RELATIONSHIP BETWEEN SELECTED CLIMATIC VARIABLES AND CEREBROSPINAL MENINGITIS (CSM)

Richard Bayel Trumah

(BA. Geography and Rural Development)

A Thesis Submitted to the School of Graduate Studies,

Kwame Nkrumah University of Science and

Technology, Kumasi, in partial fulfillment

of the requirements for the degree of

Master of Science in Environmental

Resources Management.

June, 2013.

DECLARATION

I hereby declare that this work is the result of my own field research and it has not been submitted either in part or whole for any other degree elsewhere. Specific references and sources of information used have been duly acknowledged. Where there appear to be statement(s) which have similarity to any other statement(s) elsewhere but has or have not been acknowledged is/are my own statement(s) and not an attempt to plagiarize.

Trumah Bayel Richard	..………………....…………	..….……………....………
(Student)	Signature	Date

Certified by:

Mr. John Ayer	..………………....…………	..….……………....………
(Supervisor)	Signature	Date

Certified by:

Professor Samuel Kwofie	..………………....…………	..….……………....………
(Head of Department)	Signature	Date

DEDICATION

To my parents, Mr. Joseph Trumah Bayel and Mrs. Baduro Trumah and my siblings. I dedicate this work to them for their love and support during the duration of the programme.

ACKNOWLEDGEMENT

My deepest appreciation goes to the Almighty God for His divine protection and guidance throughout this post graduate study.

I am particularly grateful to my academic supervisors Mr. John Ayer and Dr. Dadson Awunyo-Vitor for their patience, guidance, support, corrections and comments made for a successful completion of this thesis.

My sincere gratitude to all my lecturers on the Environmental Resources Management program and staff of the Department of Materials Engineering, Kwame Nkrumah University of Science and Technology. Special thanks go to Maxwell Asem of the Department of Geomatic Engineering KNUST.

I extend gratitude also to Ghana Meteorological Agency and AngloGold Ashanti especially Mr. Peter Owusu-Yeboah and Mr. Ebenezer Asare Opong of the Environment and Projects department respectively all of AngloGold Ashanti.

I am equally indebted to staff of Obuasi Municipal and Ashanti Regional Health Directorates.

Finally, to all colleagues for their assistance and the various authors from whose work I extracted very valuable information to complete my study.

God bless you all.

ABSTRACT

This study evaluates the effects of environmental factors on the outbreak of Cerebrospinal Meningitis (CSM) in the Obuasi Municipality and identified other places of similar climatic conditions in order to ascertain population susceptibility to the CSM epidemic. Specifically, it evaluates: (i) the prevalence rate of Cerebrospinal Meningitis (CSM) in Obuasi (ii) the relationship between climatic parameters and the outbreak of CSM in Obuasi (iii) the identification of places of similar climate conditions as Obuasi through cluster analysis of climate variables (iv) the investigation of outbreaks in these similar cluster towns to ascertain the importance of climate variables in disease epidemiology. Data on monthly maximum temperature, rainfall and reported cases of CSM in the study region as well as all cluster towns were collected and analyzed. The results reveal that there were 21 patients affected with CSM in the study area in 2010. Correlation analysis indicates that the reported cases of CSM are positively and significantly related to temperature but not with rainfall. Regression analysis suggests that 64% of the variations in the outbreak of CSM can be attributed to temperature. This result seem to suggest that climate is a major influencing factor in disease outbreak and hence the likelihood of similar situations in areas of similar climate conditions. Clustering methods were therefore used to identify such places. Analysis of health data in these cluster towns however did not reveal reported cases so whereas climate may be an influencing factor to the disease, it appears to only aid the propagation of the outbreak but not causative. The implications of the study are that etiology of diseases may not be solely based on medical parameters but also environmental factors at least in their propagation

TABLE OF CONTENTS

DECLARATION ..... **ii**

DEDICATION ..... **iii**

ACKNOWLEDGEMENT ..... **iv**

ABSTRACT ..... **v**

TABLE OF CONTENTS ..... **vi**

LIST OF TABLES ..... **ix**

LIST OF FIGURES ..... **x**

LIST OF ACRONYMS ..... **xi**

CHAPTER ONE **1**

1.0 Background and Introduction 1

1.1 Conceptualization of Key Issues 3

1.2 Statement of the problem 4

1.3 Justification 5

1.4 Project Hypothesis 5

1.5 Objectives of the study 6

1.5.1 Specific objectives: 6

1.6 Research questions 6

1.7 Methodology 7

1.8 Organization of the study 7

CHAPTER TWO **8**

2.0 CONCEPTUAL FRAMEWORK AND LITERATURE REVIEW **8**

2.1 Conceptual Framework 8

2.2 History of MCM (MCM) 8
2.3. Correlation Analyses 15
2.4 Basic Concepts and Algorithms of Cluster Analysis 16
2.4.1 Clustering techniques. 16
2.4.2 Types of data and measures of distance in cluster analysis. 17
2.4.2.1 Euclidean distance 17
2.4.3 Hierarchical agglomerative methods 18
2.4.4 Selecting the optimum number of clusters 19
2.4.5 Non-hierarchical or k-means clustering methods 19

CHAPTER THREE 21
3.0. MATERIALS AND METHODS 21
3.1 Study area 21
3.2 Climate of Ghana 24
3.3 Materials. 26
3.3.1 Types and Sources of Data Required 26
3.3.2 Software 27
3.4. Methods of Data Analysis 27

CHAPTER FOUR 30
4.0 RESULTS AND DISCUSSION 30
4.1 Results of Correlation Analysis 30
4.2 Results for the clustering. 31
4.3 Validation 37

CHAPTER FIVE 38

5.0 CONCLUSION AND RECOMMENDATIONS. 38

5.1 Conclusion 38

5.2 Recommendations for Further Studies 39

REFERENCES 40

LIST OF TABLES

Table 3.1 Location of Weather Stations. 27

Table 4.1 Correlation analysis 30

Table 4.2. Summarized Clustering results showing Towns in same cluster as Obuasi. 32

Table 4.3. Table of cluster classes based on Dendogram in 4.1. 34

Table 4.4 Results after using temperature to cluster stations. Source: Fieldwork2012 36

LIST OF FIGURES

Fig.2.1 Map of Africa showing the meningitis belt. 10

Fig. 3.1. Map of Obuasi Municipality.. 23

Fig 3.2 Showing annual rainfall and temperature maps of Ghana. 25

Fig 3.2 Clustering Flow Diagram 29

Fig.4.1 Dendogram for monthly rainfall from 1980-2011 by Ward's Method. 33

Fig. 4.2 Annual Temperature Map of Ghana after clustering. 35

LIST OF ACRONYMS

TERM	DEFINITION
AIDS	Acquired Immunodeficiency Syndrome
AMB	African Meningitis Belt
CSM	Cerebrospinal Meningitis
GIS	Geographic Information System
HIV	Human Immunodeficiency Virus
ICG	International Coordinating Group
ITCZ	Inter-Tropical Convergence Zone
KMA	Kumasi Metropolitan Assembly
MCM	Meningococcal Meningitis
OND	October November December
UNDP	United Nations Development Programme
WHO	World Health Organisation

CHAPTER ONE

1.0 Background and Introduction

Health is a major issue in the world. Both the developed and less developed countries spend great deals of their budgets on health, to combat, eradicate, prevent and sometimes contain the outbreaks of various types and kinds of diseases ranging from airborne, waterborne through to malaria, cancer, and HIV AIDS. Lifestyles generally change with economic wellbeing and so it is with diseases and illnesses. In the developed world, cancer, obesity and Human Immunodeficiency Virus/Acquired Immunodeficiency Syndrome (HIV/AIDS) are among the major illnesses and diseases that are prevalent. Developing Countries have numerous diseases and illnesses among which are malaria tuberculosis, hepatitis, cerebrospinal meningitis and HIV AIDS.

Meningitis is an inflammation of the protective membranes covering the brain and spinal cord known collectively as the meninges. The inflammation may be caused by infection with viruses, bacteria, or other microorganisms, and less commonly by certain drugs (van de Beek et al., 2006).

The most common symptoms of meningitis are headache and neck stiffness associated with fever, confusion or altered consciousness, vomiting, and an inability to tolerate light (photophobia) or loud noises (phonophobia) (Sáez-Llorens, McCracken, 2003).

The fatality rate of cerebrospinal meningitis in the world is not available but in Ghana it is said to have almost wiped a whole village, Tizza, in the Upper West region off from existence in the colonial days (Grischow, 2006). The Ghana health service reports that 31 people were infected with CSM in Ghana in 2010 out of which 6 died (Ghana health service, 2011).

Ghana lies on the fringes of the sub-Saharan Africa's "Meningitis Belt", and as such seasonal epidemics that are associated with CSM expectedly occur in a cyclic pattern. Dry weather, dusty winds, cold nights, and large populations living in overcrowded conditions which leave people vulnerable to respiratory infections, and are known to be among some of the reasons behind the Meningitis Belt's high burden of meningococcal disease

In other West African countries, people have also noted that the outbreak of the epidemic nearly always coincides with the setting in of the harmattan, a north to east wind blowing from the Sahara towards the gulf of Guinea (Grischow, 2006)..

Disease-mapping studies have flourished and grown in importance along with the development of computer technology and GIS, though the practice of mapping already played an important role in medical geography and epidemiology in the late eighteenth century. Disease mapping methods were first used for communicable diseases in an attempt to identify the sources of infection and to describe the rate of spreading of disease (Howe 1989). Mapping of chronic diseases started with the recognition that environmental factors play an essential role in their aetiology. Geographical epidemiological studies, in which health and environmental exposure data are analysed in fine geographical detail, represent an important new approach (Elliot, Cuzick, English & Stern, 1992).

GIS applications related to health have been introduced and used for example, in the surveillance and monitoring of vector-borne and water-borne disease and in environmental health (Kistemann, et al., 2002). In Finland for example, GIS has been used in health service research and in mapping studies of non-communicable diseases. (Vauromo, Rusanen & Naha, 2001).

Cluster analysis includes a number of different algorithms, methods and catalogues for grouping objects of similar kinds into respective categories. Broadly defined, cluster analysis is a method of classification that places objects in groups based on the characteristics they possess. Bailey and Gatrell (1995) note that all clustering techniques begin in the same fashion with each beginning with the calculation of a (n×n) matrix, D, of dissimilarities between every pair of observations. Based on (D), cluster analysis breaks observations into groups, linking the most similar observations together in a cluster. Clustering techniques are used in this study to identify suitable climate condition clusters which may influence CSM occurrences.

1.1 Conceptualization of Key Issues

Definitions

Meningitis: According to Gale Encyclopedia of Medicine (2000), meningitis is a serious inflammation of the meninges, the thin, membranous covering of the brain and the spinal cord. Meningitis is most commonly caused by infection (by bacteria, viruses, or fungi), although it can also be caused by bleeding into the meninges, cancer, diseases of the immune system, and an inflammatory response to certain types of chemotherapy or other chemical agents. The most serious and difficult-to-treat types of meningitis tend to be those caused by bacteria. In some cases, meningitis can be potentially fatal. Meningitis infection affects the spinal cord and brain because of a virus or a bacterium. Bacterial infection is usually more life-threatening and is indicated by the sudden onset of a stiff neck, headache, fever, and vomiting; may cause stupor, confusion, and convulsions if untreated.

Cerebrospinal meningitis: This is an inflammation of the membranes of the brain and spinal cord (Dictionary of Modern Medicine, 2002). Cerebral Spinal Meningitis

(CSM) is most often caused by the bacteria *Neisseria meningitides*. Bacterial meningitis is an infection of the meninges, the thin covering of the brain and spinal cord. Symptoms of the disease include stiff neck, high fever, rash, headache, vomiting, and confusion. Even with rapid diagnosis, 5-10% of patients typically die within 24-48 hours of symptom onset. Although sometimes fatal, CSM is most often treatable with antibiotics administered upon hospital admission (Healthmap, 2011).

The rapid spread of the disease is due to the ease in which the bacteria are transmitted. Droplets of respiratory or throat secretions transmit the bacteria through methods such as kissing, sneezing, coughing, and sharing of eating or drinking utensils (Healthmap, 2011).

1.2 Statement of the problem

Offsetting the rapid incidence and fatality of CSM globally with its greatest impact in sub-Saharan Africa especially in the meningitis belt has been a growing concern of stakeholders in the health sector. There is evidence pointing to the fact that CSM is an environmentally induced problem that depended a lot on climate variables even though the exact nature of this relationship is not clearly understood. Ghana normally experiences its fair share of the devastating effects of CSM between the months of January and May mostly in and around districts in the Upper East and West as well as the Northern Regions. Coincidentally these months mark the peak of the harmattan and the draught seasons experienced in these regions (Grischow, 2006). Grischow (2006) as well reported of the incidence of CSM in southern Ghana with changing climatic patterns. The incidence that was reported in Obuasi had a fatality of six (6) out of the twenty-one (21) cases that were recorded. It is worthwhile investigating the possibility of CSM occurrence in places of such reported cases and other places with similar climatic conditions.

1.3 Justification

Cerebrospinal meningitis is a fast killing disease as a result of severe climatic factors. Areas where it is prevalent are normally characterized by drought, high temperatures and overcrowding. The disease has recently been reported in Obuasi in the middle belt in August 2010. The reported occurrence was during the rainy season and at a time when temperatures were actually low and humidity high. This case seems not to follow the norm and raises the question of whether the correlation between climate and CSM is understood. This project would provide a validated climatic pattern and serve as reference point to:

1. Health administrators on CSM emergency preparedness which could lead to the prevention of fatalities as measures would be put in place to address an occurrence.
2. Environmentalists on the environmental factors that cause CSM outbreak.
3. Health consultants for sensitization and creations of awareness of the causes of CSM.
4. Stakeholders for planning and implementation of outbreak preparedness methods and strategy.

1.4 Project Hypothesis

1. Selected climatic variables influenced the occurrence of CSM.

2. Areas with similar climatic conditions as those of Obuasi will also record incidence of CSM

1.5 Objectives of the study

The main objective of the study is to assess the role that climatic variables, (temperature, rainfall and humidity) play in CSM infection in the Southern sector of Ghana.

1.5.1 Specific objectives:

1. Establish the relationship between the selected climatic variables and Cerebrospinal Meningitis.

2. To map out areas with same selected climatic conditions as that of the Obuasi municipality.

3. To find out whether mapped out areas with same climatic conditions have actually experienced an outbreak.

1.6 Research questions

The research seeks answers to the following questions:

1. To what extent is the correlation between the prevailing climatic conditions in Southern Ghana and the susceptibility and/or infection period?

2. Which areas in Southern Ghana have similar variable characteristics as Obuasi?

3. To what extent do areas with similar characteristics as Obuasi also experienced an outbreak in CSM?

1.7 Methodology

Data is collected on the climatic variables for the country and a correlation analysis carried out to analyze the significance of the correlation between the climatic variables and the CSM cases. Cluster analysis is then used in analyzing the climatic data to classify places of similar climatic conditions together. ArcGis software (version (9.3) is used in the drawing map of areas with similar characteristics based on the cluster analysis.

1.8 Organization of the study

The study is organized into five chapters. Chapter One, which is the introduction chapter, presents the background information of the research topic, defining the statement of the research's concern, stating the research questions that the project seeks to answer and highlighting the significance of the study. Chapter Two is dedicated to the review of literature in the field. Chapter Three discusses the methodology used in gathering data for the study. It also provides justification for the approaches used in gathering data. Furthermore, chapter Four is an analysis and discussion of the findings of the study. Finally, Chapter Five includes summary, conclusions and recommendations for further study and for policy development by stakeholders.

CHAPTER TWO

2.0 CONCEPTUAL FRAMEWORK AND LITERATURE REVIEW

2.1 Conceptual Framework

Epidemic conditions can be defined as an unacceptable incidence rate requiring emergency control measures. Whilst the epidemics of meningococcal disease affect mainly areas within the meningitis belt which in Ghana do not generally include the Middle and Southern sectors of the country, changing climatic conditions and other environmental influences have made it possible for the disease to affect any part of the country. If this is a truly new feature of the epidemiology of meningococcal disease, then it could be experienced due to climate change with subsequent extension of drought areas, and also due to increased mobility of the population by voluntary travels. The outbreaks due to such importations of the disease may also reflect the introduction of a new meningococcal strain into susceptible populations. As climatic factors play an important role in the seasonal upsurge of meningococcal disease, it is important to establish these relationships as well as investigate if this could lead to an identification of population/areas at risk.

2.2 History of MCM (MCM)

Meningococcal disease was first described in Geneva, Switzerland in 1805. However it was not until 1887 before the causative agent, *Neisseria meningitidis*, was identified. The first outbreak in the history of the deadly bacterial meningitis came in 1913 when Simon Flexner began treating bacterial meningitis with intra theca equine meningococcal antiserum (Whitson, 2005).

MCM is a disease that has had some form of impact on nearly every part of the world. In the past thirty years Asia has suffered a series of major epidemics: China in 1979 and 1980, Viet Nam in 1977, Mongolia in 1973 and 1974 and again in 1994 and 1995, Saudi Arabia in 1987, and Yemen in 1988. Europe and the Americas have also experienced epidemics, though not with the magnitude as those other parts of the world have experienced within the same period (Whitson, 2005).

Currently, the commonest and most reoccurring outbreaks have been in the semi-arid areas of sub-Saharan Africa in an area known as the African meningitis belt (AMB). (Fig, 2.1). The AMB stretches across Africa from Senegal to Ethiopia, encompassing an estimated 300 million people with the disease occurring in seasonal cycles between late November and late June.

The meningococcal epidemic season can vary in intensity due to location and the arrival of the rainy season. Within the AMB, epidemics of meningococcal disease often occur in cycles of eight to fifteen years (Whitson, 2005).

The most recent pandemic of MCM occurred in the mid- 1990s. Burkina Faso, Chad, Niger, Mali, Nigeria and other countries reported 190,000 cases of MCM to the World Health Organization in 1996. This epidemic quite literally overwhelmed and paralyzed the local health care systems of the affected countries and quickly exhausted the international stocks of vaccine. "In 1997, the International Coordinating Group (ICG) of the African meningococcal belt, Courtesy of World Health Organization for Vaccine Provision for Epidemic Meningitis Control, was established." Six countries in the AMB experienced large epidemics in 2001 namely Benin, Burkina Faso, Central African Republic, Chad, Ethiopia, and Niger (Whitson, 2005).

Fig.2.1 Map of Africa showing the meningitis belt.

Yaka & Sultan et al (2008) used statistical analysis of annual incidence of MCM and climatic variables to highlight the relationships between climate and MCM for two highly afflicted countries: Niger and Burkina Faso. They found that disease resurgence in Niger and in Burkina Faso is likely to be partly controlled by the winter climate through enhanced Harmattan winds. The authors generated a Gaussian time series that was used to detect relationships between climate and MCM incidence. The relationships between climate and MCM disease at inter-annual and country scales identified in their study suggested that the links were particularly clear in Niger and weak but significant in Burkina Faso. The disease resurgences in Niger and in

Burkina Faso are linked with enhanced Harmattan winds over Niger in November/December and over Burkina Faso in October.

These findings are coherent with previous studies which showed a positive correlation between the October dust and meningitis incidence in Burkina Faso, Mali and Niger (Thomson et al 2006). The researchers defined relevant climatic variables for the construction of linear models to forecast MCM epidemics intensity from year to year. The statistical models worked well for Niger showing that 25% of the disease variance from year-to-year can be explained by the winter climate but fail to represent accurately the disease dynamics in Burkina Faso. Although this study points out significant statistical results, it also stresses the difficulty of relating climate to inter-annual variability in meningitis outbreaks. Numerous reasons can be pointed out to explain this limitation but two were the most of importance to the researchers:

First, the final size of the outbreak clearly does not depend only on climate but implies many other factors. The size of the epidemics will be also (and perhaps mainly) be driven by the immunity of the affected population against the serotype involved in the outbreak and socio-economic factors (pilgrimages, migrations) (Hodgson, Smith et al 2001, Leimkugel, Hodgson et al 2007). The proportion of carriers might also play an important role in the disease dynamics. Vaccination, even if there is a debate on the efficiency on the meningitis control, activities (Robbins, 2003, Robbins, Towne et al 1997, Chippaux, Dubois et al 2002) has certainly an impact on the final size of the outbreak as it is suggested by Broutin et al. 2007, in their comparative studies of meningitis dynamics across several African countries. The second important limitation corresponds to the meningitis data themselves. Missing values as well as suspected underreporting may introduce biases in the incidence time series. As a consequence, it is very likely that the meningitis incidence data contain trends, strong or low incidence events or periods that cannot be related to any climate effect. The weak correlation between climate and disease in Burkina Faso does not necessary confound the hypothesis of the dry northerly winds being implicated in the outbreaks of meningitis but could point out that climate is not the only major driver of the disease dynamics. Alternatively, since the variability of the meningitis incidence from one year to another results from numerous processes acting at different spatial hierarchical scales in various medical, demographical and socio-economic conditions, the results obtained with the Niger model, suggest that climate is an important driver for the triggering of epidemics in Niger and validate the large-scale approach that allows to smooth local data heterogeneities. Therefore, statistical study can only demonstrate a statistically significant association and not causation. It is always possible that changes in climate are linked to other factors, such as a change in social behavior which could be the key determinant of the effect. This point is of importance as there is no robust physiological mechanism for the role of climate in disease occurrence.

In Yaka et al. (2008) study, which is corroborated by that of Thomson et al. (2006), the two groups of researchers agree that the correlations between climate and disease are depicted very early in the meningitis epidemic season and do not persist during the epidemic season. It is however not clear how atmospheric conditions in October-November-December (OND) affect an outbreak occurring 3–4 months later since the incubation period of MCM is a day to a few weeks. Different climate influences with longer and shorter relationships to disease incidence may be at work to explain these correlations. Thomson et al. (2006) indicate that on one hand, climate could have a cumulative effect on the vulnerability of the population to the infection. Long-term exposure to air dryness and strong dust winds might weaken resistance of human oropharyngeal membranes through successive respiratory infections making propitious conditions to the passage and inner release of the bacteria responsible for the disease when the organism is carried. Notwithstanding the influence different climate has on disease incidence, October-November-December (OND) hamattan conditions could act with a shorter time-lag by enhancing meningococcal invasiveness during the pre-epidemic season through the same mechanism explained above, i.e. direct damage of the mucosal barrier and/or an inhibition of the mucosal immune defenses (Yaka et al. 2008). The early cases induced by climate effect could then have an influence on the final size of the outbreak through contacts within and among households and communities since these contacts increase the risk of acquiring infection (Tikhormirov et al. 1997) and increase the carrier rate of the pathogenic serogroup. The importance of early cases in the final size of the outbreak has been stressed by WHO (2000), that consider early cases in the season as a warning sign of large epidemic.

Molesworth et al.(2003), stated that epidemics occurrence throughout Africa in the dry seasons, coincide with periods of very low humidity and dusty conditions, and disappear with the onset of the rains, suggesting that these environmental factors may also play an important role in the occurrence of the disease. A logistic regression model was used to identify associations between a district ever having experienced an epidemic and a district that has never experienced an epidemic. The researchers among others concluded that the most important factor associated with the distribution of epidemics was humidity as areas without a marked distinction between wet and dry seasons were less likely to have had epidemics than those with contrasting seasons. Areas without distinction between wet and dry seasons include deserts and the humid parts mostly coastal and forested regions whereas areas with contrasting seasons comprise the semiarid savannah and the grasslands of the Sahel regions. The surface maps of Africa demonstrated a close correspondence between humidity and land-cover types in these regions. The Sahel, which has a prolonged dry season with low humidity, was identified as the area with the greatest risk. Peripheral regions along its southern borders, where the dry season is shorter and less extreme, carry a moderate risk. The peripheral region extends from southern Sudan and Ethiopia to the Great Lakes and Rift Valley regions and parts of southern Africa peripheral to desert areas.

Many researchers have looked at the influence climatic variables have on disease incidence from other angles. One such work was effects of *Climate Change on Health Risks in Nigeria* by Eke Patrick Omoruyi and Onafalujo Akinwumi Kunle. Their work stated among other observations that, the implications of climate change on human health could be direct and indirect. The direct consequences in Nigeria include cerebra-spinal meningitis, cardiovascular respiratory disorder of the elderly, skin cancer, high blood pressure, malaria, cholera and dangers to child and maternal health. The danger of unmanaged climatic variability is the increase in morbidity rate caused by exacerbation of old and new viscera health risks like skin cancer, high blood pressure, heat stroke, influenza, psychosis and possibly neurosis. Dukic et al (2012). looked at the subject from the domain of weather and pointed out that high temperature coupled with low humidity may favor the conversion of carriage to disease as the meningococcal bacteria in the nose and throat are better able to cross the mucosal membranes into the blood stream. Similarly, respiratory diseases such as influenza, and pneumonia might weaken the immune defense and add to the mucosal damage. Although the transmission dynamics are poorly understood, outbreaks regularly end with the onset of the rainy season and may begin anew with the following dry season.

MCM epidemics remain a major problem in sub-Saharan Africa, stretching from Senegal to Ethiopia (Greenwood, 1999 & Lapeyssonnie, 1963). This region, first defined by Lapeyssonie in 1963, is characterized by seasonal epidemics during the dry season which usually stop with the onset of rains, and also by large epidemics which occurred every 8–12 years, culminating in a massive epidemic in which nearly 200,000 cases were reported in 1996 (Greenwood, 1999 & Broutin et al 2007). Among the well-known different serotypes of *Neisseria meningitis* isolated in Africa such as serogroups A, C, Y and W135, group A remains the major serogroup responsible for African epidemics (Greenwood, 2006) despite a recent emergence of serogroup W135.

These epidemics have a profound impact on health systems, economic activity, and political and social life. Health services are confronted with major challenges in terms of means of control, vaccine, medicines, injection materials and other logistics (WHO, 2002).

2.3. Correlation Analyses

Correlation coefficients (denoted *r*) are statistics that quantify the relation between X and Y in unit-free terms. When all points of a scatter plot fall directly on a line with an upward incline, $r = +1$; When all points fall directly on a downward incline, $r = -1$. Such perfect correlation is however seldom encountered but there is still the need to measure *correlational strength,* –defined as the *degree* to which data points adhere to an imaginary trend line passing through the “scatter cloud” as an indication of the existence or otherwise of relationship between variables. Strong correlations are associated with scatter clouds that adhere closely to the imaginary trend line. Weak correlations are associated with scatter clouds that adhere marginally to the trend line. The closer r is to +1, the stronger the positive correlation. The closer r is to -1, the stronger the negative correlation.

2.4 Basic Concepts and Algorithms of Cluster Analysis

Cluster analysis is a convenient method for identifying homogenous groups of objects called clusters. Objects (or cases, observations) in a specific cluster share many characteristics, but are very dissimilar to objects not belonging to that cluster. The objective of cluster analysis is to identify groups of objects (in this case, climatic variables) that are very similar with regard to their pattern of occurrence and assign them into clusters. After having decided on the clustering variables (rainfall, temperature and relative humidity), a decision needs to decide on the clustering procedure to form groups of objects. This step is crucial for the analysis, as different procedures require different decisions prior to analysis (Mooi & Sarstedt, 2011).

2.4.1 Clustering techniques.

There are a number of different methods that can be used to carry out a cluster analysis and these are classified as:

Hierarchical methods – Agglomerative methods, in which subjects start in their own separate cluster. The two ’closest’ (most similar) clusters are then combined and this is done repeatedly until all subjects are in one cluster. At the end, the optimum number of clusters is then chosen out of all cluster solutions.

Divisive methods, in which all subjects start in the same cluster and the above strategy is applied in reverse until every subject is in a separate cluster.

Agglomerative methods are used more often than divisive methods.

Non-hierarchical methods (often known as k-means clustering methods) (Everitt, et al 2001).

2.4.2 Types of data and measures of distance in cluster analysis.

The data used in cluster analysis can be interval, ordinal or categorical. However, having a mixture of different types of variable will make the analysis more complicated. This is because in cluster analysis one needs to have some way of measuring distance between observations and the type of measure used will depend on what type of data there is.

A number of different measures have been proposed to measure ’distance’ for binary and categorical data. For interval data the most common distance measure used is the Euclidean distance.

2.4.2.1 Euclidean distance

This is probably the most commonly chosen type of distance and is simply the geometric distance in the multidimensional space.

Euclidean distance is usually computed from raw data and not from standardized data and has the advantage that, the distance between any two objects is not affected by the addition of new objects to the analysis. However, the distances can be greatly affected by differences in scale among the dimensions from which distances are computed (Everitt et al 2001).

2.4.3 Hierarchical agglomerative methods

Within this approach to cluster analysis there are a number of different methods used to determine which clusters should be joined at each stage. The main methods are summarized below.

Nearest neighbor method (single linkage method) in which the distance between two clusters is defined to be the distance between the two closest members, or neighbors. This method is relatively simple but is often criticized because it does not take account of cluster structure and can result in a problem called chaining whereby clusters end up being long and straggly. However, it is better than the other methods when the natural clusters are not spherical or elliptical in shape.

Furthest neighbor method (complete linkage method) in which the distance between two clusters is defined to be the maximum distance between members — i.e. the distance between the two subjects that are furthest apart. This method tends to produce compact clusters of similar size but, as for the nearest neighbor method, does not take into account of the cluster structure. It is also quite sensitive to outliers.

•Average (between groups) linkage method (sometimes referred to as UPGMA). The distance between two clusters is calculated as the average distance between all pairs of subjects in the two clusters. This is considered to be a fairly robust method.

•Centroid method. Here the centroid (mean value for each variable) of each cluster is calculated and the distance between centroids is used. Clusters whose centroids are closest together are merged. This method is also fairly robust.

•Ward's method. In this method all possible pairs of clusters are combined and the sum of the squared distances within each cluster is calculated. This is then summed over all clusters. The combination that gives the lowest sum of squares is chosen. This method tends to produce clusters of approximately equal size, which is not always desirable. It is also quite sensitive to outliers. Despite this, it is one of the most popular methods, along with the average linkage method. It is generally a good idea to try two or three of the above methods and if they agree reasonably well then the results will be much more believable (Everitt, et al 2001).

2.4.4 Selecting the optimum number of clusters

As stated above, once the cluster analysis has been carried out it is then necessary to select the ’best’ cluster solution. There are a number of ways in which this can be done, some rather informal and subjective, and some more formal.

When carrying out a hierarchical cluster analysis, the process can be represented on a diagram known as a dendrogram. This diagram illustrates which clusters have been joined at each stage of the analysis and the distance between clusters at the time of joining. If there is a large jump in the distance between clusters from one stage to another then this suggests that at one stage clusters that are relatively close together were joined whereas, at the following stage, the clusters that were joined were relatively far apart. This implies that the optimum number of clusters may be the number present just before that large jump in distance (Everitt, et al 2001).

2.4.5 Non-hierarchical or k-means clustering methods

In these methods the desired number of clusters is specified in advance and the ’best’ solution is chosen. The steps in such a method are as follows:

1. Choose initial cluster centers (essentially this is a set of observations that are far apart— each subject forms a cluster of one and its center is the value of the variables for that subject).

2. Assign each subject to its' nearest cluster, defined in terms of the distance to the centroid.

3. Find the centroids of the clusters that have been formed

4. Re-calculate the distance from each subject to each centroid and move observations that are not in the cluster that they are closest to.

5. Continue until the centroids remain relatively stable.

Non-hierarchical cluster analysis tends to be used when large data sets are involved. It is sometimes preferred because it allows subjects to move from one cluster to another (this is not possible in hierarchical cluster analysis where a subject, once assigned, cannot move to a different cluster). Two disadvantages of non-hierarchical cluster analysis are:

- It is often difficult to know how many clusters are likely and therefore the analysis may have to be repeated several times.

- It can be very sensitive to the choice of initial cluster centers. (Hair et al 1995).

One possible strategy to adopt is to use a hierarchical approach initially to determine how many clusters there are in the data and then to use the cluster centers obtained from this as initial cluster centers in the non-hierarchical method (Everitt et al., 2001).

CHAPTER THREE

3.0. MATERIALS AND METHODS

3.1 Study area

The Obuasi Municipality is one of the 27 districts of the Ashanti Region and was created as part of the government's effort to further decentralized governance. It was carved out of the erstwhile Adansi West District on the strength of executive instruments (E. I.) 15 of December, 2003 and Legislative Instrument (L. I) 1795 of 17th March, 2007. The Municipality is located at the southern part of Ashanti Region between latitude 5.35N and 5.65N and longitude 6.35N and 6.90N. (Fig. 3.1) It covers a land area of 162.4sqkm. There are 53 communities in the Municipality which share 30 electoral areas.

It is bordered to the east by Adansi South, to the west by Amansie Central and to the north by Adansi North, to the south by Upper Denkyira District in the Central Region. It has Obuasi as its Administrative Capital where the famous and rich Obuasi Gold Mines, now Anglo Gold Ashanti is. The Municipality has a rather undulating topography and the climate is of the semi-equatorial type with a double maxima rainfall regime. Mean annual rainfall ranges between 125mm and 175mm. Mean average annual temperature is $25.5^{O}C$ and relative humidity is 75% - 80% in the wet season.

The population of the Municipality is estimated at 205,000 using the 2000 Housing and Population Census as a base and applying a 4% annual growth rate. The vegetation is predominantly a degraded and semi-deciduous forest. The forest consists of limited species of hard wood which are harvested as lumber. The

Municipality has nice scenery due to the hilly nature of the environment (Ghanadistricts.com, 2012)

.

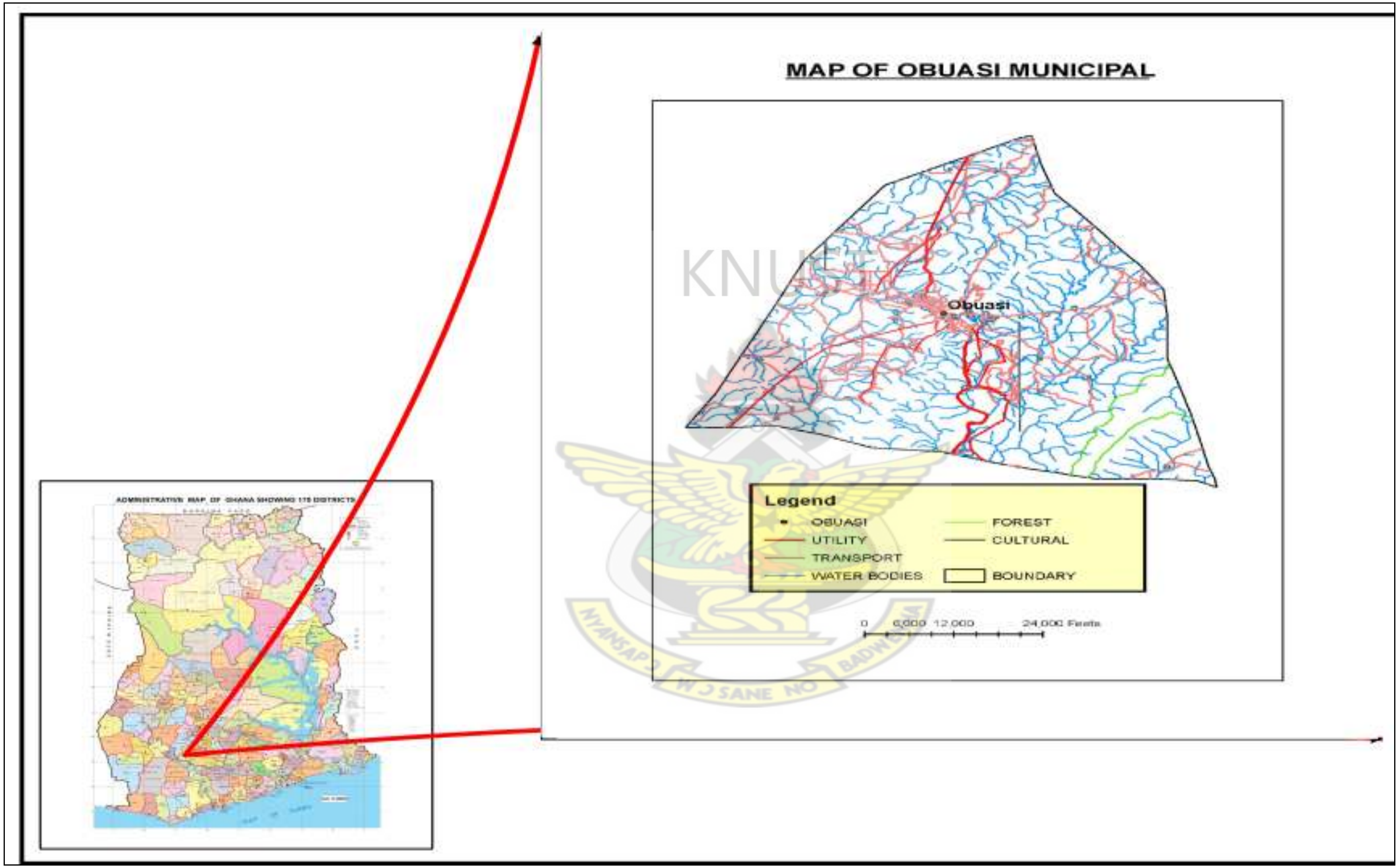

Fig. 3.1. Map of Obuasi Municipality

3.2 Climate of Ghana

Ghana's close location to the equator is one of the most significant factors that determine its weather. Variation in climate across the entire country is solely dependent on the temperature, rainfall and humidity. Temperatures are high all year round, except on the hills and the mountainous areas though there is a drop in the wet seasons but with relatively high humidity. The annual mean temperature is about 28°C though, especially in the northern parts of the country, temperatures can reach highs of 35°C during the harmattan. (Lizcano and New, 2008)

Ghana has Wet and a Dry Seasons caused mainly by two air masses, the continental air mass and the maritime tropical air mass, each which move towards the equator but meet at different places due to their varying intensities with earth motion. The zone in which the two air masses meet is known as the Inter-Tropical Convergence Zone (ITCZ). This zone oscillates each year, following the apparent seasonal movement of the sun between the northern and southern hemisphere, reaching the farthest north position in the mid-June, and furthest south in December.

Much of the seasonal rainfall is generated in the belt that lies just south of the ITCZ (Kowal & Kassam, 1978). During the periods that the sun is in the northern hemisphere (March to September), the monsoon winds push northwards across the country from the southwest. These warm air masses carried by the winds bring torrential rains. This normally occurs between April and September, with July-August as the peaks in most areas to constitute a Rainy Season.

Again during the periods that the sun is in the southern hemisphere (October to March), the dry northeast trade winds from the northern hemisphere travel across to the south, bringing dry dusty warm air from the Sahara desert. This normally occurs between late November and Late March, with December-February being the peaks to constitute the Harmattan Season.

Thus the Inter-tropical front, oscillates to produce alternate dry and wet seasons but the northern parts of Ghana has somewhat different climates than the southern parts in terms of the rainfall patterns and peaks to constitute two zone types (Levy, 1999). In the northern regions, there are two main seasons - the drier Harmattan season, which lasts from about November to April, and the wet season, which lasts from April to October. In the southern portions of the Kwahu plateau, there are four seasons. Heavy rains fall from April to late June, followed by a short period of drier weather in August. Then another spate of rainy season begins in September and lasts until November before the Harmattan season brings the driest weather until March or early April (Lizcano and New, 2008).

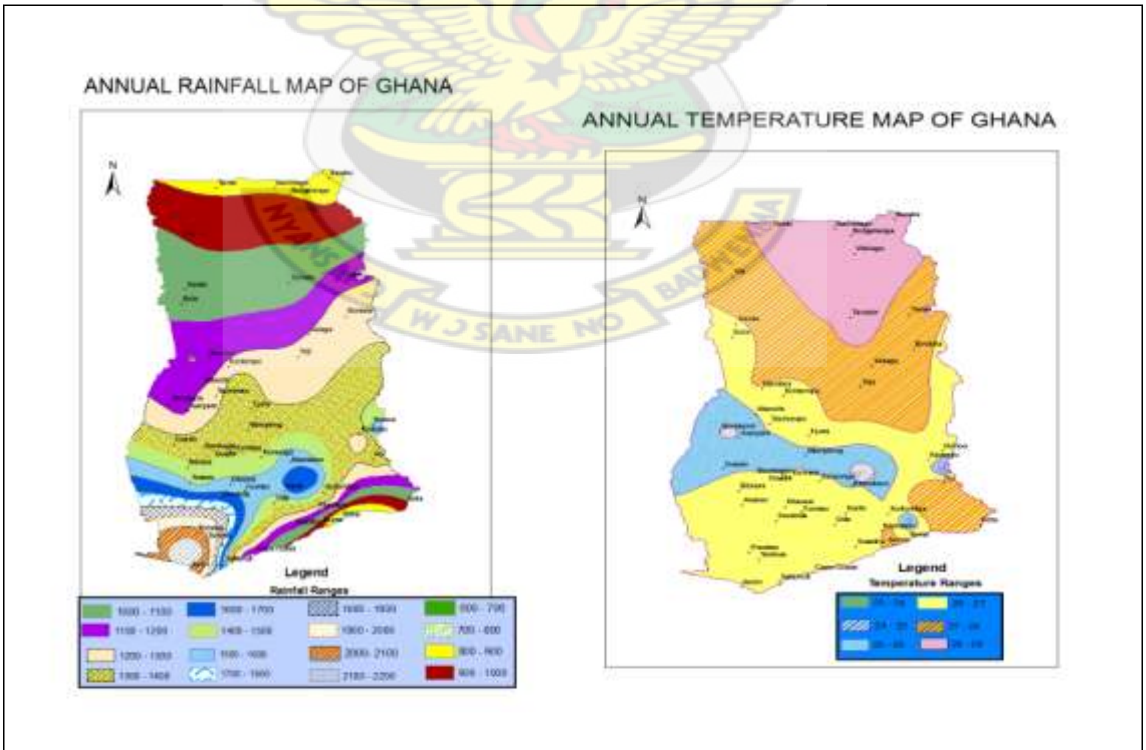

Fig 3.2 Showing annual rainfall and temperature maps of Ghana. Source: Fieldwork, 2013

3.3 Materials.

3.3.1 Types and Sources of Data Required

The main types of data used for this research include Patients' hospital data required for determining the prevalence rate of Cerebrospinal Meningitis in Obuasi. Climate data of temperature, rainfall and humidity data is required for identifying the relationship between climatic parameters and the outbreak of Cerebrospinal Meningitis. The climatic data was obtained from the Ghana Meteorological Agency in Accra (2012) and AngloGold Ashanti, Obuasi mine (2012). The rainfall and temperature values were taken from 1980 to 2011, while that of relative humidity was drawn from 1987 to 2011 due to the unavailability of data between 1980 and 1987. Temperature, relative humidity and rainfall data values were arranged in monthly and yearly values where the monthly values of rainfall were aggregated from daily values for that particular month and the temperature and relative humidity figures were the mean of the daily values for the month.

Monthly Rainfall, Temperature and Relative Humidity data covering 54, 18 and 8 towns with rain gauges, thermometer and barometer stations respectively distributed evenly across the entire country were obtained for use in this research. The meteorological stations for rainfall, temperature and relative humidity measurements are in table 3.1

Table 3.1 Location of Weather Stations. Source, Ghana Meteorological Agency

Id	Station_Names	Latitude_DD	Longitude_DD	Id	Station_Names	Latitude_DD	Longitude_DD
1	Tumu	10.87154	-1.870227	24	Ejura	7.382326	-1.347705
2	Navrongo	10.87154	-0.997064	25	Sunyani	7.3617	-2.303371
3	Bolgatanga	10.771848	-0.773617	26	Kumasi	6.694796	-1.605528
4	Bawku	11.029671	-0.182342	27	Berekum	7.468267	-2.554319
5	Wulugu	10.452146	-0.728928	28	Goaso	6.832302	-2.516505
6	Wa	10.070567	-2.39275	29	Bibiani	6.461036	-2.310246
7	Sawla	9.269595	-2.344623	30	Awaso	6.223838	-2.265557
8	Tamale	9.3796	-0.787368	36	Obuasi	6.196337	-1.663968
9	Yendi	9.427727	0.017041	31	Kade	6.086333	-0.849245
10	Bole	9.04271	-2.399625	32	Koforidua	6.07602	-0.264845
11	Bimbila	8.850202	0.075481	33	Keta	5.893824	0.986458
12	Salaga	8.56144	-0.488292	34	Nsawam	5.794132	-0.357662
13	Bamboi	8.183298	-1.993982	37	Tema	5.646313	-0.000146
14	Kintampo	8.056105	-1.694907	35	Accra	5.553497	-0.19953
15	Yeji	8.210799	-0.649862	38	Oda	5.900699	-1.000502
16	Wenchi	7.753592	-2.073048	39	Swedru	5.525996	-0.715177
17	Techiman	7.592023	-1.883978	40	Cape Coast	5.09629	-1.289264
18	Hohoe	7.134815	0.474248	41	Sekondi	4.938158	-1.760222
19	Kpandu	6.986997	0.28174	42	Axim	4.848779	-2.27587
20	Ho	6.595105	0.477686	43	Tarkwa	5.309424	-2.031797
21	Nkawkaw	6.553853	-0.766742	44	Dunkwa	5.955702	-1.798036
22	Konongo	6.622606	-1.203323	45	Prestea	5.429742	-2.169303
23	Mampong	7.059187	-1.399269				

3.3.2 Software

ArcGIS 9.3 software was used for the construction of maps and presentation of the climatic variable stations on the map. Unscramble X10.2: multivariate statistical software was used for solving statistical problems including the cluster analysis. The Statistical Product for Service Solutions (SPSS) was used for correlation analysis.

3.4. Methods of Data Analysis

Statistical techniques were applied to determine the prevalence rate of CSM in Obuasi using the reported cases of CSM for each month of the year obtained from the hospital records. To identify the relationship between temperature, Rainfall, humidity and the outbreak of CSM, simple correlation analysis was applied to show how much variation in the outbreak of Meningitis was due to temperature, rainfall or humidity and for that matter relationship between the outbreak of meningitis and environmental factors. The correlation co-efficient was taken at 0.05 levels of significance. The Statistical Product for Service Solutions (SPSS) software of the computer was used.

Cluster analysis fig. 3.4 was used to identify and classify stations together with same temperature and rainfall characteristics as Obuasi. These stations are the areas that are most likely to record an occurrence of cerebrospinal meningitis if the climatic variables were the sole agents for causing the disease. Individual clusters were generated for monthly rainfall, mean monthly temperature and mean monthly relative humidity across the country from 1980-2011, and 1987-2011respectively. The results of the cluster for monthly rainfall for fifty four (54) rainfall stations across showed that Akrokerri, Barekese, Fumso, Kwadaso, Goaso and Owabi are in the same class with Obuasi. A similar approach used in clustering the mean monthly temperature from eighteen (18) stations also showed Accra, Ada and Wenchi in the same class with Obuasi.

Finally a similar cluster approach was employed in clustering the mean relative humidity for eight (8) stations showed Obuasi alone in a class.

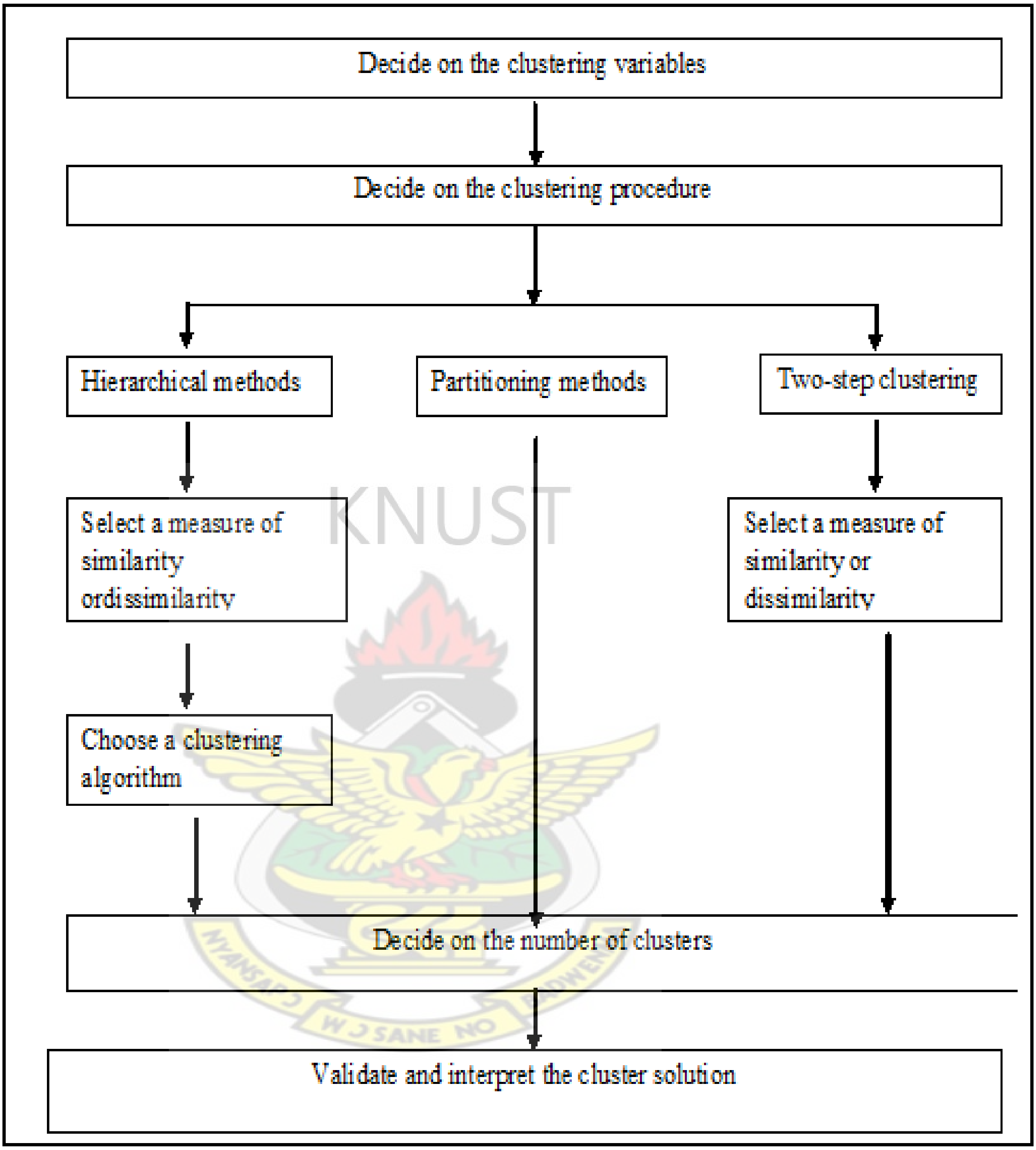

Fig 3.2 Clustering Flow Diagram

(source: Mooi and Sarstedt, 2011)

CHAPTER FOUR

4.0 RESULTS AND DISCUSSION

4.1 Results of Correlation Analysis

The correlation analysis carried out here was to establish correlation between the climatic variables and the disease incidence as recorded in the Obuasi municipality and also the level of significance and if that significance could trigger an outbreak of the disease in the other areas which are in the same cluster as Obuasi. The outcome of the statistical analysis (Table 4.1) shows that climatic parameters have influence on the outbreak of CSM. However, the analysis shows that the various climatic parameters of rainfall and temperature have varied degree of impact on the outbreak of cerebrospinal meningitis.

Table 4.1 Correlation analysis

		csm	rainfall	temperature	humidity
csm	Pearson Correlation	1	.814	.775	.730
	Sig. (2-tailed)		.186	.225	.270
	N	4	4	4	4
rainfall	Pearson Correlation	.814	1	.871	.793
	Sig. (2-tailed)	.186		.129	.207
	N	4	4	4	4
temperature	Pearson Correlation	.775	.871	1	.990*
	Sig. (2-tailed)	.225	.129		.010
	N	4	4	4	4
humidity	Pearson Correlation	.730	.793	.990*	1
	Sig. (2-tailed)	.270	.207	.010	
	N	4	4	4	4

*. Correlation is significant at the 0.05 level (2-tailed).
Source: Fieldwork 2012

The correlation only established relationship between the climatic variables and the CSM cases. The analysis here indicates clearly that there is correlation between the climatic variables and the occurrence of the disease. What the correlation does not establish is that, the relationship between the climatic and the disease incidence is solely responsible for the disease outbreak as recorded in the Obuasi municipality.

In the Table above, it can be seen that the Pearson's correlation level between rainfall, temperature and relative humidity and the incidence of CSM is at 0.814, 0.775 and 0.730 respectively which are very high considering that the highest correlation level is at 1. However, the level at which this correlation becomes significant is given as 0.186, 0.225, and 0.270 respectively which are far below a statistical significance level of 0.05. These make these correlations rather weak. In a nutshell, though there is a high positive correlation between the climatic variables and CSM, they were however not significant. This led to rejection of the null hypothesis, that, selected climatic variables solely influence the incidence of CSM. Other factors acting in association with the climatic variables may be responsible for the occurrence of CSM so in this respect, it maybe concluded that the occurrence of CSM in Obuasi in August 2010 was accidental and did not have anything to do with the prevailing climate at Obuasi. In order to validate this result, clustering was done to investigate other towns with similar climatic conditions as Obuasi.

4.2 Results for the clustering.

Individual clusters were generated for monthly rainfall, mean monthly temperature and mean monthly relative humidity across the country from 1980-2011, 1980-2011 and 1987-2011 respectively.

The results of the clustering for monthly rainfall for fifty four (54) rainfall stations across the country showed that Akrokerri, Barekese, Fumso, Kwadaso, Goaso and Owabi are in the same class with Obuasi. Similarly clustering the mean monthly temperature from eighteen (18) stations showed Accra, Ada and Wenchi in the same class with Obuasi. For the mean relative humidities, Obuasi appear to be in its class alone.

Different clustering approaches performed for climate variables produced results given by the dendoogram (Fig. 4.1) and the results summarized in Table 4.2.

Table 4.2. Summarized Clustering results showing Towns in same cluster as Obuasi.

Clustering method	Climate variable	Cluster towns with Obuasi.
Single Linkage clustering	**Temperature**	Ho, Wenchi, Tema, Akim Oda, Ada, Takoradi, Accra, Saltpond
Complete Linkage clustering		Ho, Akim Oda, Ada, Accra Wenchi
Wards Method		Accra, Ada, Wenchi
Single Linkage clustering	**Rainfall**	Akrokerri, Barekese, Goaso, Fumso, Owabi , Kwadaso .
Complete Linkage clustering		Akrokerri and Fumso
Wards Method		Akrokerri, Barekese, Goaso, Fumso, Owabi, Kwadaso.
Single Linkage clustering	**Relative humidity**	None
Complete Linkage clustering		None
Wards Method		None

Source: Fieldwork 2012

The three algorithms use in the cluster analysis all placed Obuasi alone in its cluster class for relative humidity. This could probably be due to the limited number of stations available with relative humidity data (eight stations) for long enough periods to be used in the clustering.

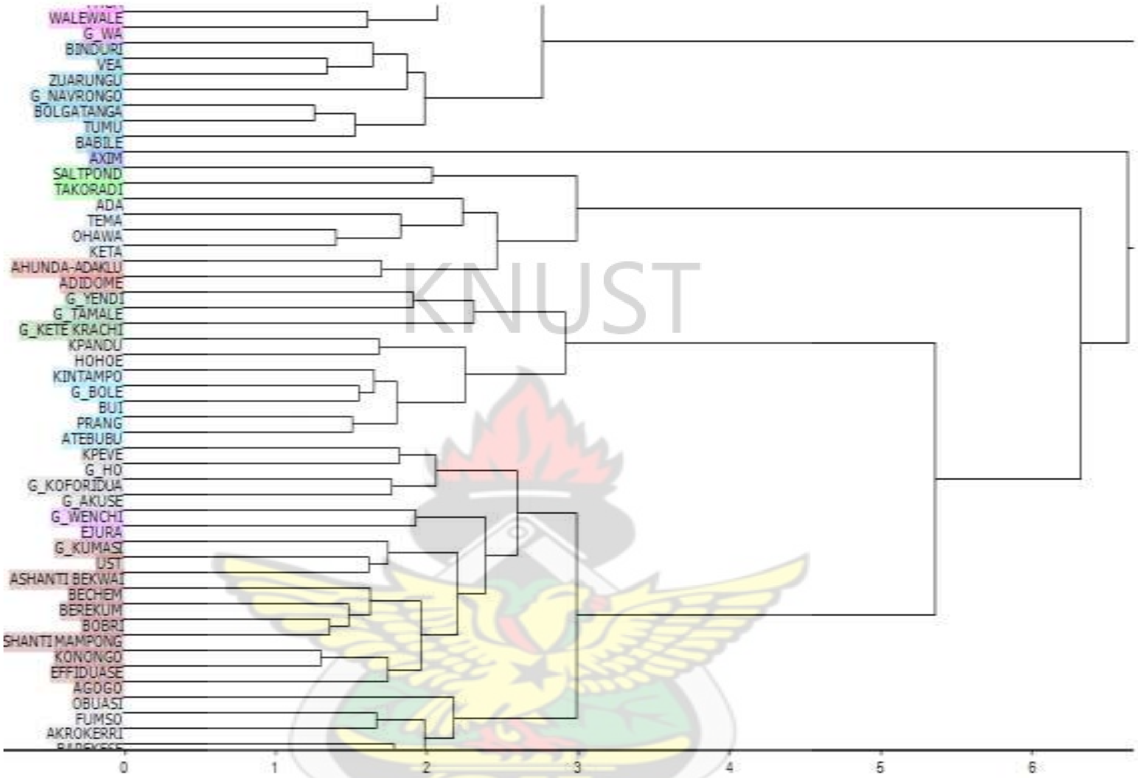

Fig.4.1 Dendogram for monthly rainfall from 1980-2011 by Ward's Method.

Source: Fieldwork, 2012

Table 4.3. Table of cluster classes based on Dendogram in 4.1.

CLASS	STATION
1	Axim
2	Lawra
3	Keta Krachi
4	Ada
5	Akrokerri, Barekese, Fumso, Goaso, Kwadaso, Owabi, Obuasi
6	Wa, Paga, Sandema, Walewale
7	Akuse, Ho, Koforidua,Kpeve
8	Takoradi, Saltpond
9	Babile, Navrongo, Tumu, Zuarungu, Bolgatanga, Vea,Binduri
10	Agogo, Ashanti Mampong, Bechem, Berekum, Bobri, Effiduase, Konongo
11	Ejura, Wenchi
12	Tamale, Yendi
13	Keta, Ohawa, Tema
14	Atebubu, Bui, Bole, Kintampo, Prang
15	Ashanti Bekwai, KNUST, Kumasi
16	Adidome, Ahunda-Adaklu
17	Hohoe, Kpandu

source: Fieldwork 2012

In order to determine stations with similar climatic conditions as that of Obuasi based on the three climate variables, the stations within the class 5 of the monthly rainfall cluster were superimposed on the annual temperature map of Ghana to determine those with similar rainfall and temperature conditions as that of Obuasi. It was found that Kwadaso, Fumso, Akrokerri, Barekese and Owabi had similar rainfall and temperature conditions as that of Obuasi. Though Goaso had similar rainfall condition as Obuasi, however it was discovered that its temperature was dissimilar to Obuasi. Fig. 4.2.

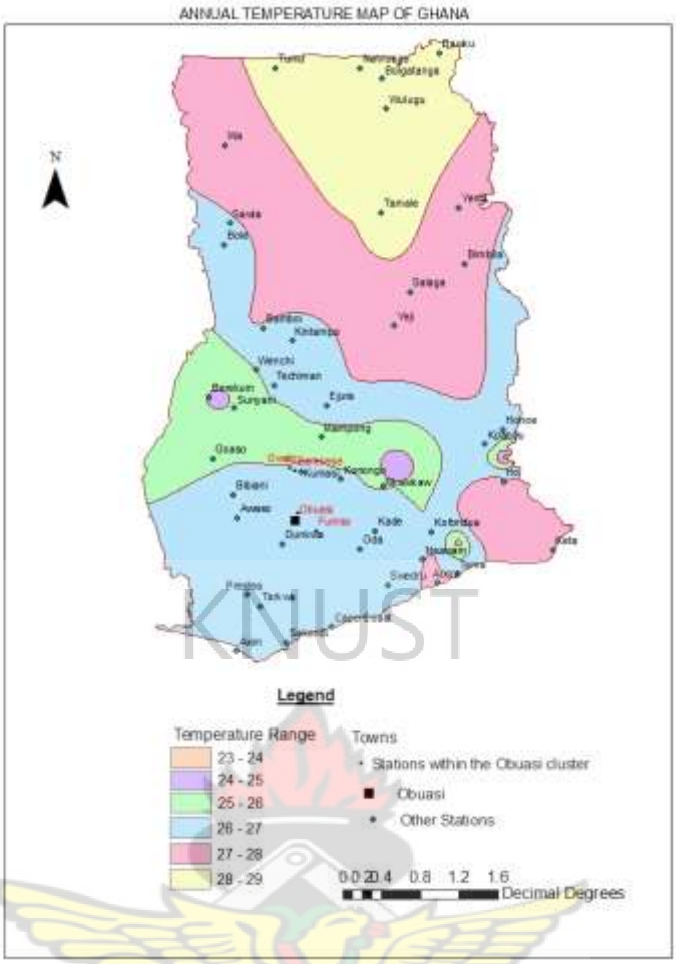

Fig. 4.2 Annual Temperature Map of Ghana after clustering.

Source: Fieldwork 2012

Fig. 4.2 represents a temperature cluster map on which is superimposed a rainfall cluster to produce the temperature-rainfall cluster map. Table 4.4 below shows the stations in the various clusters as seen on the map.

Table 4.4 Results after using temperature to cluster stations. Source: Fieldwork2012

Cluster Group	Name of station
23-24	
24-25	Brekum
25-26	Goaso, Mampong, Sunyani, Nkwakaw,
26-27	Bole, Bamboi, Sawla,Kintampo, Wenchi, Techiman, Ejura, Kpandu, Hohoe, Cape Coast, Sekondi, Bibiani, Awaso, Dunkwa, Takwa, Axim, Swedru, Prestea, Kumasi, Barekese, Owabi, Obuasi, Fumso, Oda, Kade, Nsawam, Konongo, Koforidua, Tema
27-28	Ho, Keta, Wa, Yeji, Salaga, Bimbila, Yendi, Accra
28-29	Tumu, Navrongo, Wulugu, Bolgatanga, Bawku

The first cluster containing only Brekum indicates that in terms of the combined effect of rainfall and temperature the Brekum station has no similarity with any other station. If this station were to be a closed society and recorded an outbreak of cerebrospinal meningitis, the other stations nearby need not be alarmed if climatic conditions of temperature and rainfall were the only contributory causative and/or propagative factors. It would on the other hand inform health administrators to educate the people of that station to be cautious.

The second cluster containing Goaso, Mampong, Sunyani, and Nkwakaw means if there were a reported case in any of these stations, the other stations must instantly take precautionary measures to contain an eminent outbreak provided conditions depend solely on temperature and rainfall.

It is of interest to note that Goaso has similar rainfall characteristics as Obuasi but showed marked dissimilarities when the rainfall map was superimposed on the temperature map. The Obuasi cluster of both temperature and rainfall includes Akrokerri, Barekese, Fumso, Kwadaso and Owabi. These stations had similar rainfall and temperature characteristics as those of Obuasi. This means that should any of those stations record an outbreak, the other stations would also have recorded an outbreak if climate has a causative effect on CSM.

In line with the third objective of this study, an attempt was made to either confirm the results occurrence of the outbreak in these towns. Information made available from the regional disease control office in Kumasi, however, did not contain evidence of a reported case of CSM much more an outbreak. This information therefore goes further to indicate that climate is not the only factor responsible for an outbreak of CSM.

4.3 Validation

The study went further to validate the findings by checking with the disease control office located in the premises of the Komfo Anokye Teaching Hospital (KATH) polyclinic in Kumasi. The information gathered there indicated that there have been no recorded case(s) of CSM in the other five stations with same climatic conditions as Obuasi i.e. Akrokerri, Barekese, Fumso, Kwadaso and Owabi. This information disproves the second hypothesis which postulated that areas with similar climatic conditions as those in Obuasi would have also recorded occurrence of CSM.

CHAPTER FIVE

5.0 CONCLUSION AND RECOMMENDATIONS.

5.1 Conclusion

This study has evaluated the effects of environmental factors on the outbreak of (CSM) in Obuasi. It can be inferred based on the findings of the study that CSM in the study area may only have been an accidental or imported case. It can also be deduced that climatic parameters though significant statistically in the outbreak of CSM, it also stresses the difficulty of relating climate alone meningitis. The results show that though climate may be important in the incubation of the disease, it could not be a causative factor alone. In a correlations analysis done on the CSM cases and the climatic variables and in reference to the research questions and objectives, we would conclude that:

1. The results show a correlation between the locations that recorded the outbreak of the disease in the Obuasi municipality and the frequency of occurrence in those locations. There is a correlation between the local climatic variables and the incidence of CSM. It therefore means that the incidence of CSM was not necessarily accidental and if the climatic variables in other stations with same characteristics as Obuasi existed in the sub-station level, then, CSM can occur in those stations.

2. The stations (Obuasi, Akrokerri, Barekese, Fumso, Kwadaso and Owabi) were within the Obuasi cluster when all the three climatic factors were used together for the clustering.

3. There were no reported cases of CSM occurrence in other towns with the same climatic conditions as Obuasi so climatic factors could not be solely be the factor in CSM outbreak in Obuasi.

4. Climatic factors may serve as catalyst for the occurrence of CSM and that without the complex interplay amongst all the factors CSM will not break out.

5.2 Recommendations for Further Studies

As earlier noted in the literature review, the generally held view about CSM occurring during the dry season and ending when the rains set in is thrown in doubt here as the disease incidence was recorded in August which is within the rainy season (Whitson, 2005).

1. As seen from study, CSM is not caused exclusively by climate but by a multiplicity of factors including climate, therefore it is recommended that other variables can be included in addition to the climatic variables used separately to determine the cause of CSM in Obuasi in 2010.
2. Monthly data of CSM cases and the climatic variables of all the districts of Ghana could be collected for the study on seasonality.
3. The local climatic characteristic must be used in future studies as the averages used to represent the entire municipality throws into doubt the conditions necessary for an outbreak of CSM.
4. Notwithstanding, the held notion that the disease occurs in the dry season, incidence of the disease could occur at other places which may not have conditions similar to those experienced in the arid regions but that occurrence could be accidental as seen in the case of Obuasi and would not mean that the disease would always occur under those humid conditions.

REFERENCES

1. Greenwood B: Manson Lecture (1999). MCM in Africa.Trans R Soc Trop Med Hyg, 93:341-353. PubMed Abstract | Publisher Full Text

2. Lapeyssonnie L (2008): The MCM in Africa (in french). Bull WHO 1963, 28–3:114

3. Thomson MC, Molesworth AM, Djingarey MH, Yameogo KR, Belanger F, Cuevas LE (2006): Potential of environmental models to predict meningitis epidemics in Africa. Trop Med Int Health, 11:781-788. PubMed Abstract | Publisher Full Text

4. Hodgson A, Smith T, Gagneux S, Adjuik M, Pluschke G, KumasenuMensah N, Binka F, Genton B (2001): Risk factors for MCM in northern Ghana. Trans R Soc Trop Med Hyg, 95:477 480. PubMed Abstract | Publisher Full Text

5. Leimkugel J, Hodgson A, Forgor AA, Pflüger V, Dangy JP, Smith T, Achtman M, Gagneux S, Pluschke G (2007): Clonal waves of Neisseria colonisation and disease in the African meningitis belt: eight- year longitudinal study in northern Ghana. PLoS Med, 4:e101. PubMed Abstract | Publisher Full Text | PubMed Central Full Text

6. Trotter CL, Greenwood BM (2007): Meningococcal carriage in the African meningitis belt. Lancet Infect Dis, 7:797-803. PubMed Abstract | Publisher Full Text

7. Robbins JB (2003): MCM in sub-Saharan Africa: the case for mass and routine vaccination with available polysaccharide vaccines.Bull WHO. PubMed Abstract | Publisher Full Text.

8. Robbins JB, Towne DW, Gotschlich EC, Schneerson R: (1997) "Love's labours lost": failure to implement mass vaccination against group A MCM in sub-Saharan Africa. Lancet, 350:880-882. PubMed Abstract | Publisher Full Text

9. Chippaux JP, Debois H, Saliou P: (2002) A critical review of control strategies against MCM epidemics in sub-Saharan African countries. Infection, 30:216-224. PubMed Abstract | Publisher Full Text

10. Broutin H, Philippon S, Constantin de Magny G, Courel F, Sultan B, GueganJF: (2007) Comparative study of meningitis dynamics across nine African countries: a global perspective. Int J Health Geo, 6:29.doi:10.1186/1476-072X-6-29. BioMed Central Full Text.

11. Tikhomirov E, Santamaria M, Esteves K: (1997) Meningococcal disease: public health burden and control. Rapp Trimest Stat SantMond, 50:170-177.

12. WHO (2000): Detecting MCM epidemics in highly-endemic African countries. Weekly Epidemiological Record., 38.

13. Pascal Yaka, Benjamin Sultan, Hélène Broutin, Serge Janicot, Solenne Philippon and Nicole Fourquet: (2008) Relationships between climate and year-to-year variability in meningitis outbreaks: A case study in Burkina Faso and Niger. International Journal of Health Geographics, 7:34 doi:10.1186/1476-072X-7-34.

14. Molesworth AM, Cuevas LE, Connor SJ, Morse AP, Thomson MC. (2003) Environmental changes and meningitis epidemics in Africa. Emerg Infect Dis

[serial online] Oct [date cited]. Available from: URL: http://www.cdc.gov /ncidod/ EID/vol9no10/03-0182.html.

15. Vanja Dukic, Mary Hayden, Abdulai Adams Forgor, Tom Hopson, Patricia Akweongo, Abraham Hodgson, Andrew Monoghan, Christine Wiedinmyer, Tom Yokass, Madeleine C. Thomson, Sylvia Trzaska and Ray Pandya: (2012) The Role of Weather in Meningitis Outbreaks in Navrongo: A Generalized Additive Modeling Approach. Journal of Agricultural, Biological and Environmental Studies September, Volume 17, Issue 3, pp 442-460.

15. Atif Iqbal Butt, *Usefulness of Geodemographics & GIS for Banking Sector in Pakistan* http://www.nadra.gov.pk/gis.html (visited 15 Nov, 2004).

16. E. Mooi and M. Sarstedt, 2011. A Concise Guide to Market Research, DOI 10.1007/978-3-642 12541-6_9, # Springer-Verlag Berlin Heidelberg

17. P. Miliotis, M. Dimopoulou, I. Giannikos, March 2002, *A hierarchical location model for locating bank branches in competitive environment. Paper presented at Internation Transaction in Operational Research.*

18. WHO. (1979), *Bulletin of the World Health Organisation*: 57 (6):943-946 (1979))

19. Vauromo M, Rusanen J, Naha S, (2001*), Small Area variation in mortality in the city of Oulu, Finland, during the period 1978-1995, Health Place 2001;7:75-79.*

20. English D. Geographical epidemiology and ecological studies. In Elliot P, Cuzick J, English D and Stern R,Eds. (1992) *Geographical and Environmental Epidemiology: Methods for Small-Area Studies*. Oxford: Oxford Press; 3-13.

21. Howe GM. (1989) *Historical evolution of disease mapping in general and specifically of cancer mapping. Recent Results Cancer Res; 114: 1-21.*

22. Jason K. Whitson, (2005). *Disease Research Report: Meningococcal Disease (Meningitis)Biology 240 summers.*

23. Swartz, Morton N. (2004) "Bacterial Meningitis – A View of the Past 90 Years." The New England Journal of Medicine Boston: Oct 28, 2004. Vol. 351, Iss. 18; pg. 1826, 3 pgs. Proquest; Cannell Library, Vancouver WA. http:// 0-proquest.umi.com.oswald.clark.edu

24. Department of Communicable Disease Surveillance and Response Campagne GA et al. (1999). Epidemiology of bacterial meningitis in Niamey, Niger, 1981-96. *Bulletin of the World Health Organization*, 77:499–508.

25. Woods CW et al. (2000). Emergency vaccination against epidemic meningitis inGhana: implications for the control of meningococcal disease in West Africa. *Lancet*, 355:30–33.

26. WHO (2001). Meningococcal disease, serogroup W135: Central African Republic, France, Norway, Saudi Arabia, Singapore, United Kingdom. *Weekly Epidemiological Record*, 2001, 76:141–148.

27. WHO Working Group. (1998*) Control of epidemic meningococcal Disease: WHO practical guidelines*. Lyon, Fondation Marcel Merieux.

28. Gale Encyclopedia of Medicine. (2008) The Gale Group, Inc. Jeff Grischow: *Globalisation, Development And Disease In Colonial Northern Ghana, 1906-1960*, Wilfrid Laurier University Waterloo, Canada

29. Mary Gover Glee Jackson (1946) .United States Public Health Service: *The reported incidence of meningococcus meningitis in the United States.*

30. A Chronological Record of Reported Cases and Deaths. Public Health Reports Vol. 61 *, 0 No. 13 Printed with the Approval of the Bureau of the Budget as Required by Rule 42 of the Joint Committee on cerebrospinal meningitis

31. Ghanadistricts.com visited on the 6th of February 2012. A repository of all districts in the republic of Ghana. Ashanti – Obuasi municipality.

32. Basford.G. J, M. K. (1988). *Inference and Applications to Clustering.* New York: Marcel Dekker.

33. Gordon, A. D. (1981). *Classification: Methods for the Exploratory Analysis of Multivariate Data.* London: Chapman and Hall.

34. Hartigan, J. (1975). *Clustering Algorithms.* New York: Wiley.

35. Kaufman, L. a. (1990). *Finding groups in data: An introduction to cluster analysis.* . New York : Wiley.

36. E. Mooi and M. Sarstedt, (2011), *A Concise Guide to Market Research*, DOI 10.1007/978-3-642-12541-6_9, # Springer-Verlag Berlin Heidelberg

37. Everitt, Brian S., Sabine Landau, & Morven Leese (2001). *Cluster analysis, 4th Edition*. London: Edward Arnold Publishers Ltd.

38. J.F. Hair, Jr., Rolph E. Anderson, and Ronald L. Tatham, (1995), *Multivariate Data Analysis with Readings, 2nd Edition, MacMillan Publishing Co., New York, PP 303*

39. Sáez-Llorens X, McCracken GH (June 2003). "Bacterial meningitis in children". *Lancet* **361** (9375): 2139–48. doi:10.1016/S0140-6736(03)13693-8. PMID 12826449

40. van de Beek D, de Gans J, Tunkel AR, Wijdicks EF (January 2006). "Community-acquired bacterial meningitis in adults". *The New England Journal of Medicine* **354** (1): 44–53. doi:10.1056/NEJMra052116. PMID 16394301.