™) were visualized on maps. The EpiScanGIS (epidemiology software) enables dynamic generation of animated maps. The system is based on open source components; its architecture is open for other infectious agents and geographic regions. It exemplifies GIS applications and early-warning systems in laboratory surveillance of infectious diseases.

GIS has proven to be one of the most useful tools in public health research. It has been widely used in disease surveillance and monitoring, research hypotheses generation, identification of high-risk area and population at-risk, targeting resources and the monitoring of interventions (Gupta et al., 2003).

GIS provides a spatial database containing environmental, social and epidemiological data. Such data provide a basis for statistical analysis. For example, with GIS one can explore the statistical relationship between infectious disease data and environmental data, and then map the risk level in the area of interest (Kolivras, 2006).

GIS based models have been developed to map malaria in data poor areas using combinations of climate data and malariometric data. Climate models of vector-borne disease are essentially models of environmental suitability for a vector. Areas where environmental conditions are unsuitable are classed as outside the distributional limits of the vector as shown in the mapping process (Rogers et al., 2002).

Maps are heuristic models, used to communicate, interpret, and explain data. They aid in the visualization of differences, clustering, heterogeneity, or homogeneity within data. Spatial patterns can be perceived and correlations visualized through the use of maps. Symbols and colours can communicate detail or the relative importance of certain features. (Coetzee et al, 2000*).*

Crude maps have been utilized in disease epidemiology. The disease incidence are often subject to considerable random error, particularly if either the disease is rare or the population per spatial unit is small, so that the rate may be influenced by a relatively small number of c**a**ses. This leads to map**s** in which attention is drawn to those areas whose rates are based on the least stable estimates (Cuzick, 1992.)

Mapping of malaria is normally challenging because of the difficulty in data access. Gemperl et al. (2004) used Bayesian geostatistical models to produce smooth maps of estimates of the entomological inoculation rates obtained from the Garki model, necessitating the effect of environmental covariates**.** When the Garki –model (software for geostatistics) was used, there was a conversion of the kriged entomological inoculation rates values to age-specific malaria

prevalence**.** The process have proved more credible than other mapping methods. (Gemperl et al**,** 2004)

WHO (1997) reported the use of maps to represent the world-wide burden of malaria. The maps showed the reported distribution of the clinical episodes of malaria. The limitation of these reports was, however, the extent of health care coverage, the efficacy of surveillance and reporting systems, and other factors that have little to do with the underlying force of malaria transmission.

In Sri Lanka, Breit et al. (2005) used maps to help health professionals to control and manage malaria. The paper provided the first publicly available maps of both *P. vivax* and *P. falciparum* malaria incidence distribution on the island of Sri Lanka at sub-district resolution,which are useful to health professionals, travellers and travel medicine professionals in their assessment of malaria risk in Sri Lanka.

Maps of malaria continue to be a vital tool for optimal allocation of resources for anti-malarial activities. There is a lack of reliable contemporary malaria maps in endemic countries in sub-Saharan Africa. This problem is particularly acute in low malaria transmission countries such as those located in the horn of Africa. Bayesian geostatistical models, with environmental and survey covariates, were used to predict continuous maps of malaria prevalence across Somalia and to define the uncertainty associated with the predictions.

2.8 SPATIAL AND STATISTICAL ANALYSIS

Spatial statistical methods have become a useful tool in epidemiological studies. It incorporates spatial correlation according to the way geographical proximity is defined. Proximity further depends on the geographical information, which can be available at areal level or at point-

location level. Areal unit data are aggregated over contiguous units which partition the whole study region. Proximity in space is defined by their neighbouring structure. Point-referenced or geostatistical data are collected at fixed locations (households, villages) over a continuous study region. Proximity in geostatistical data is determined by the distance between sample locations. (Gemperli et al, 2004).

2.8.1 GEOSTATISTICS

Geo-statistics refers to the collection of statistical methods in which location data plays an important role in the study design or data analysis. Exploratory data analysis using geo-statistics refers to describing patterns in the distribution of a disease using location data. The technique employed is Kriging which is one of the methods used for disease mapping. It is a group of geo-statistical techniques to interpolate the value of a variable at non sampled locations based on the observations at known locations. (Bautista et al., 2006)

Geostatistical prediction, i.e. kriging of the empirical Bayesian smoothed rates, is based on appropriate modeling of the data. Here, the constant mean assumption for the spatial mean surface is chosen and justified by visual inspection of the empirical semivariogram which levels out and reaches a sill. The spatial dependence structure is modelled by an isotropic exponential semivariogram without nugget effect, which is fitted by weighted least squares estimation to the robustly estimated empirical semivariogram. (Cressie, 1993)

2.8.2 KRIGING

Kriging has to do with spatial prediction. There are different models with respect to the knowledge and estimation of the spatial mean function, i.e. $\mu(s)$. Ordinary kriging is concerned with an unknown but constant mean function, i.e. $\mu(s) = \mu$. Furthermore, universal kriging is based on a polynomial trend surface model which is to be removed prior to estimation of the semivariogram from the residuals, i.e. $\delta(s)$. This technique may be the most widely-used in practice. An outlier-resistant alternative is median polish kriging. This method starts by the robust and non-parametric estimation of the non-constant mean surface via median polishing followed by robust semivariogram estimation. Kriging is sometimes termed a smoothing method. This is due to the fact that the predicted residuals are in absolute not larger than the model residuals $\delta(s) = Z(s) - \mu(s)$, i.e. the variability of the predictions around the estimated mean surface is smaller than the variability of the observations $\{Z(s)\}$. When the semivariogram is modelled without nugget effect, i.e. without small-scale variability at spatial scales smaller than the observational scale, then kriging leads to direct interpolation at the sampling sites. In this case the prediction equals the observation at the sample sites and thus the predicted residuals are equal to the model residuals, i.e. predictions at any other sites have the tendency to shrink towards the value of the estimated trend surface at that place. On the other hand, when a semivariogram with nugget effect is appropriate, the prediction tends to be closer to the mean surface, which gives smaller residuals i.e. a smoother prediction surface (Cressie, 1993).

2.8.3 POISSON KRIGING

Geostatistics was employed in the isopleth mapping of cancer mortality risk using area-to-point Poisson kriging. The statistical and spatial capability of geostatistics accounted for spatially varying population sizes and spatial patterns in the filtering of choropleth maps of cancer mortality that was developed. The strength of Poisson kriging lies on the fact that it produces risk surfaces that are less smooth than the maps created by a usual point kriging of empirical Bayesian smoothed rates. It ensures that the population-weighted average of risk estimates within each geographical unit equals the areal data for this unit. The new approach according to simulation studies yields more accurate predictions and confidence intervals than point kriging of areal data where all counties are simply collapsed into their respective polygon centroids. (Gooverts, 2006).

Diseases occur in space at varying times and understanding the spatio-temporal variation of malaria incidence would therefore provide a basis for effective disease control planning and monitoring. County-level Bayesian Poisson regression models of incidence were constructed, with effects for rainfall, maximum temperature and temporal trend. The model allowed for spatial variation in county-level incidence and temporal trend and dependence. The models revealed strong associations of malaria incidence with rainfall and temperature (Archie et al, 2009).

2.8.4 CORRELATION ANALYSIS

Kigbafori et al. (2008) applied geostatistics in malaria studies in Côte d'Ivoire observing spatially-explicit risk profiling of plasmodium falciparum infections at a small scale. Bayesian variogram models for spatially-explicit risk modelling of *P. falciparum* infection prevalence

were employed, assuming for stationary and non stationary in the spatial processes. This method was relevant in malaria control interventions identifying hot sports for the eradication process.

Mapping malaria risk in West Africa using a Bayesian nonparametric non-stationary model by Gosoniu et al. (2009) showed malaria transmission is highly influenced by environmental and climatic conditions but their effects are often non linear. The climate-malaria relation is unlikely to be the same over large areas covered by different agro-ecological zones. Similarly, spatial correlation in malaria transmission are mainly due to spatially structured covariates which could vary across the agro-ecological zones, introducing non-stationarity.

CHAPTER THREE

MATERIALS AND METHODOLOGY

3.0 STUDY AREA

Amansie West District is one of the twenty six (26) districts in the Ashanti Region of Ghana which lies in the rainforest belt. It lies in the south-west of Ashanti with a projected population of 142,068. It is situated between latitudes 6° 00 N and 6° 45 N and longitudes 1° 30 W and 2° 15 W. The district is 1,336km^2 with the capital at Manso-Nkwanta. About 70% of the population are farmers whiles 22% are engaged in mining.The topography of the district is generally undulating with an average elevation of 210m above mean sea level. It has a wide range of hills, which stretches across the north-western part of the district, especially around Manso-Nkwanta and Abore. These hills have an elevation of between 560m and 630m. The District is drained by the Offin and Oda rivers with an annual average rainfall of 1200mm. The District falls within the highest rainfall belt of Ghana having a double maximium rainfall pattern thereby supporting all year round farming activities. The temperature ranges from 22 °C to 30°C with a vegetation normally made up of secondary forests, thicket, and swamp and forb regrowth. There are four main forest reserves in the district; the Oda river forest reserve, Apamprama Forest Reserve, Gyeni river forest reserve and Jimira forest reserve. The area also abounds in small scale mining and illegal mining also locally known as "galamsey". The geology of the district is that of Proterozoic volcanic green stones with sedimentary rocks and granitoid intrusions. It is one of the areas with low economic social status in the Ashanti region and a target for most vector diseases such as malaria

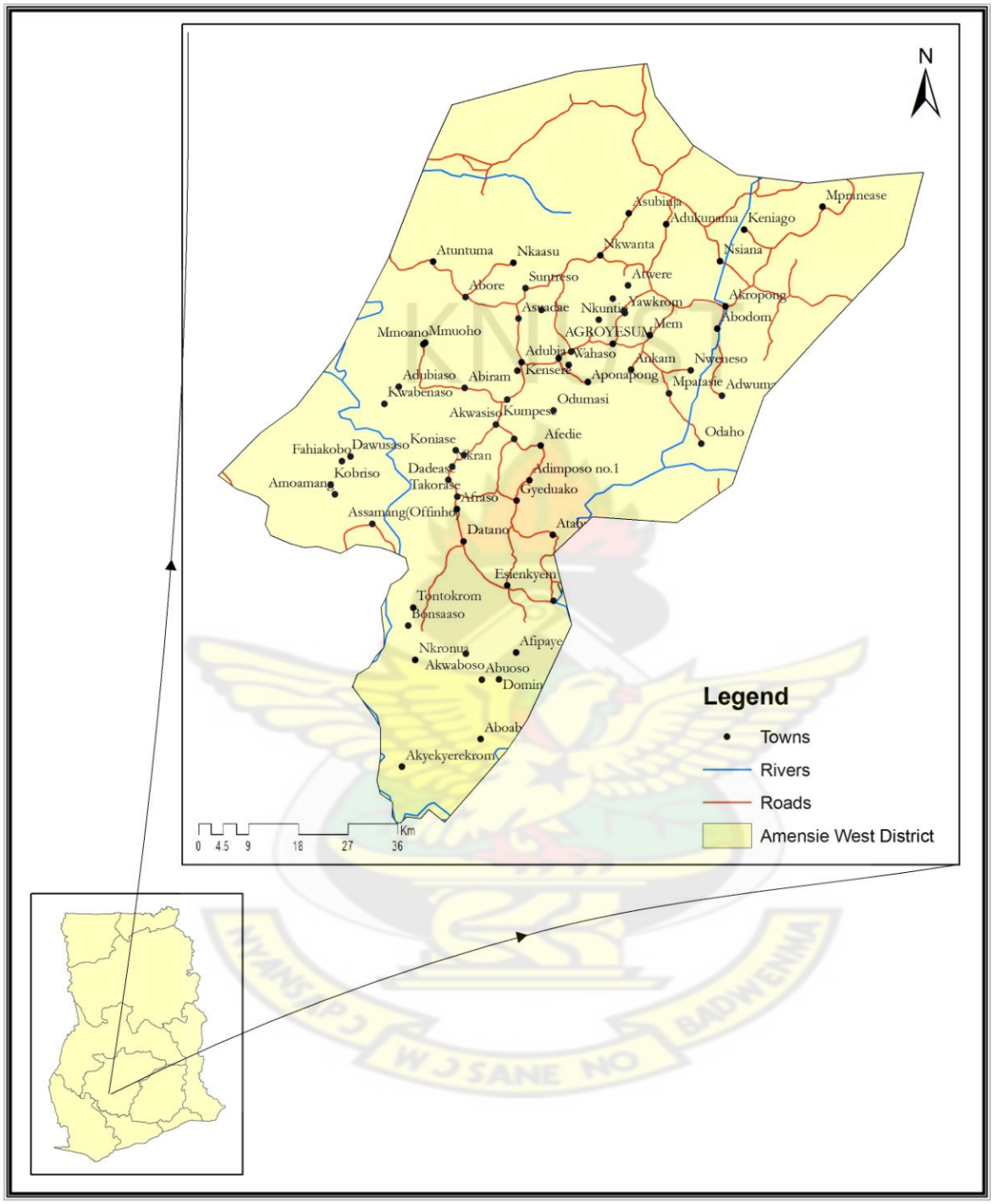

Fig 3.1: Map of Ghana showing Amansie West District.

3.1 MATERIALS USED

A digitized Boundary map of the district (Amansie West District map (at a scale of 1:250,000).

Topographic maps (Sheet 0602C1, C3, 0602D2 and D4 at a scale of 1:50,000) showing location of settlements of Amansie West District were obtained from the Survey and Mapping Division Accra, Ghana.

Etrex Hand Held GPS used to obtain the spatial coordinates.

ASTER Image acquired in the month of May 2007.

Application softwares: BayesX, Microsoft Excel, GIS software: ArcGIS, P_K and Minitab SP

3.1.1 SPATIAL DATA SOURCE

Spatial data were obtained by extracting the coordinates from the digitized boundary map of the Amansie west district using the topographic map from the Survey and Mapping Division Accra, Ghana at a scale of 1:50,000.

3.1.2 POPULATION DATA.

The demographic data of the areas involved in the study was obtained using the 2000 Ghana population Census Data. The populations from 2004 to 2009 used in the study was extrapolated using the 1984 and 2000 growth rates computed with the help of the Ashanti Region Statistical service, Kumasi.

3.1.3 METEOROLOGICAL DATA

The meteorological data comprising the rainfall and temperature data was obtained from the Ashanti Regional Meteorological office, Kumasi. The monthly rainfall readings were recorded in meters at the Akrokeri sub station whiles the temperature reading were in degrees celcious.

3.2 METHOD

3.2.1 DIGITAL ELEVATION MODEL

Elevation data of the area used was derived by creating a Digital Elevation Model (DEM) using contours of the Amansie West District from the Ghana topographic map at a scale of 1:50,000 using ArcGIS software. The heights extracted from the DEM was used to create a raster surface covering the whole area of study. To improve the height data not necessarily as a point data (the heights vary from within the community), a block statistics using the focal point analysis in ArcGIS was utilized to create a buffer of circles with radius 500m, 1,000m, 1,500m and 2,000m. The final elevations were then extracted using the mean of these buffer heights.

3.2.2 MALARIA PREVALENCE RATE

The malaria cases data were obtained form the St. Martins Hospital, Agroyesum, at Amansie West District. The malaria incidence per hundred (100) people of the population was then calculated i.e. Prevalence= {(number of cases/population)*100} for the communites under study. The malaria rates from 2004-2009 were thus computed as well as the total rates of the years under study.

3.2.3 GRAPHS/LINEAR REGRESSION

The Minitab statistical software was used for the graph of relations between malaria prevalence and temperature/rainfall. It was also used in the linear regression analysis of the buffered distances from the rivers/forest /elevations and malaria rates.

3.31 BUFFER/OVERLAY OPERATIONS

The spatial data analysis in GIS was executed using ArcGIS 9.2. The digital map of the district was exported from the Ghana topographic map database. The towns, rivers and streams were in Ghana War office coordinate systems and clipped to fit the study area. This therefore created a spatial subset of the raster dataset.

Buffering and overlay are two of the most common operations in disease modeling. A buffer zone is an area that is within a given distance from a map feature. Points, lines, or polygons can be buffered. Buffers are used to identify areas surrounding geographic features.

An overlay is the primary way to combine information from two separate themes. Overlays are most common for polygonal data, and perform a geometric intersection, which results in a new layer with the combined attributes of both initial layers.

With malaria areas closer to rivers/streams are seen to suffer most (Shilpa et al., 2004). A buffer distance of 500m, 1000m, 1500m and 2000m was generated since the 2000m, is not sufficient because of current ecological differences as far as mosquito flight distance is concerned. The 2000m is the average flight distance of the mosquito (Wim et al., 2003). The forest areas in the study area was classified using Erdas Imagine and buffered at a distance of 1km from the edge of the forest to the towns.

The combination of the risk i.e (elevation, rivers/streams and forest cover) were overlayed with the disease rates to investigate the combined influence of multiple factors on the disease prevalence. Assigned weights of 1, 3 and 5 generated the combined risk map using elevation, forest and rivers respectively according to their level of influence on the disease as suggested in other studies (Haque et al., 2009).

The Poisson risk values represented as points in terms of their relative risk sizes were then overlayed on the raster image obtained in buffering the forest, rivers/ streams and topography.

For the extraction of the forest cover, the ASTER image (2007) data acquired in WGS 84 system was projected to the Ghana War Office. The image was enhanced using Erdas Imagine. About 250 points were selected in the field using the stratified random sampling method. Furthermore 150 points were then used to train the image for supervised classification to obtain the land use/land cover. The remaining 100 was then used to validate the land use/land cover giving rise to the forest extraction as the final product.

3.4 SPATIAL STATISTICAL ANALYSIS

Poisson kriging accounts for population rates in its modelling process as well as its generally flexible nature in the modelling and implementation of disease risk. The method is therefore utilized in this study.

We estimate the risk of contracting a disease at a given location m_α as $r(m_\alpha)$ using a linear combination of K neighboring data: $r_{PK}(m_\alpha) = \sum_{I=1}^{K} \lambda_i(m_\alpha) Z(m_i)$ ..... (1)

Where Z (m_i) is the rate observed at location m_i . The kriging weights are found by solving the following system of (k+1) linear equations:

$$\sum_{j=1}^{k} \lambda_j(m_\alpha)[C_R(m_i - m_j) + \delta_{ij}\frac{d^*}{n(m_i)}] + \mu(m_\alpha) = C_R(m_i - m_\alpha) \quad \text{..... (2)}$$

$$\sum_{j=1}^{k} \lambda_j(m_\alpha) = 1 \quad \text{..... (3)}$$

Where $d^*/n(m_i)$ is an error variance term that represents the variability arising from population size and is derived directly under the Poisson model for the counts as used by (Gooverts, 2005)

where δ_{ij} = 1 if m_i .= m_j and 0 otherwise, $n(m_i)$ and *d** is the population-weighted mean of the *N* rates calculated below:

$$d^* = \frac{\sum_{\alpha=1}^{N} n(m_\alpha)Z(m_\alpha)}{\sum_{\alpha=1}^{N} n(m_\alpha)} \quad \text{..... (4)}$$

The incorporation of this term for a zero distance m_i .= m_j leads one to assign smaller kriging weights to rates that are computed from smaller populations and deemed less reliable. The term

$\mu(m_\alpha)$ α) is the Lagrange parameter which is the results from the minimization of the estimation variance subject to the unbias constraint on the estimator.

In solving the kriging system in (2) above there is a need to have a model of the spatial covariance of the unknown risk, $C_R(h)$, or equivalently its semivariogram $\gamma R(\mathbf{h}) = C_R(o) - C_R(h)$. The experimental semivariogram of the risk as used by Monestiez et al is computed and shown below:

$$\gamma_R(\mathrm{h}) = \frac{1}{2\sum_{\alpha=1}^{N(h)} \frac{n(m_\alpha)n(m_\alpha+h)}{n(m_\alpha)+n(m_\alpha+h)}} \sum_{\alpha=1}^{N(h)} \{ \frac{n(m_\alpha)n(m_\alpha+h)}{n(m_\alpha)+n(m_\alpha+h)} [z(m_\alpha) - z(m_\alpha+h)]^2 - d^* \} \text{ ..... (5)}$$

where $N(h)$ is the number of communities separated by a vector $(\mathbf{h})$. The different spatial increments $z(m_\alpha) - z(m_\alpha+h)]^2$ are weighted by a function of their respective population sizes, $\frac{n(m_\alpha)n(m_\alpha+h)}{n(m_\alpha)+n(m_\alpha+h)}$), a term which is inversely proportional to their standard deviation.

This therefore accounts for the accuracy and reliability of the data given the small standard deviation involved. As inferred from Gooverts (2005), A permissible model $\gamma_R(\mathrm{h})$, is then fitted to the experimental semivariogram in order to obtain the semivariogram, or covariance value, for any possible distance (h). The model follows the weighted least-square regression procedure.

3.5 BAYESIAN REGRESSION MODEL

The present study hypothesizes that the risk of malaria infection has a dynamic relationship with elevation. Here, the study adopts a non linear nonparametric Bayesian modeling approach for the effect of elevation on the risk of malaria infection.

Consider the observations $(y_i, h_i), i = 1,...,n,$ with response y_i, and h_i the elevation in communities $s_i \in \{1,...,S\}$. The study assumes that the response variable follows Gaussian distribution, i.e. $y_i | \eta_i, \sigma^2 \sim N(\eta_i, \sigma^2/c_i)$, with unknown mean η_i of a nonparametric *additive* model of the form:

$$\eta_i = f(h_i)$$

where $f(h)$ is nonlinear smooth functions of $h(s)$

3.5.1 PRIOR ASSUMPTIONS

The unknown model parameters were estimated by a fully Bayesian approach. A Bayesian P (enalized)-splines (Stefan and Andreas, 2004) was used to model the unknown function $f(h)$. This approach assumes that an unknown smooth function f of a covariate h can be approximated by a polynomial spline of degree l defined on a set of equally spaced knots $h^{\min} = \zeta_0 < \zeta_1 < \cdots < \zeta_{s-1} < \zeta_s = h^{\max}$ within the domain of h. Such a spline can be written in terms of a linear combination of $d = s + l$. B-spline basis functions B_m, i.e.

$$f(h) = \sum_{m=1}^{d} \xi_m \cdot B_m(x).$$

The B-splines form a local basis since the basis functions B_m are only positive within an area spanned by $l+2$ knots. This property is essential for the construction of the smoothness penalty for P-splines. The estimation of $f(x)$ is thus reduced to the estimation of the vector of unknown regression coefficients $\xi = (\xi_1, ..., \xi_m)'$ from the data. An essential factor in the estimation procedure is the choice of the number of knots. We chose a moderately large number of equally spaced knots (20) to ensure enough flexibility to capture the variability of the data. In the Bayesian approach, penalized splines are introduced by replacing the difference penalties with their stochastic analogues, i.e., first or second order random walk priors for the regression coefficients. A first order random walk prior for equidistant knots is given by:

$$\xi_m = \xi_{m-1} + u_m, \qquad m = 2, ..., d$$

and a second order random walk for equidistant knots by:

$$\xi_m = 2\xi_{m-1} - \xi_{m-2} + u_m, \qquad m = 3,...,d$$

where the $u_m \sim N(0, \tau^2)$ are Gaussian errors. Diffuse priors $\xi_1 \propto const$, or ξ_1 and $\xi_2 \propto const$, are chosen as initial values, respectively. The joint distribution of the regression parameters ξ_m for a first order random walk is defined as:

$$\xi_m \left| \xi_{m-1} \sim N(\xi_{m-1}, \tau^2) \right.$$

and a second order random walk is defined as:

$$\xi_m \left| \xi_{m-1}, \xi_{m-2} \sim N(2\xi_{m-1} - \xi_{m-2}, \tau^2). \right.$$

The first order random walk induces a constant trend for the conditional expectation of ξ_m given ξ_{m-1} and a second order random walk results in linear trend depending on the two previous values ξ_{m-1} and $\xi_{j,m-2}$.

The joint distribution of the regression parameters $\xi = (\xi_1,...,\xi_m)'$ is computed as a product of the conditional densities defined by the random walk priors. The general form of the prior for ξ is a multivariate Gaussian distribution with density:

$$p\left(\xi \left| \tau^2 \right.\right) \propto \exp\left(-\frac{\xi' K \xi}{2\tau^2}\right)$$

where the precision matrix K acts as a penalty matrix that shrinks parameters towards zero, or penalizes too abrupt jumps between neighboring parameters. Since the penalty matrix K is rank deficient, i.e. $k = \text{rank}(K) < \dim(\xi) = d$, it follows that the prior for $\xi \left| \tau^2 \right.$ is partially improper with Gaussian prior $\xi \left| \tau^2 \right. \propto N(0; \tau^2 K^-)$, where K^- is a generalized inverse of K. The tradeoff between flexibility and

smoothness is controlled by the variance parameter τ^2. The larger the variance, the rougher is the estimated functions, and vice versa.

3.5.2 POSTERIOR ESTIMATION

Fully Bayesian inference is based on the posterior distribution of the unknown parameters. In this approach, samples are drawn from the full conditionals of the unknown parameters given the data through MCMC simulations. For simplicity, let β represent the unknown function to be evaluated (i.e., $\beta = \left(f\left(h\right)\right)$ and τ the variance component; the posterior distribution then equals

$$p\left(\beta,\tau|y\right) \propto p\left(y|\beta\right) p\left(\beta|\tau\right) p\left(\tau\right)$$

where $p\left(y|\beta\right)$ is the likelihood function of the data given the parameters and $p\left(.\right)$ represents the probability density function. Full conditional for the unknown function $f\left(h\left(s\right)\right)$ is multivariate Gaussian and, as a consequence, a Gibbs sampler for MCMC simulation is employed. Cholesky decompositions for band matrices have been used to efficiently draw random samples from the full conditional. The model has been implemented in public domain software for Bayesian analysis, BayesX ver 2.0 (Stefan and Andreas, 2004).

CHAPTER FOUR

RESULTS AND DISCUSSION

4.0: RESULTS

One of the objectives of this study was to create a risk map using geostatistical approach. The risk map created in such instances highlights areas of high risk that needs to be identified so as to tailor major interventions and monitoring activities. The Malaria risk surface was created using the Poisson semivariogram model of the disease incidence.

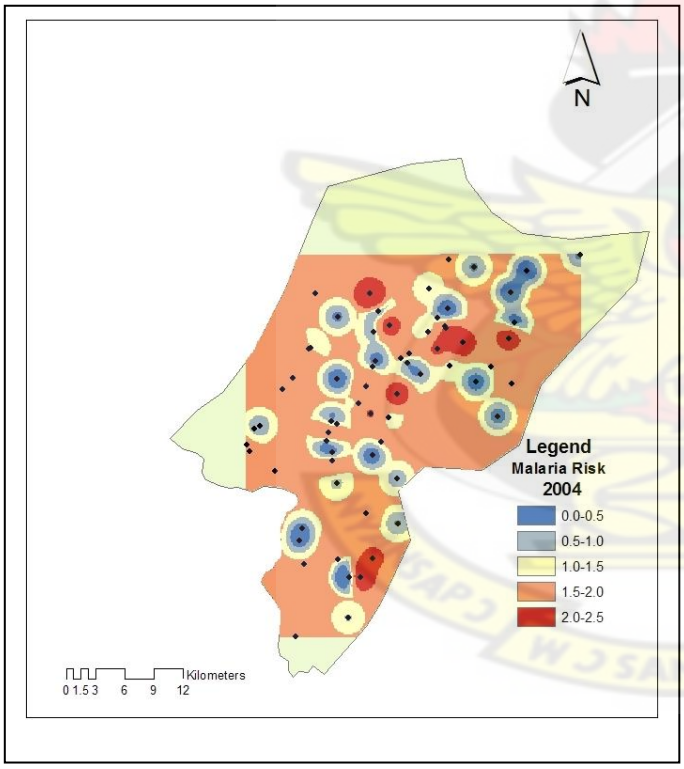

Fig 4.1.1: 2004 Malaria Risk Map

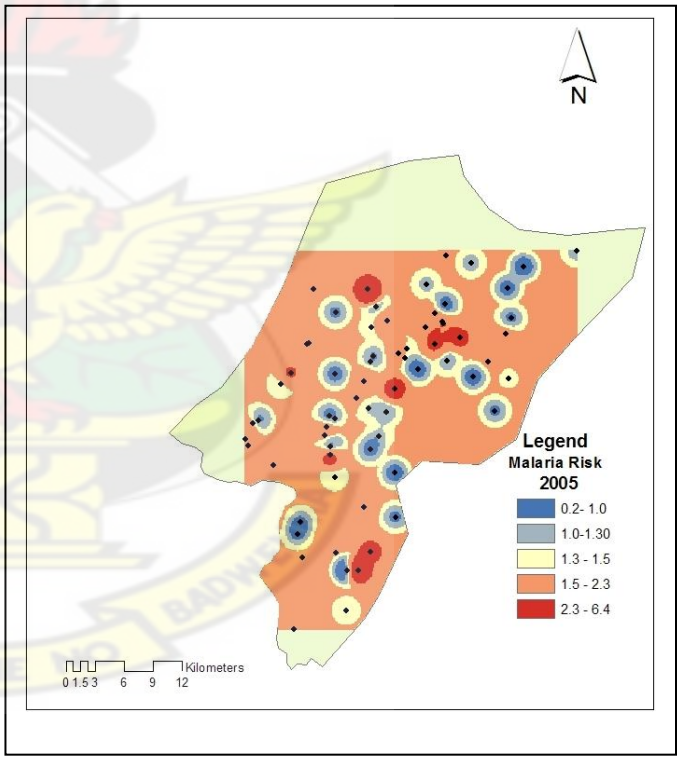

Fig 4.1.2: 2005 Malaria Risk Map

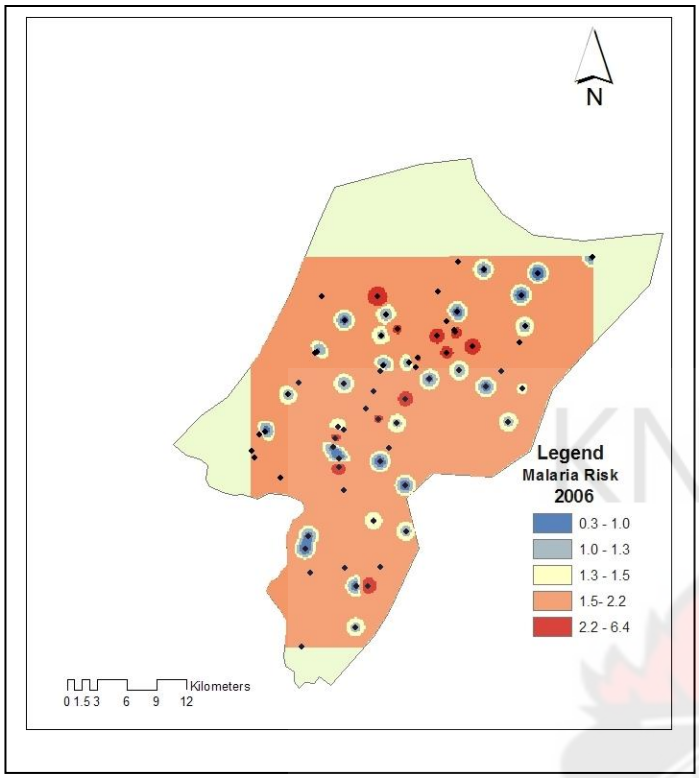

Fig 4.1.3:2006 Malaria Risk Map

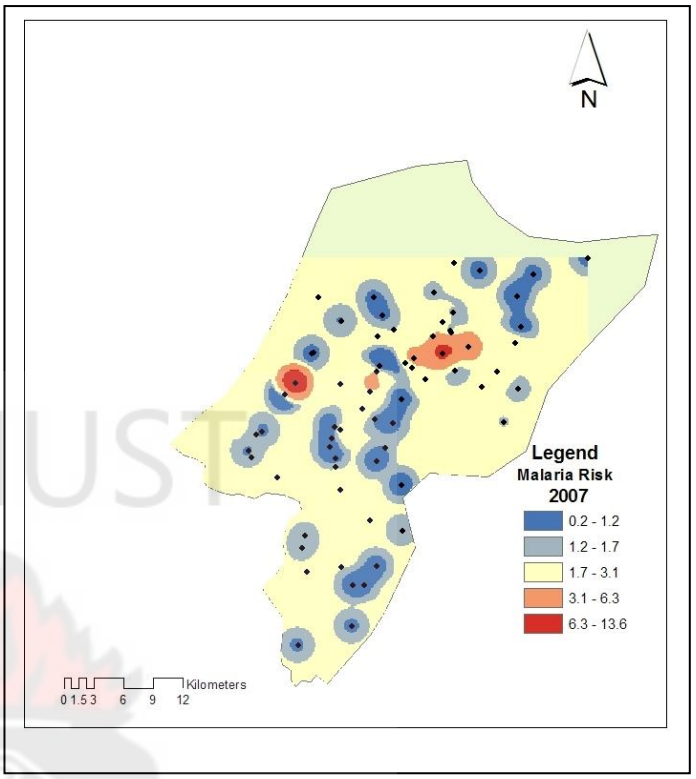

Fig 4.1.4: 2007 Malaria Risk Map

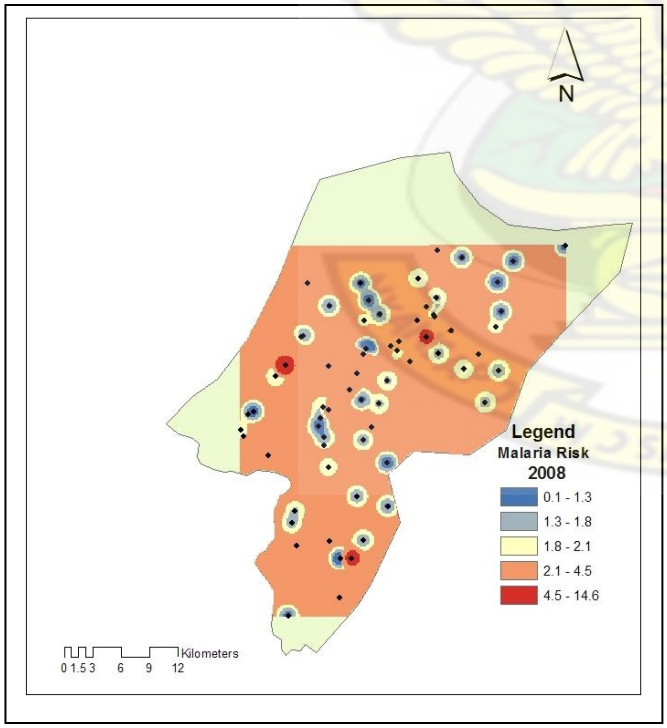

Fig 4.1.5: 2008 Malaria Risk Map

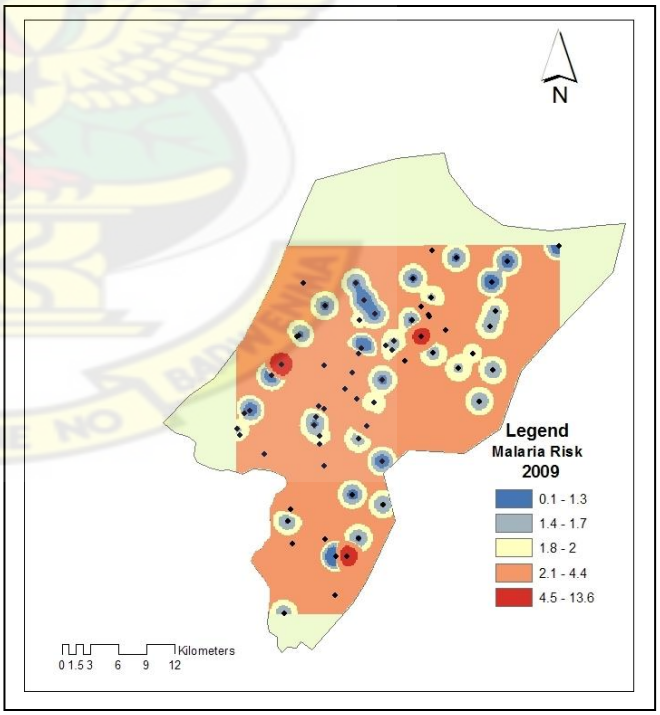

Fig 4.1.6: 2009 Malaria Risk Map

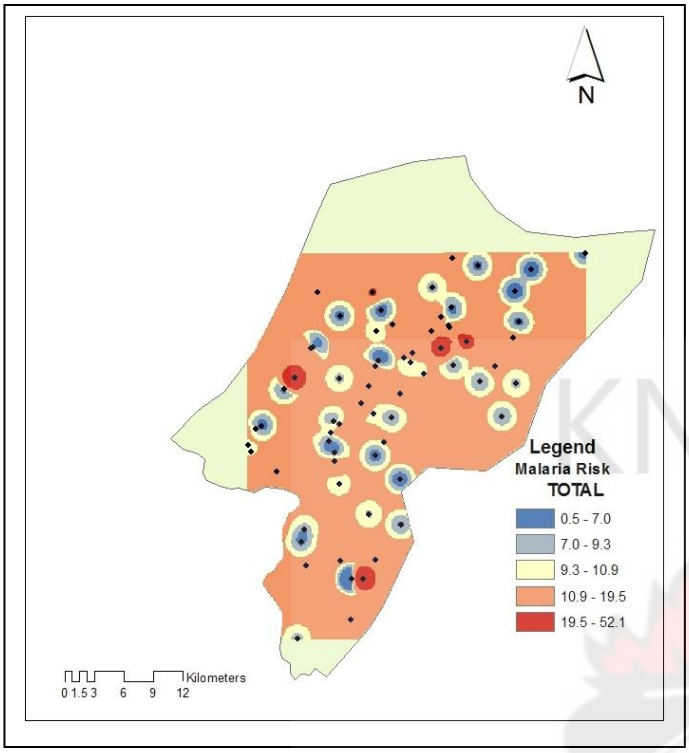

Fig 4.1.7: Total Malaria Risk Map

There was a steady rise in the general prevalence of the disease but a reduction in the key towns that were reporting in the previous years. A great improvement concerning risk was seen in 2007. There was an average risk occurrence in those areas except for areas around the district capital that was still reporting very high cases. The cummulative malaria risk was consistent with the general steady rise in the incidences of the years under study in Fig 4.1.3.

4.2**:** EFFECT OF RIVERS/STREAMS ON MALARIA RISK

The results in Fig 4.2.1 showed areas within 2km away from the water source (rivers/streams) recording relatively higher cases except for some few areas within 1km just nearer the Offin and Oda rivers that recorded higher cases. These results were consistent with some of the communities reporting high cases on the Poisson risk Map

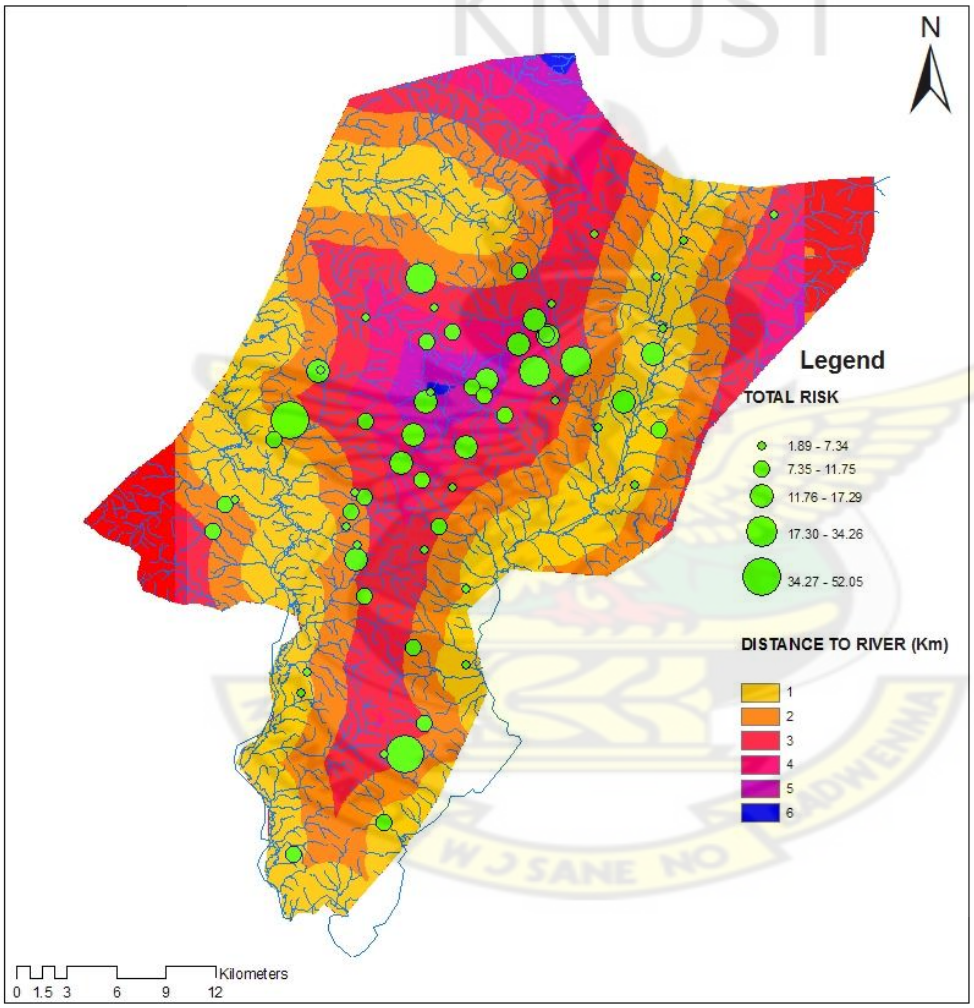

Fig 4.2.1: Distance Risk Map of Malaria in relation to rivers/streams

4.3: MALARIA AND FOREST COVER

The results in Fig 4.3.1 showed areas nearer the forest reporting higher cases though statistically weak as shown in Table 4.1. There is a general trend of high disease incidence between 1-3 km from the forest edge. Beyond 4km however there are varied disease incidence.Most settlements are not within the forest except for two towns Dominase and Abore.

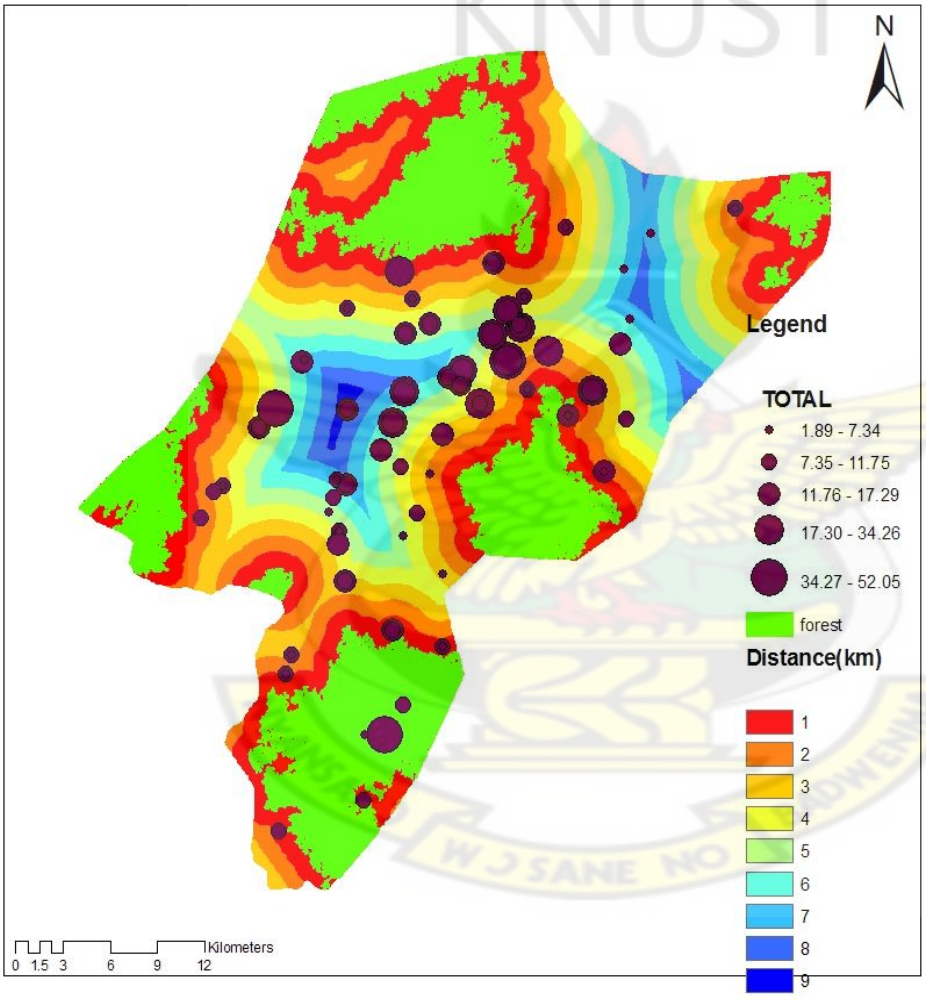

Fig 4.3.1: Distance Risk Map of Malaria in relation to the Forest Cover

COVARIATE	P-VALUE	R-SQUARE	T-VALUE
RIVERS/STREAM	0.140	0.36	1.5
FOREST	0.32	0.16	0.26
ELEVATION	0.47	0.10	0.64

Table 4.1: Regression Results of Covariates

4.4: MALARIA AND TOPOGRAPHY

The results in Fig 4.4.1 showed the areas with very high elevations have no settlements. Settlements on the higher and lower elevations showed varied cases

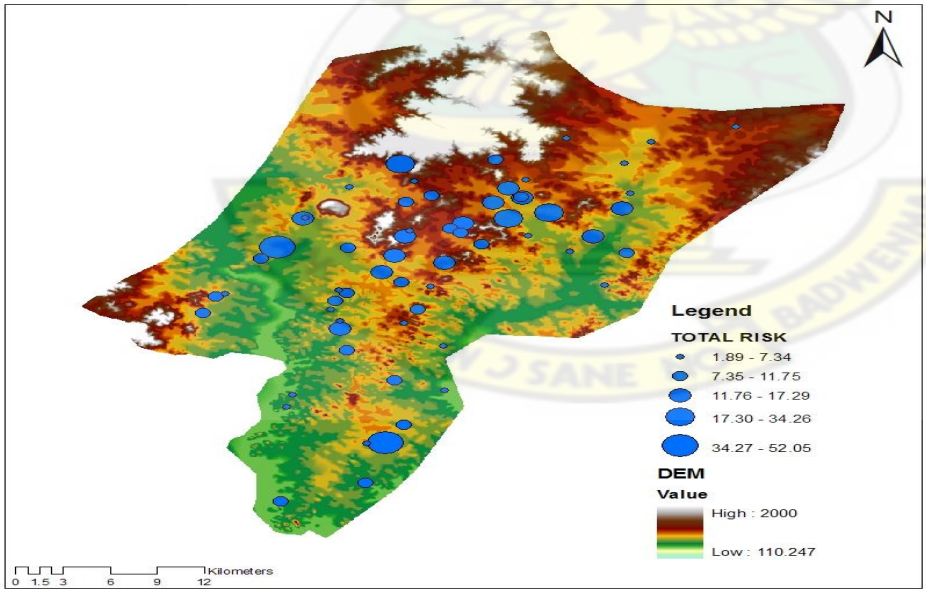

Fig 4.4.1: Digital Elevation Model (DEM) and malaria prevalence

The model in Fig 4.4.2 above shows that higher elevations in some instances resulted in fewer cases which follows the normal trend that higher altitudes have less favourable ecological factors like low temperatures that can trigger malaria rise. However some higher elevations recorded higher cases consistent with the malaria incidence in the Poisson risk Map.

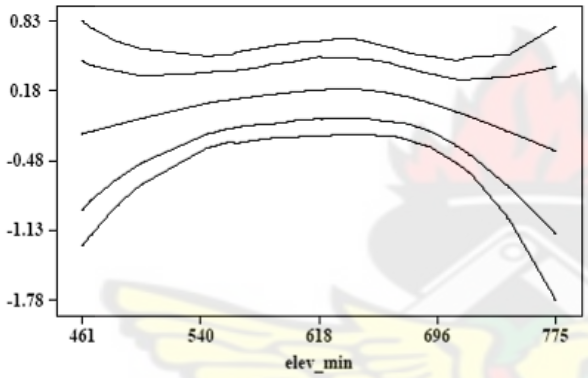

Fig 4.4.2: shows the Bayesian regression model of the elevation with the total malaria prevalence.

4.5**:** TOTAL COVARIATES AND MALARIA

The combination of the risk: elevation, water and forest cover using assigned weights generated the combined risk as shown in Fig 4.5.2 below according to their level of influence on the

disease. These results also showed a varied relationship. Fig 4.5.1 is the non-weighted overlays of the combined covariate.

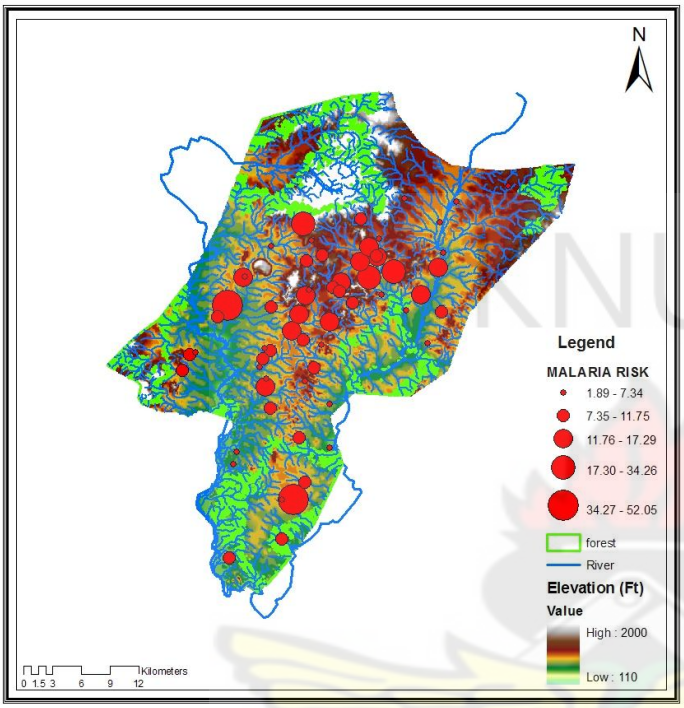

Fig 4.5.1:Overlay of Total Covariates

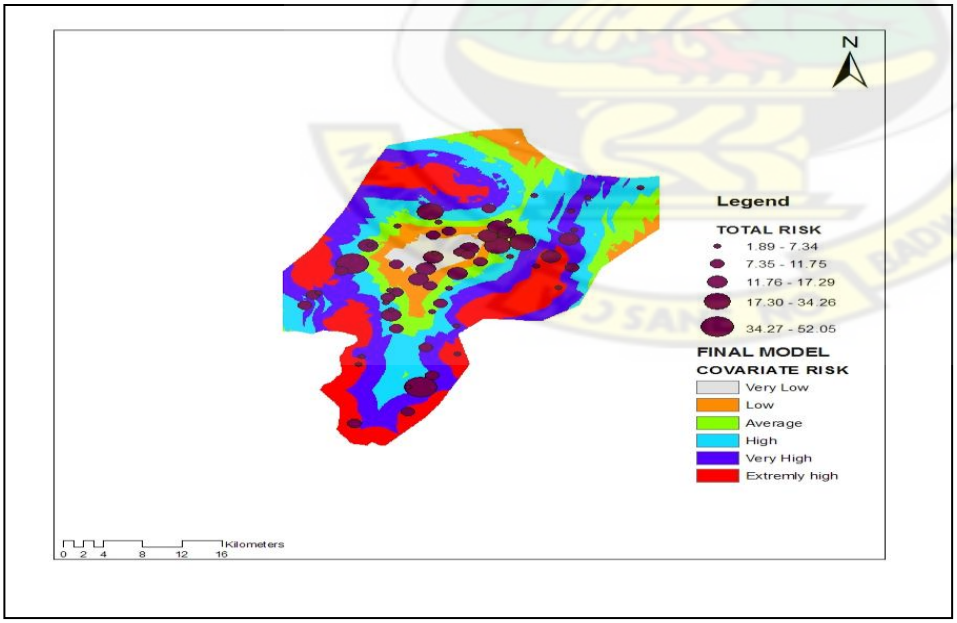

Fig 4.5.2: Total Covariate map with weights

4.6: SEMI-VARIOGRAM ANALYSIS

The Poisson semi-variogram analysis accounts for population size in the computation as compared to the traditional semi-variograms. The major range of the semi- variograms from the years 2004 to 2009 showed a shorter range of an average of 2km from the observations. The other years also showed shorter ranges in the variogram. It therefore highlights a statistically significant but weak spatial auto-correlation using the Poisson model variogram. The variograms created from the years 2004 to 2009 aided in explaining the spatial dependencies in the disease spread as shown in Figures 4.6.1-4.6.4.

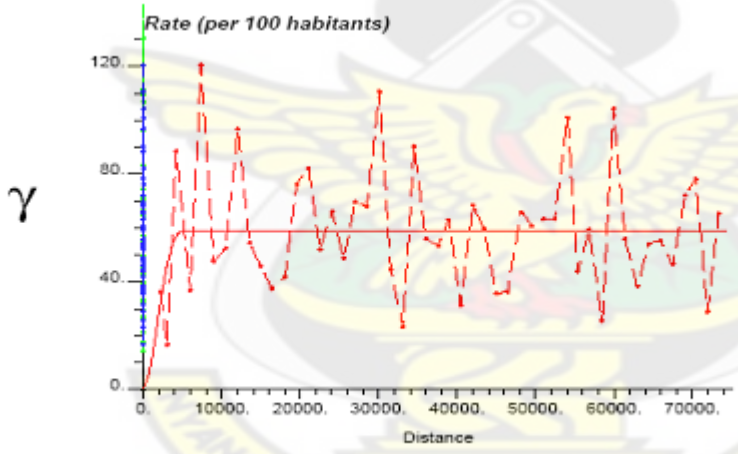

Fig 4.6.1: Total risk semi- variogram

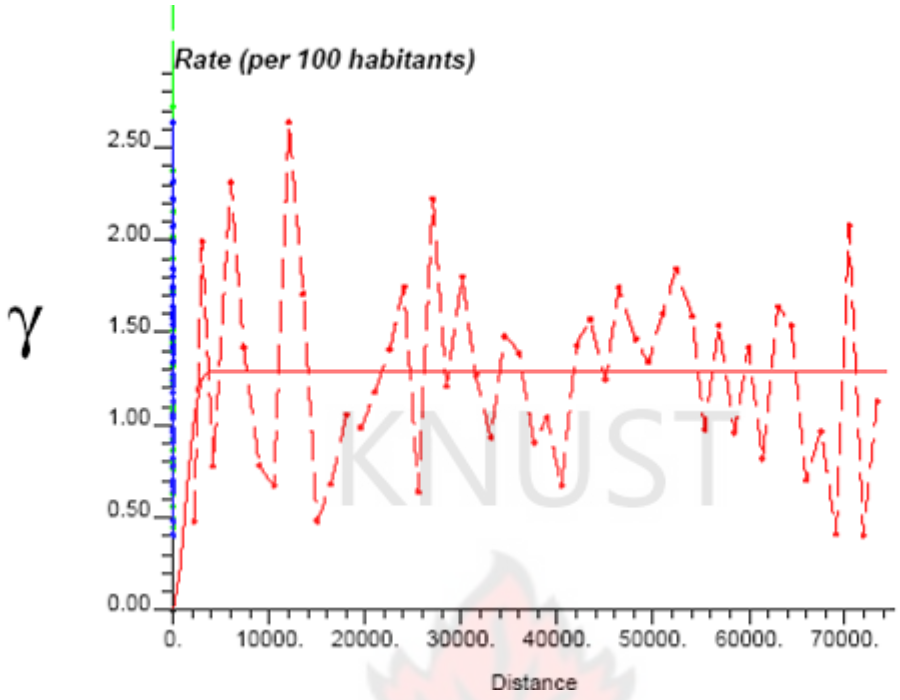

Fig 4.6.2: 2004 semi-variogram

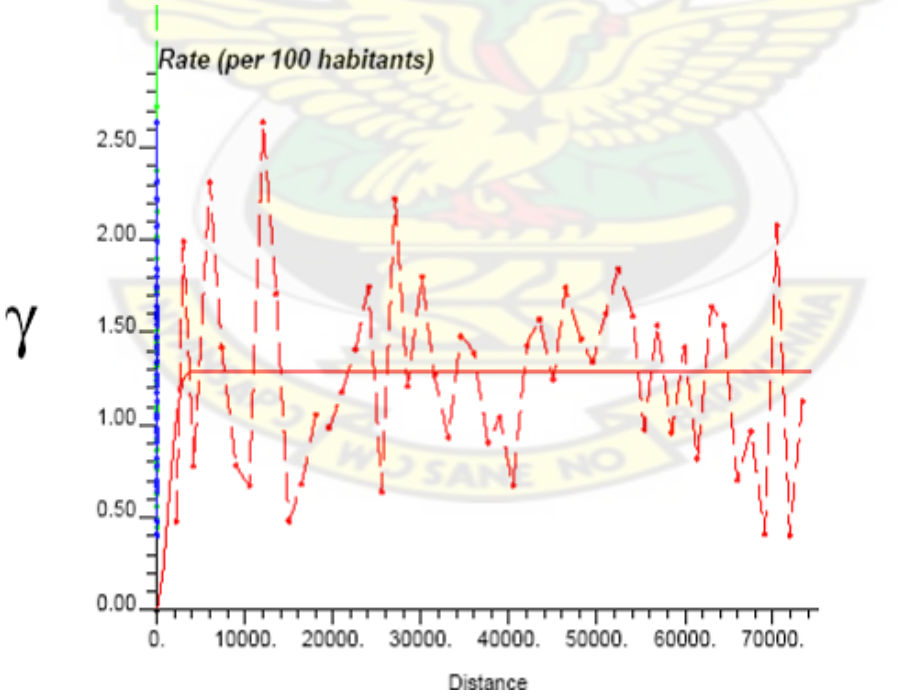

Fig 4.6.3:2006 semi-variogram

4.7.1: MALARIA AND RAINFALL

The graph in Fig 4.7.1 shows the disease prevalence increasing with increasing rainfall in the study area.

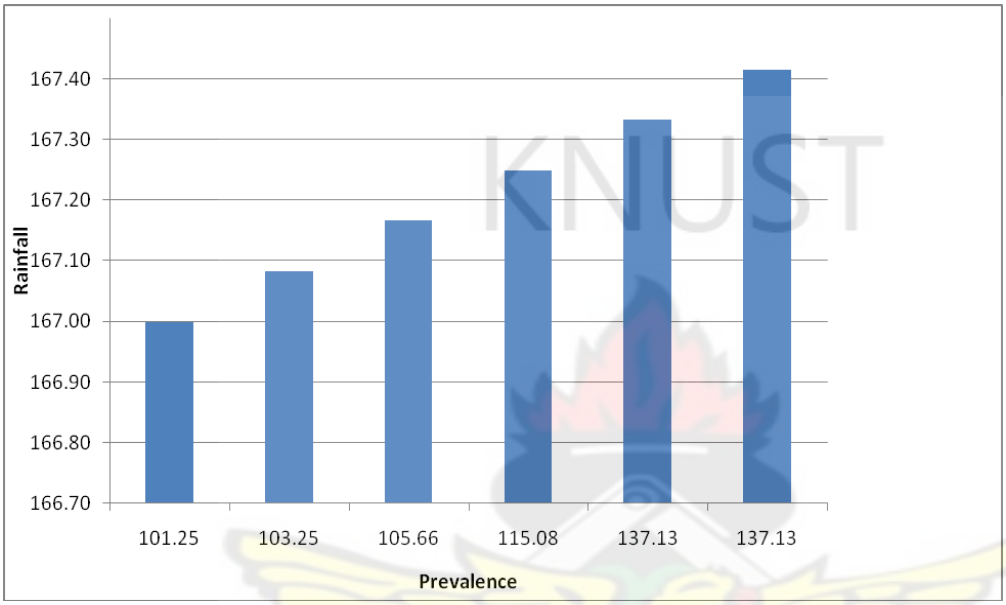

Fig 4.7.1: Graph of Prevalence against Rainfall

4.7.2: MALARIA AND TEMPERATURE.

The results of the effect of temperature on malaria prevalence in Fig 4.7.2 did not show any pattern

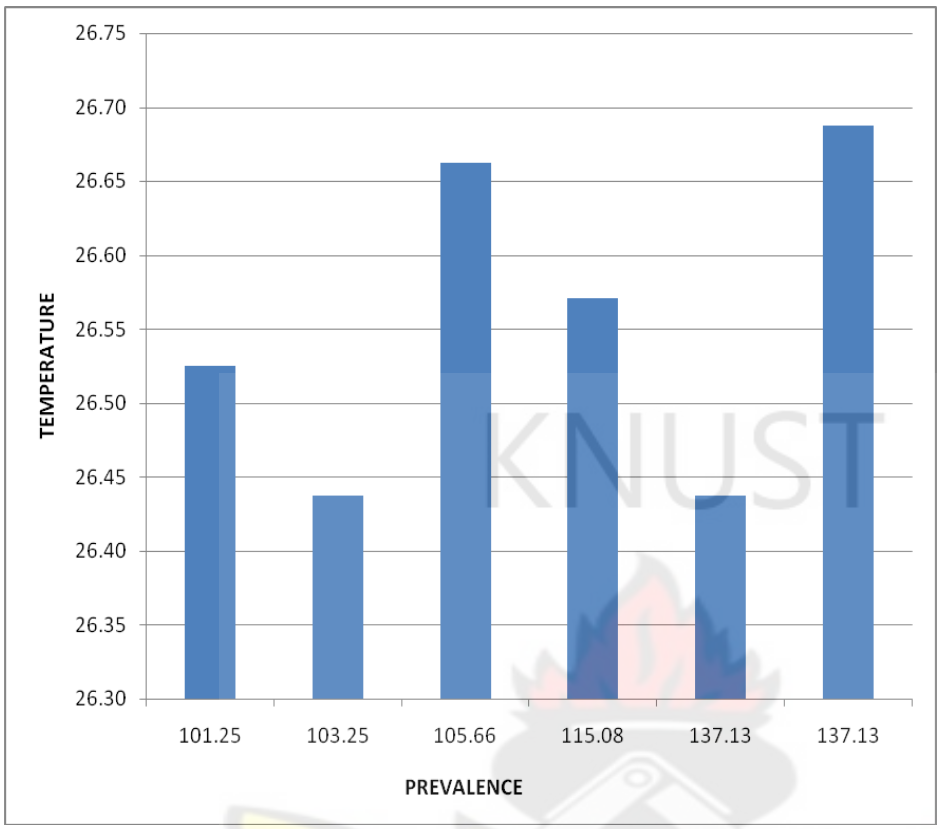

Fig 4.7.2: Graph of malaria prevalence against Temperature

4.7.3: MALARIA YEARLY CASES

The results as shown on the graph in Fig 4.7.3 highlights the fact that malaria cases rose quite steadily every other year.

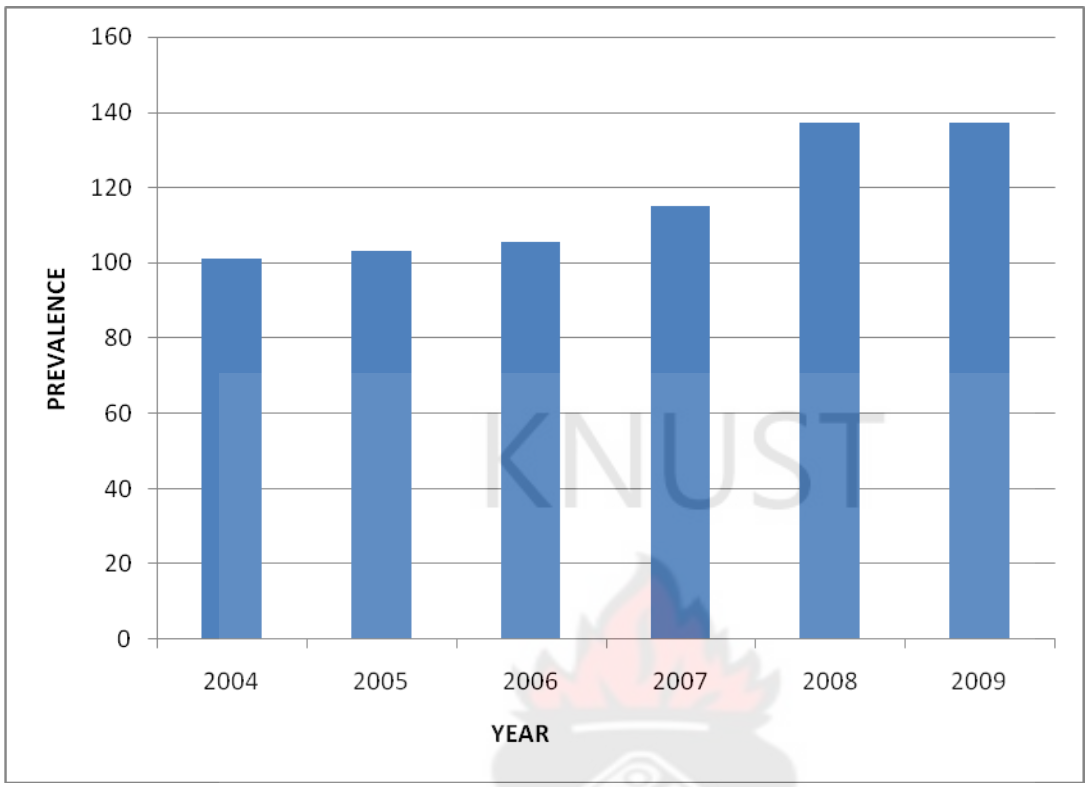

Fig 4.7.3: Malaria and Yearly cases

4.8: DISCUSSION

The risk map created for the Amansie West District corresponded with the Ghana Health Service report that shows a great challenge in malaria control in the District. The disease prediction map was enhanced in the study because the data was smoothed using the Poisson statistical methods as it incorporated the population rates in the process. The risk map showed a high number of cases of malaria in most areas especially around the district capital. It can be seen that the prevalence of malaria tended to increase every year.

There was generally a fair increase in the malaria risk from the year 2004 to 2009. Malaria rose averagely by 16% from 2004 to 2007 and by 20% during the period 2008 to 2009. There were many areas reporting high risk and low risk respectively in the recurring years. Other high risk areas saw some gradual reduction especially in the other years (e.g 2006 and 2007). Millenium Village Project (MVP) started the malaria campaign programme in the district in 2006 and may have contributed a great deal to reduce prevalence only to see a rise in the ensuing years. In 2006 and 2007 the MVP gave free medications to the whole community. The free medications led to a lot of referrals to the hospital thereby increasing the number of reported cases. The campaign and distribution of insecticide bed nets especially at the MVP coverage area in 2006 and 2007 therefore saw a reduction as evidenced in the Poisson map. The coverage of these bednets according to the MVP report increased from 13% to 59% by 2008 reducing the disease prevalence except for the district capital areas. Under reporting as a result of economic challenges and transport around those areas may have also increased the disease burden.

The distance to the rivers showed a varied relationship with the disease prevalence. Some areas nearer the water bodies rather showed a low prevalence as a result of the fact that the main river

is effectively being utilized and because the river flows fast, there is no stagnation of the water body. However in some communities water ponds are created close to the streams and rivers in order to preserve water during the dry season. These ponds created become stagnant points that enhances the breeding of mosquitoes that may increase the malaria prevalence at areas far off from the rivers/streams. Mining pits also nearer the river/streams may enhance mosquito breeding. The dug out pits from minnning left uncovered also become breeding grounds for the malaria vector to replicate. Furthermore some of the areas are marshy areas that leave a lot of water residue which serve suitably for the vector to thrive and therefore increases malaria rate.

The disease incidence was seen to be very high in the forest and forest fringes as compared to plains or non forested areas within 1km-3km.These areas as a result of their high humid conditions with corresponding higher rains as seen in Fig 4.7.1 enhances the ecology of the vector to thrive thereby increasing the disease prevalence. Mosquitoes in forested areas according to Afrane et al. (2006) live longer than those in the deforested area in both dry and rainy seasons in the highlands. They have shortened gonotrophic cycles thereby producing more eggs and reproducing faster. The forest habitats coupled with its humid conditions therefore support rapid multiplication of the vector. This may have resulted in the high cases in the forested areas. Most of the settlements are not within the forest except for the few (within the forest) that are not only influenced by the forest conditions but also on valley bottoms where the streams and rivers pass.

These environments often have areas where water could stagnate. Beyond 4km the disease prevalence could be attributable to other factors such as minning pits, untidy surroundings marshy areas and the non usage of mosquito treated nets and repellants.

Higher elevation in general has long been recognized to be associated with malaria due to its association with cooler temperatures that slows the development of anopheline vectors and the Plasmodium parasites they transmit. Most of the hills in the study area have no settlements as they normally even have forests in those areas. Settlements around higher elevations however showed varied malaria cases as can be confirmed by the Bayesian regression models clearly showing that disease incidence is not homogeneous. In this case malaria risk displayed an alternating results with elevation.

The other areas on lower elevations may be closely related to the streams/swamps and forest impact. This may have been as a result of the terrain being suitable for water accumulation on valley bottoms. In those areas water is not washed away when it rains as in the mountainous or higher altitudes.

The fact that the elevation varied in some instances with the disease prevalence may have been as a result of the fact that the elevation differences was generally insignificant on the district spatial scale as compared to generally known above 2000m altitudes.

The combined covariate risk map shown in Fig 4.5.2 with weights revealed a weak correlation with the malaria risk. This is in conformity with the results of the semi –variogram analysis that showed that there was a weak spatial dependence on the malaria risk. It can therefore be deduced that different factors (rivers/streams, forest, elevation, temperature and rainfall) affect the disease risk differently.

This study suggests that population-based spatial and temporal analyses of initial surveillance data would be very helpful in managing malaria epidemiology, by highlighting when and where limited public health preventive medical resources should be concentrated.

The graph in Fig 4.7.1 shows that the increase in rainfall resulted in an increase in the malaria prevalence. The study area according to the meteorological office, generally record one of the highest amount of rainfall in the Ashanti Region of Ghana. Rainfall therefore increases parasitic density soon after the start of the rainy season because the rains provided good breeding sites for the mosquito vectors. As the vector population increased, transmission of infection was enhanced thus the increase in the vector density. Moreover, rainfall may have increased the humidity which could have improved mosquito survival rates.

The relationship between temperature and malaria prevalence in Fig 4.7.2 showed no trend. There may have been more overriding factors other than temperature such as agricultural practice, human migration, population density, poverty and access to health services resulting in this high prevalence at low temperatures. Temperature could not be justified in this study to be accounting for the lower prevalence that escalates malaria at higher altitudes because of the fairly stable temperature all round the district.

The use of Insecticide treated Nets and the Malaria drugs supplied in the ongoing malaria campaign may have waned in the area. This is also indicative of the fact that Malaria transmission drivers go beyond topographical variables, and may have socio-demographic influences in the vector habitat variation.

The lower risk areas were seen to be the small settlements with better sanitary conditions probably due to their lower population. These areas may not even report to the hospital at all. It was also realized that most of the low risk areas made progress in the malaria campaign involving the distribution of Insecticide Treated Nets, drug supply and sensitization programmes by the MVP in the district. In the highland areas most farmers farm leafy crops such as cocoyam,

plantain and pawpaw. On these crops water often collect for some time over their leaves. Such a condition could also enhance the growth of the vector.

Flooding in the area coupled with erosion and the creation of gullies where water stagnate may also have contributed significantly to the increase of the disease.

The semi-variogram analysis confirmed that the malaria incidence is local and not global. The range of the semi-variograms shown on Fig 4.6.1 to Fig 4.6.3 shows the weak spatial relationship and dependencies on the malaria cases. It therefore shows that malaria is not as infectious as cholera and other communicable diseases. This results also highlights the fact that malaria occurrence within each town was not imported and that the local differences in topographic variables, rainfall, temperature, forest cover and mining pits may be the reason accounting for the small spatial dependencies in the malaria transmission.

There also exist local peculiarities like environmental covariates, topography, dug out pits, the distribution of the mosquito Insecticide Treated nets and drug supply that varies from community to community. These demonstrate the different peculiarities in the disease risk factors in each of the communities.

CHAPTER FIVE

CONCLUSION AND RECOMMENDATION

5.0 CONCLUSION

Malaria maps have always being a precursor to monitoring, evaluation and interventions in epidemiological control. Identifying geographic risk factors, the spatial distribution and populations at risk are all critical steps towards the disease eradication. The risk map created with Poisson statistical methods showed areas at risk especially in the central portions of the district capital. It also showed an average of 20% rise yearly from 2004 to 2009. The results in the semi-variogram analysis with an average range of 2000m showed how the disease incidence was local and not global. The local nature of the disease occurrence gives credence to the fact that the covariates used which were rivers/streams, forest, temperature, rainfall and elevation had different and independent influence on the malaria prevalence. Areas nearer the rivers/streams more than 2km away from the water source (rivers/streams) recorded relatively higher cases except for some few areas within 1km just nearer the Offin and Oda rivers. Moreover there was a varied effect of elevation with the disease prevalence although there was an alternating relationship using the Bayesian regression model. This varied statistical relationship may have resulted from the small spatial scale of the district with elevation differences less than 50m. There was a general trend of high disease incidence between 1-3 km from the forest edge and different factors beyond 4km.

The annualized rainfall pattern showed a relationship with the disease prevalence. With the high levels of rains increasing the disease occurrence as it served as effective breeding grounds for the mosquitoes to thrive.

There was no trend as far as annualized temperature was concerned. This may be a limiting factor as a result of the general temperate conditions in the area which has no effect on the shortening of the lifecycle of the malaria vector.

5.1: RECOMMENDATIONS

The study results suggest that there are 'malaria hot-spots' in the study area. The government, Millenium Village Project and other Health related Non Governmental Organizations should consider these results when planning malaria control measures. In particular, malaria Risk maps should be updated on a regular basis as new data emanates and a concerted effort targeted towards areas nearer the forest zones.

Efficient data gathering systems should be employed to obtain data in most of the areas to improve prediction of the risk in the area. If the malaria data is graded by month, there can be a seasonal evaluation of the disease burden.

There should be a further study using remote sensing technologies for a change detection to further explore the effect of landuse/Landcover on the disease.

Since there was a trend with elevations but not too significant, it would be important to do further studies on a larger spatial scale in the region or national level. This would even bring to light the rate at which the different malaria species can thrive with changing altitudes.

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