Climate Influences on Infectious Diseases in Nigeria, West Africa

By:

Auwal Farouk Abdussalam

A thesis submitted to the University of Birmingham for the degree of
DOCTOR OF PHILOSOPHY

School of Geography, Earth, and Environmental Science
College of Life and Environmental Science
University of Birmingham
August, 2014

Abstract

Meningitis and cholera have remained a major health burden in Nigeria, especially in the heavily populated northwest region – which is identified as one of the "hotspots" of climate change. The strong sensitivity that both diseases exhibit to climate is raising concern that future anthropogenic climate change may exacerbate the occurrence of the diseases. This thesis is aimed at modelling the influences of climate on the incidence of the selected diseases, and assessing their future risk in northwest Nigeria. The aim is achieved by first, investigating and understanding the spatial and time characteristics of both meteorological and diseases conditions in the region. This was followed by developing and validating suites of empirical statistical models capable of explaining and predicting both diseases. Models that are specifically designed for climate change studies were applied to estimate the future impact of climate change, by forcing them with simulations from an ensemble of statistically downscaled Atmosphere-ocean Global Climate Models (AOGCMs), for three different scenarios in the early and late 21st century. Results from developed models indicate the significant roles of both meteorological and socioeconomic factors on incidence of diseases. Evaluation of models developed with 1-month lagged explanatory variables suggest the potential to predict both diseases cases up to a month to aid decision making. Projection results suggest that future temperature increases due to climate change has the potential to significantly increase diseases cases in all scenarios and time slices. It is noteworthy that the projections result represents only the climatological potential for increased cases due to climate change, assuming that the present prevention strategies remain similar in the future.

Dedication

To my beloved parents.

Acknowledgements

It’s my pleasure to acknowledge the following persons and institutions that contributed directly or indirectly towards the accomplishment of my PhD programme.

First of all, my gratitude goes to my supervisors, Dr. Gregor C. Leckebusch and Prof. John E. Thornes for their continual support, guidance, encouragement, tolerance, patience, and friendship throughout my programme.

I sincerely appreciate the contribution and host given to me by Andrew J. Monaghan, Mary H. Hayden, Thomas M. Hopson, and Vanja M. Dukic during my two times visit to the National Centre for Atmospheric Research (NCAR), Boulder, Colorado, USA.

Funding for this research came from the Nigerian Tertiary Education Trust Fund, and Kaduna State University – Thank you.

I would like to thank the World Health Organization, the Nigerian National Primary Health Care Development Agency, the Nigerian Ministry of Health, the Nigerian Meteorological Agency, and the management of the four state-owned hospitals for providing data and assistance. Also, the Earth System Grid - Program for Climate Model Diagnosis and Intercomparison (ESG-PCMDI) for making the CMIP5 data available.

I Thank the Advanced Study Programme, and Research Application Laboratory, all of the National Centre for Atmospheric Research, Boulder, Colorado, USA, for awarding me with visitors grants that facilitates my visits to the centre in 2012 and 2013 respectively. NCAR is sponsored by the United State National Science Foundation.

During the course of my PhD, travel grants that facilitate the presentation of my work at different international meetings were provided by the World Climate Research Programme (2011), World Health Organisation (2012), and World Meteorological Organisation (2013) – Many thanks to these institutions for funding my travelling.

Hearty appreciation goes to my beloved and wonderful family for the, love, prayers, patience, tolerance, support, understanding and the encouragement they have given me throughout this period.

This acknowledgement will be grossly incomplete without mentioning the encouragement and support of friends.

Table of contents

List of Illustrations

List of Tables

Abbreviations

AEW	African Easterly Waves
AMMA	African Multidisciplinary Monsoon Analysis
AOGCM	Atmosphere-ocean Global Climate Model
AR	Assessment Report
BIC	Bayesian Information Criteria
CFR	Case Fatality Rate
CLIVAR	Climate Variability and Predictability Research Project
CMIP5/3	Coupled Model Intercomparison Experiment Phase 5/3
CRD	Climate Research Division
CVC	Cross Validation Correlation
DALYs	Disability-adjusted Life Years
DJF	December, January, and February
DNSOs	Disease Surveillance and Notification Officers
DOF	Degree of Freedom
ECMWF	European Centre for Medium-Range Weather Forecast
ENSO	El-Niño South Oscillation
ESG-PCMDI	Earth System Grid Program for Climate Model Diagnosis
ETCCDI	Expert Team on Climate Change Detection and Indices
EWS	Early Warning System
FCT	Federal Capital Territory
FMoH	Federal Ministry of Health
GAMs	Generalised Additive Models
GCMs	Global Climate Models
GHGs	Green House Gasses

GLMs	Generalised Linear Models
GOG	Gulf of Guinea
IDPs	Internally Displaced Persons
IPCC	Intergovernmental Panel on Climate Change
IR	Incidence Rate
ITCZ	Inter Tropical Convergence Zone
ITD	Inter Tropical Discontinuity
JJA	June, July, and August
MAM	March, April, and May
MLR	Multivariate Linear Regression
NBS	National Bureau of Statistics
NCAR	National Centre for Atmospheric Research
NCDC	National Centre for Disease Control
NIMET	Nigerian Meteorological Agency
NPC	National Population Commission
NPHDA	National Primary Health Care Development Agency
RCP	Representative Concentration Pathways
RI	Relative Influence
RMSE	Root Mean Square Errors
SON	September, October, and November
SST	Sea Surface Temperature
URTI	Upper Respiratory Tract Infection
WAM	West African Monsoon
WHO	World Health Organisation
WMO	World Meteorological Organisation

Associated Publications

Peer reviewed papers:

Abdussalam, A. F., Monaghan, A. J., Dukić, V. M., Hayden, M. H., Hopson, T. M., Leckebusch, G. C., & Thornes, J. E. (2014). Climate Influences on Meningitis Incidence in Northwest Nigeria. *Weather, Climate, and Society, 6*(1), 62-76. doi: 10.1175/wcas-d-13-00004.1

Abdussalam, A. F., Monaghan, A. J., Steinhoff, D. F., Dukic, V. M., Hayden, M. H., Hopson, T. M., Leckebusch, G. C. (2014). The impact of climate change on meningitis in northwest Nigeria: an assessment using CMIP5 climate model simulations. *Weather, Climate, and Society* 6(3), 371-379. doi: 10.1175/wcas-d-13-00068.1

Leckebusch, G. C., **Abdussalam, A. F**., Rachael , A. (2014) . Climate and socioeconomic influences on the interannual variability of cholera in Nigeria. To be submitted to the Journal of *Health and Place* by July, 2014.

Conference contributions:

Abdussalam, A. F., Monaghan, A. J., Steinhof, D. F., Dukic, V. M., Hayden, M. H., Hopson, T. M., Thornes, J. E., and Leckebusch, G. C. Possible impact of climate change on meningitis in northwest Nigeria: an assessment using CMIP5 climate model simulations. Geophysical Research Abstract: Vol. 16 EGU 2014–1968. 14th European Geosciences Union, Vienna, Austria, 28th April – 02nd May, 2014.

Abdussalam, A. F., Monaghan, A. J., Steinhof, D. F., Dukic, V. M., Hayden, M. H., Hopson, T. M., Thornes, J.E., and Leckebusch, G. C. The impact of climate change on meningitis in northwest Nigeria: an assessment using CMIP5 climate model simulations. First African Climate Conference (ACC 2013), Arusha, Tanzania, 14 – 18 October, 2013.

Abdussalam, A. F., Monaghan, A. J., Dukic, V. M., Hayden, M. H., Hopson, T. M., Thornes, J. E., and Leckebusch, G. C. Climate influence on meningitis cases in northwest Nigeria. Abstract: EMS 2013-471. 13th European Meteorological Society/ 11th ECAM meeting, Reading, UK, 9 – 13th September, 2013.

Leckebusch, G. C and **Abdussalam, A. F.** Influence of meteorological and socioeconomic factors on the spatiotemporal variability of cholera incidence and mortality in Nigeria. Abstract: EMS 2013-473. 13th 11th ECAM meeting, Reading, UK, 9 – 13th September, 2013.

Abdussalam, A. F., Monaghan, A. J., Dukic, V. M., Hayden, M. H., Hopson, T. M., Thornes, J. E., and Leckebusch, G. C. Meteorological influences on the interannual variability of meningitis incidence in northwest Nigeria. Geophysical Research Abstract: Vol. 15 EGU 2013–7600. 13th European Geosciences Union, Vienna, Austria, 07 – 12th April, 2013.

Abdussalam, A. F., Monaghan, A. J., Dukic, V. M., Hayden, M. H., Hopson, T. M., Thornes, J. E., and Leckebusch, G. C. Modelling the climatic influences on the interannual variability of meningitis incidence in Northwest Nigeria. 6th international Meningitis Environmental Risk Technologies (MERIT) meeting, Accra, Ghana, 27 – 28th November, 2012

Abdussalam, A. F., and Thornes, J. E. Climate change and variablity: the relationship with selceted climate sensitve diseases in Nigeria. World Climate Research Programme (WCRP) Open Science Conference, Denver, Colorado, USA. 24 – 29th October, 2011.

Abdussalam, A. F., and Thornes, J. E. Climate and climate sensitve diseases in Nigeria. Early Carrier Scientists Assembly Workshop on Regional Climate Issues in Developing Countries. National Centre for Atmospheric Research (NCAR), Boulder, Colorado, USA. 18 – 23th October, 2011.

Chapter one:

Introduction and Statement of Aim and Objectives

Chapter one

Introduction and Statement of Aim and Objectives

1.1 Introduction

It has been unequivocally established that the emission of greenhouse gases (GHGs) by man is altering the Earth's climate system. Observational data has shown that since the 1950s, the atmosphere and ocean have warmed, sea levels have risen, and GHGs' concentration is increasing (IPCC, 2013). According to the latest Intergovernmental Panel on Climate Change (IPCC) Assessment Report Five (AR5), the average global trend of land and ocean warming between 1880 and 2012 is 0.85°C, with the last three decades being the warmest in the period, while the average sea level rise is about 0.19m. These increases have been associated with anthropogenic emissions of GHGs by several studies (Hegerl et al., 2006; Ingram, 2006). The warming is expected to double even if the release of GHGs into the atmosphere by man is reduced or stabilised in the future, because of the effect of previously accumulated emissions (Meehl et al., 2005). The continual additions of these gases into the atmosphere will add to the warming that is already guaranteed.

Climate change will not only alter temperature patterns, but is also expected to potentially change many other components of the Earth's climate system (IPCC, 2013); these include, but are not limited to, atmosphere and ocean circulation systems, precipitation, humidity, and atmospheric ecosystem services (Gosling et al., 2009). Also, climate change is expected to bring about changes in large-scale weather patterns by increasing the occurrence and intensity of some extreme weather events, such as elevated temperatures, flooding (caused by rainfall intensity), and extended drought (McMichael et al., 2004).

Despite Africa's small carbon emissions, the negative impact of climate change will be more pronounced in this continent (Muller, 2009). Africa has been described as a "hot spot" and vulnerable to climate change, with respect to challenges such as extreme weather events, drought, disease, water scarcity, and low coping capacity (e.g., Collier and Venables, 2008; Connor and Mantilla, 2008; Diffenbaugh and Giorgi, 2012; Washington et al., 2006; WHO, 2013a). According to the IPCC AR4 on Africa, since 1960s, the air temperature in Africa has a significant trend of warming (IPCC, 2007a; Muller, 2009). Despite the consistency in the warming trend across the continent, spatial differences are to be noted: these are characterized by interannual variability (Kruger and Shongwe, 2004). Climate change is projected to impact on sub-Saharan Africa disproportionately, via an increase or decrease in rainfall, increase in temperature, and extended droughts (Christensen et al., 2007). Despite the uncertainties involved in climate model projections, there is seemingly a consensus that these changes might have a severe impact on Africa, although details of these are still not clear at the local level (Muller, 2009).

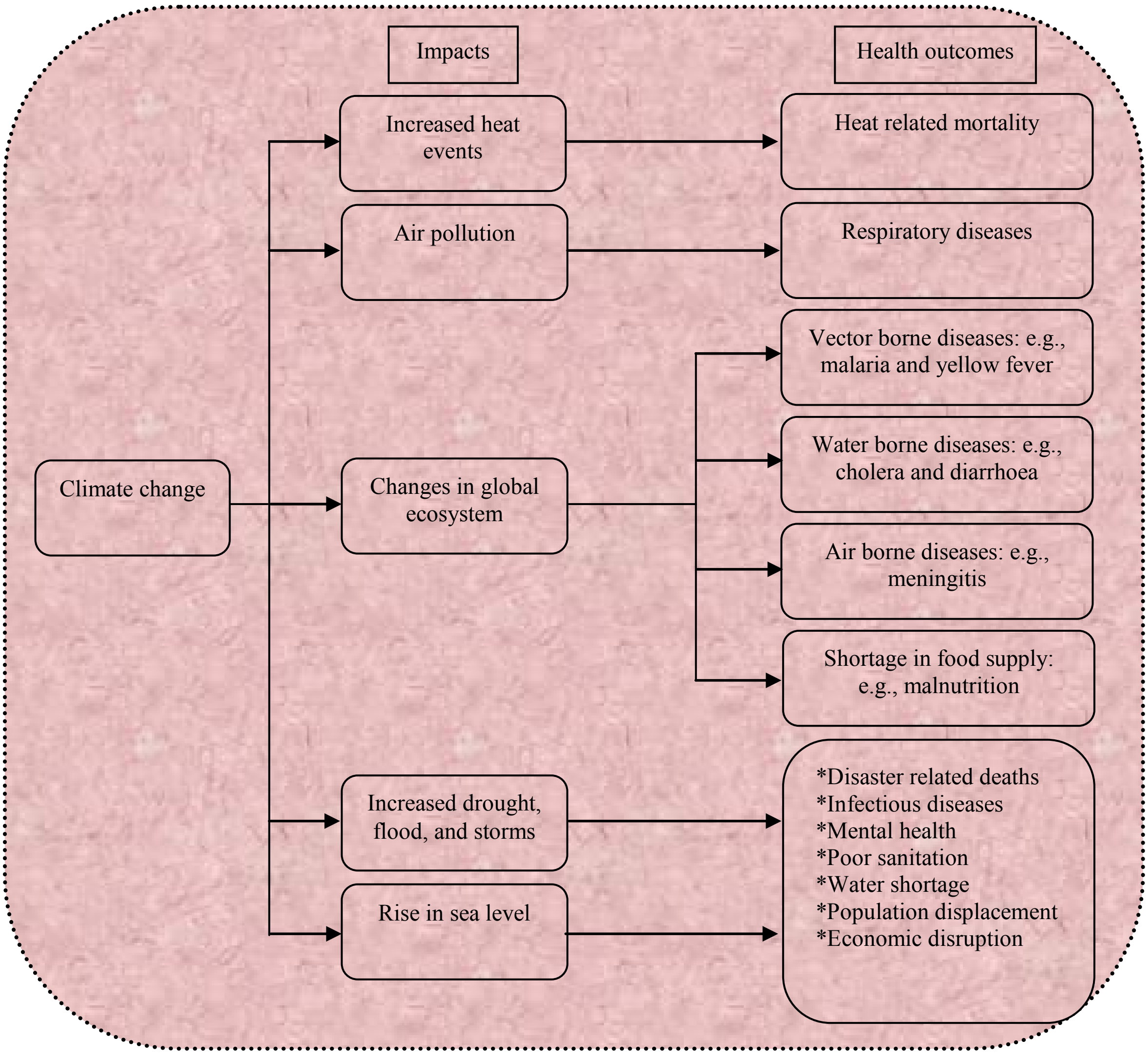

Figure 1.1: Schematic diagram showing the possible pathways through which climate change could affect health outcomes, either directly, indirectly, or a combination of both. Modified from Patz et al. (2000).

In the area of human health, the IPCC AR4 made mention that climate change has already added to the global burden of premature deaths and disease (IPCC, 2007c). This is despite the increase in scientific understanding and technological advances in medical sciences (Oluleye and Akinbobola, 2010). Climate change has the potential to affect population health in different ways. These impacts could either be direct, such as elevated temperature causing heat related mortalities, or indirect (Griffiths, 1976), for example the resurgence, or changes in the dynamics and ecological distribution, of some infectious diseases. Figure 1.1 illustrates the possible pathways through which climate change could affect health outcomes. These are (a) direct impacts such as heat-related mortality due to increasing heat events; (b) indirect impacts as a result of changes in the global ecosystem, such as the prevalence of infectious diseases; and (c) economic dislocation or mental stress (Ebi, 2006), due to extreme climate events such flooding, drought, and sea level rise.

It is evident that climate change has already started to impact on some infectious diseases like dengue, malaria, and encephalitis (McMichael et al., 2003) especially in Africa and Asia. The projected risks to health that are attributable to climate change will vary in magnitude and by region (Figure 1.2), but they are expected to be mainly negative, most especially in developing nations. Increases in malnutrition and diarrhoeal-related disease are expected, primarily in low-income populations (WHO, 2003). The increasing prevalence of morbidity and mortality will burden developing countries by increasing the monetary budget on health care, decreasing productivity, and putting pressure on fragile health care systems (IPCC, 2007b). The observed changes in climate and the likely increases in the risk of infectious diseases led to growing concern, which triggered a plethora of research about the possible dimensions of these changes and their extent, and also exploring the potential to predict climate change's future impact on important diseases (Kovats et al., 2012; Patz and Reisen, 2001). However, most of these studies have focused on developed countries as reported by Kelly-Hope and Thomson (2008).

Recently, the United Nations agencies for health (World Health Organisation (WHO)) and meteorology (World Meteorological Organisation (WMO)) revealed new evidence linking the prevalence of infectious diseases such as meningitis, diarrhoea, and malaria to climate change (Miller, 2013). The magnitude of these changes may exacerbate the dynamics and transmission of climate-sensitive infectious diseases in developing nations; because these countries host the highest burden of infectious diseases (Murray et al., 2013). However, this will largely depend on how the authorities and public health workers manage the changes, and also on the efficiency of mitigation and adaptation strategies (Ebi et al., 2013). The change is expected to be a potential danger to human health, most especially in low income populations that are predominantly located in tropical and subtropical countries (McMichael et al., 2001). The impact will be more severe in developing countries than in developed ones, due to basic and necessary resources, such as good health care services and clean drinking water, being less readily available (Huei-Ting and Tzu-Ming, 2005). This explains why there is a scientific need for the quantification of the relationship between climate and diseases, and to investigate the geographical range and extent of the impacts of climate change on infectious disease.

Projecting the potential impact of climate change on meteorologically-sensitive infectious diseases is essential (IPCC, 2007c), especially for regions where the projected climate changes impact is likely to change the distribution, and seasonality of these diseases (Murray et al., 2013; WHO, 2013a). The Sahel and tropical West Africa, where northwest Nigeria lies (Figure 1.3), are areas identified as "hotspots" of climate change (Collier and Venables, 2008; Diffenbaugh and Giorgi, 2012), and are projected to be disproportionately impacted (Suk and Sumenza, 2011) due to the countries’ large and often vulnerable populations. In respect of this projection, the degree of the impact of climate change will ultimately depend on the level of preparation and adaptive measures put in place. For this reason, authorities both at the national and regional levels need to be informed of the possible magnitude of damage that could be caused by climate change, the need for an adaptation strategy, and what damage can be avoided through mitigation measures.

Northwest Nigeria is particularly vulnerable to climate change because of its physical and socioeconomic characteristics: widespread poverty, desertification, ecological disruption, high population growth rate and extreme weather events (NBS, 2012; NIMET, 2012). The region is suffering because many important issues of human and infrastructural development require urgent attention. Despite these glaring challenges, surprisingly, no quantitative research has attempted to investigate the association between climate and infectious diseases (Kelly-Hope and Thomson, 2008) in this important country (apart from Greenwood (1984) who briefly reported on meningitis). Also, there is no known study that has projected the future impact of climate change on diseases in West Africa.

The current research intends to fill in this gap by exploring the nexus between climatic conditions and selected climate-sensitive infectious diseases in northwest Nigeria, through the development of empirical statistical models capable of explaining and predicting these diseases. The study will also assess the potential impact of future climate change on the risk of these diseases, using downscaled simulations from the Atmosphere-ocean Global Climate Models (AOGCMs) that participated in the Coupled Model Intercomparison Experiment Phase Five project (CMIP5; Taylor et al., 2012). The criteria for the selection of targeted infectious diseases will be discussed in the next section of this chapter (1.2), while details and the reasons for selecting the study area are presented in section 3.2.

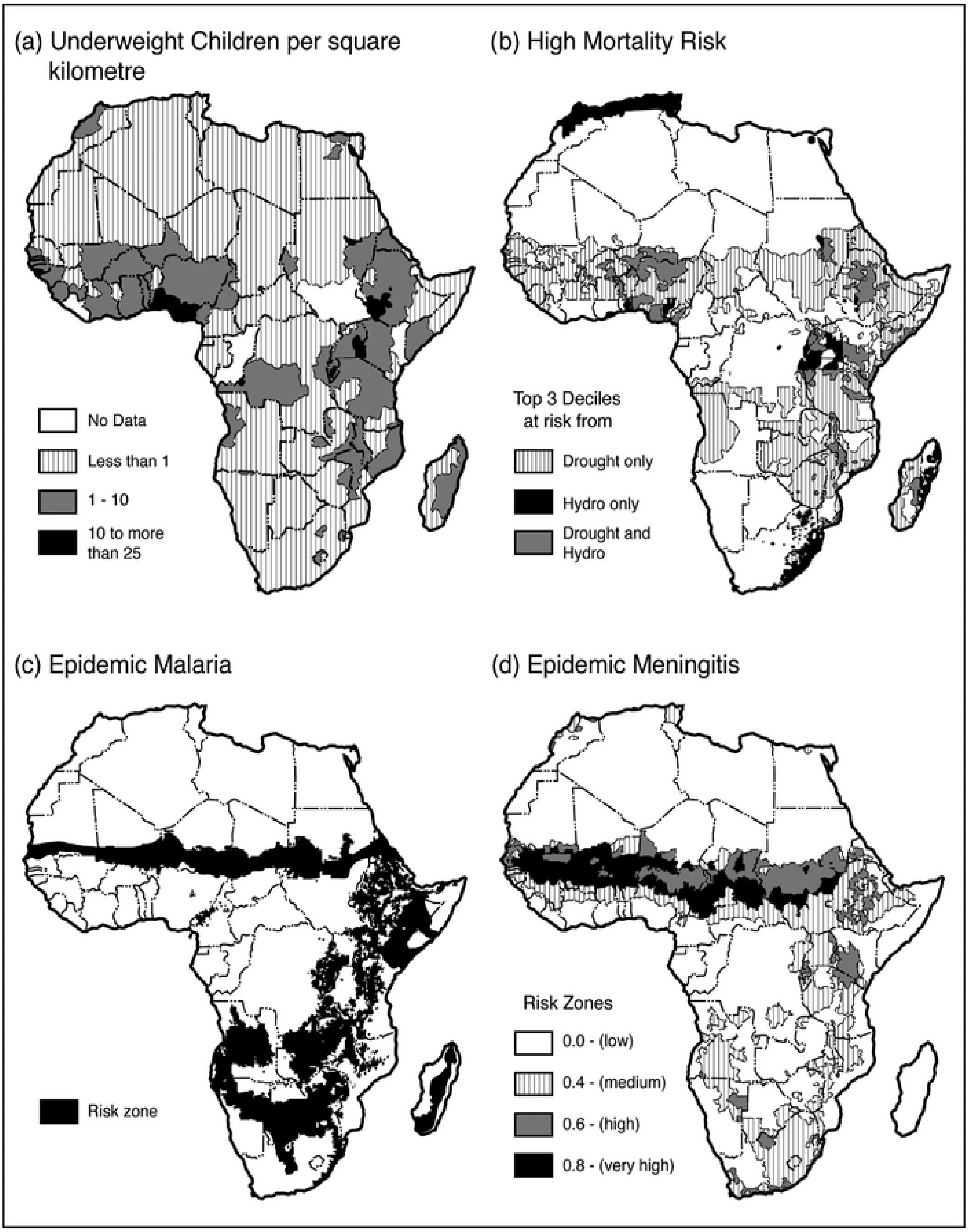

Figure 1.2: Example of regions in Africa that are at most risk, under climate change, of (a) malnutrition, (b) mortality from natural hazards, (c) malaria, and (d) meningitis. (Adapted from IPCC, 2007b)

1.2 Identifying the candidate diseases

Two climate-sensitive infectious diseases were identified for the purpose of this research on the basis of their: (a) associated burden; (2) sensitivity to climate; and (3) availability of qualitative and long time records. With respect to the above criteria, meningitis and cholera were chosen, because of their historical record of high morbidity and mortality in Nigeria based on statistics available on the WHO's website. The diseases are also among the most important infectious diseases identified using the global burden of disease classification system (Morens et al., 2004), in descending order of number of disability-adjusted life years (DALYs) lost annually (WHO, 2011c) as presented in Table 1.1. Likewise, the special report of the WHO on using climate to predict infectious diseases (WHO, 2005a) established the evidence of their sensitivity to climate (Table 1.1).

Table 1.1: Distribution of infectious diseases with respect to their epidemic potentials and sensitivity to climate, based on global burden of disease classification in descending order of number of disability-adjusted life years (DALYs) lost annually (an extract from the WHO's report, Geneva, 2005a).

Disease	Global Burden (1000 DALYs)	Transmission	Distribution	Evidence for interannual variability		Strength of temporal climate sensitivity	Climate-Epidemic relationship quantified?
Cholera	61,966	Food- and water-borne	Africa, Asia, Russia, & South America	Very strong	Increase in sea and air temperature	Primary factor	√
Meningitis	6, 192	Air-borne	Worldwide	Moderate	Increases in temperature and decreases in humidity	Significant	√

1.3 Aim and objectives

The key research priorities highlighted by working group II of the IPCC AR4 (IPCC, 2007b) underscores the purpose of this research. The report stated that "*most studies have focused on middle- and high-income countries. Gaps in information persist on trends in climate, health and environment in low-income countries"* (IPCC, 2007c). The report also emphasises the need for estimating the potential risk that climate change might have of causing an outbreak of diseases in the future, in order to inform the authorities to prepare for necessary adaptation and mitigation strategies.

In respect to the above gap and others identified in section 2.10, this study aims to model statistically the relationship between climatic conditions and the selected climate-sensitive infectious diseases, and also estimate the potential impact of future climate change on these diseases in northwest Nigeria. The aim will be achieved through the following set of objectives:

Objective 1: To compile a comprehensive literature review on the present and future relationships between climate and climate-sensitive diseases, with particular interest in meningitis and cholera;

Objective 2: To investigate the spatial and time characteristics of climatic conditions in the region under investigation;

Objective 3: To analyse the spatial and time characteristics of meningitis and cholera in Nigeria using disease surveillance data;

Objective 4: To develop and validate suites of regional empirical statistical models capable of: (1) explaining the influences of climatic conditions on the interannual variability of meningitis and cholera taking into consideration the additional effect of other non-climatic additional factors; (2) predicting these diseases with a time lead; and (3) estimating the future risk of climate change causing an outbreak of these diseases;

Objective 5: To estimate the potential impact of future anthropogenic climate change on the risk of meningitis and cholera in the near (2020-2035) and far (2060-2075) future, using empirical statistical models developed in objective 4 above and the ensemble of simulations from the most recent state-of-the-art AOGCMs that participated in CMIP5 project, which support the forthcoming Fifth Assessment Report of the IPCC.

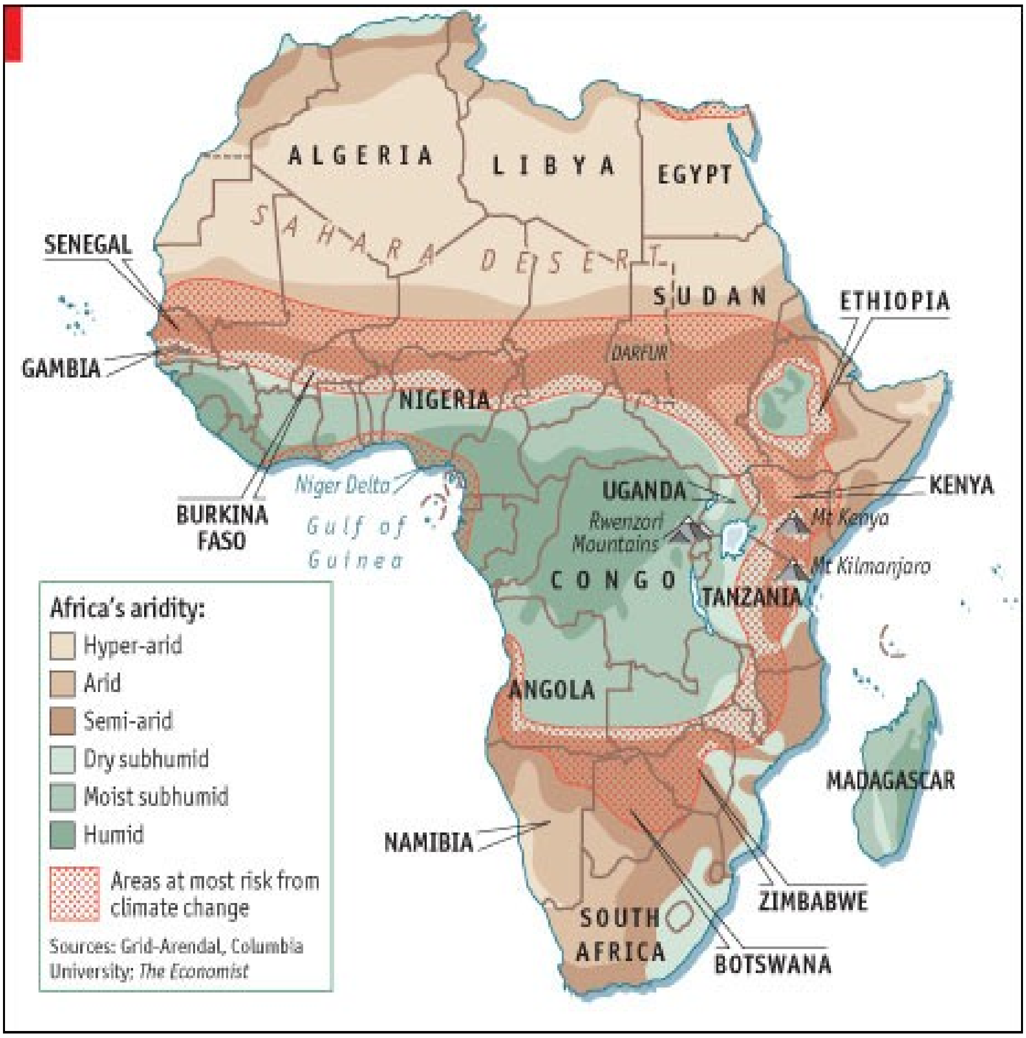

Figure 1.3: Areas vulnerable to climate change in Africa. Northern Nigeria lies in the areas that are at most risk of climate change (Adapted from: Grid-Arendal, Columbia University, IRI, 2011).

1.4 Thesis organization

The thesis presents a comprehensive and up-to-date contribution to understanding the relationship between climatic conditions and climate-sensitive infectious diseases, taking into account other non-climatic effects, and using a long and reliable disease time series. Also, the research provides the first estimate of the potential risk of future climate change impact on the dynamics of the selected diseases in Nigeria, using an ensemble of simulations from the most recent state-of-the-art AOGCMs that participated in CMIP5. An outline of the thesis is given here, while chapter three will provide the details of the research design.

The thesis is divided into nine chapters from introduction to conclusion as presented in Figure 1.4. It should be mentioned here that chapter three of the thesis presents an overview of the conceptual methodological approaches, but the statistical methodologies used are specified separately in individual result chapters.

Chapter one gives a brief overview of the research context, research problem, aims and objectives and the scientific need to conduct the study. The second chapter gives a review of the literature on the quantification of relationships between climate and selected diseases in the present day and future potential risks. In addition to what is mentioned above, chapter three presents details of the region under investigation and descriptions of all the data and methods used. Chapter four discusses the physical processes, trend, and variability of the climate of the region, while chapter five presents an analysis of the spatial and time characteristics of the selected diseases in Nigeria.

Chapters six and seven present the results of modelling the climatic influences on the interannual variability for meningitis and cholera respectively. Suites of empirical statistical models are developed in these chapters for explaining and predicting these diseases, with a lead of one month. Chapter eight presents projection results of the potential risk of the diseases in both the near and far future, using models specifically designed for climate change studies from the preceding chapters, and the ensembles of climate model simulations from AOGCMs that participated in CMIP5. The final chapter provides summary of findings, limitations, recommendations for further research, and suggested applications of the research.

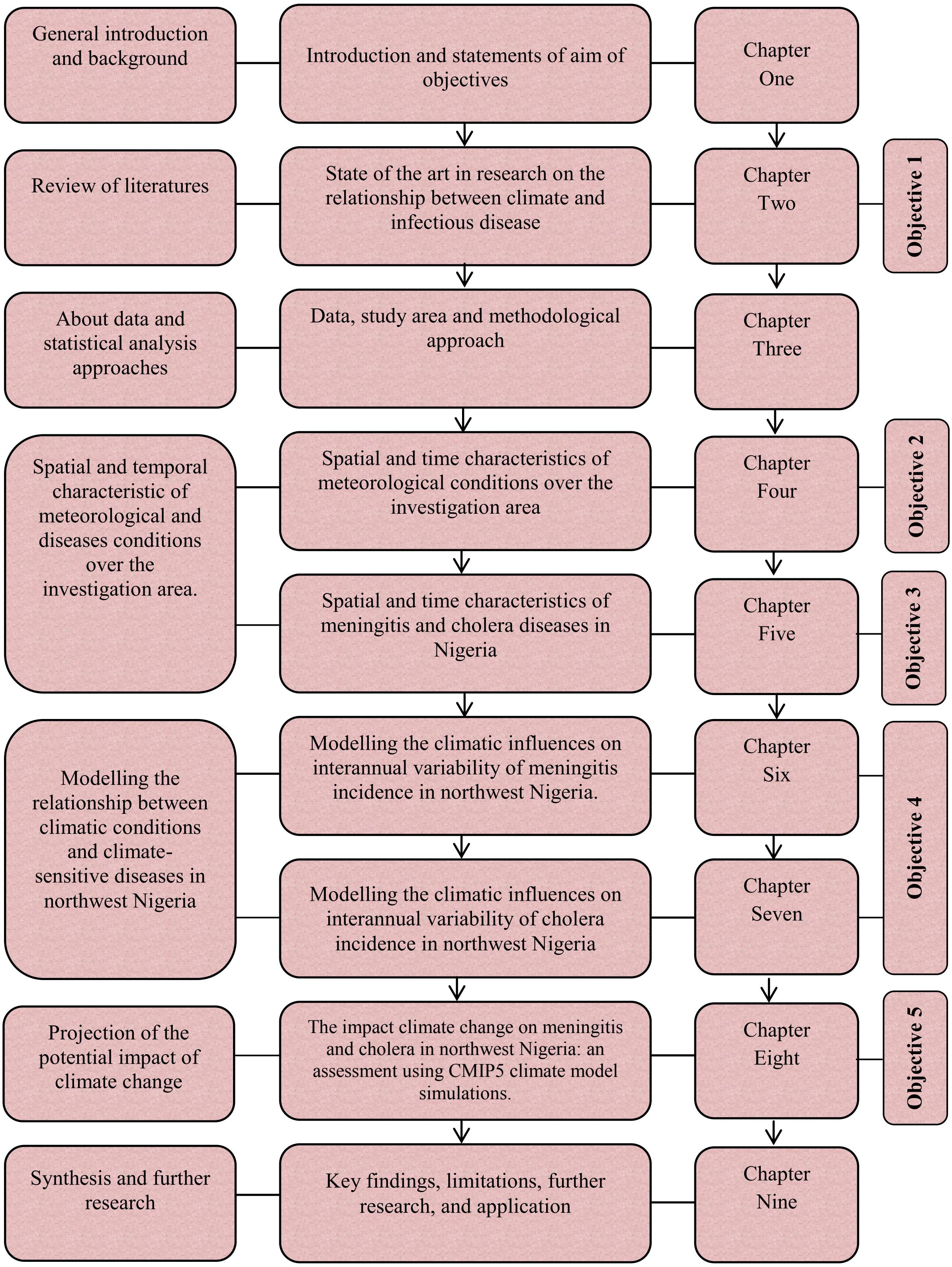

Figure 1.4: This figure shows the stages of the research by chapters and objectives.

Chapter Two:

Literature Review: Recent Research on the Relationship between Climate and Infectious Diseases

Chapter Two

Literature Review: Recent Research on the Relationship between Climate and Infectious Diseases

2.1 Introduction

The impact of climate change on human health was first mentioned briefly in the first IPCC AR1 (IPCC, 1990). In the second report (IPCC, 1996) a whole chapter was dedicated to health (McMichael et al., 2003). Since then there has been a plethora of research and policies on how climate change will affect infectious diseases, particularly malaria, dengue, diarrhoeal diseases, cholera and meningitis. Most of these studies have focused on developed countries (Kelly-Hope and Thomson, 2008). However in the past decade, a number of these studies have been carried out in African countries (e.g., de Magnay et al., 2012; Fernendez et al., 2009; Thomson et al., 2006; Yaka et al., 2008). More quantitative studies in specific regions (Grasso et al., 2012) that use long-term reliable data and consider non-climatic factors need to be carried out in Africa. They are particularly urgent in countries that have been neglected by such studies, like Nigeria (Kelly-Hope and Thomson, 2008), which has a large population, high regional political relevance, a high burden of infectious diseases, and faces a potential risk of climate change.

This chapter addresses objective one of this thesis as illustrated in Figure 1.4. Section 2.2 discusses issues related to data quality and analytical techniques with regard to the quantification of climate-disease relationships. Sections 2.3 to 2.6 review existing studies that investigate the relationships between climatic conditions and infectious diseases and the potential to predicting them, with particular reference to meningitis and cholera. Section 2.7 reviews the observed changes in climate and its impacts on infectious diseases, while 2.8 and 2.9 discuss the future risk of infectious diseases under climate change and the fundamental issues of uncertainties associated with the estimates. Finally, section 2.10 highlights the research gaps identified in the review.

2.2 Methodological approaches and related issues in quantifying relationships between climate and diseases

This section reviews relevant contributions regarding important issues on the quantification of climate-disease relationships; this includes methodological issues and data availability and quality.

2.2.1 Methodological approaches

The relationship between disease and climatic factors can be quantified by using either statistical or process-based modelling approaches. These will subsequently form the basis for future predictions of disease outbreaks (WHO, 2005a). Before this can be achieved, however, it is necessary to ensure that both disease incidence data and climate data are available at appropriate spatial and temporal resolutions and for a sufficient time period. The choice of analytical approach is informed by the nature of data and diseases under scrutiny and the availability of information about them.

Process-based models, which sometimes imply as biological or mechanistic approach, are mostly used for vector-transmitted disease (Craig et al., 1999). This model estimates how habitat suitability is influenced by environmental factors. In-depth understanding of the disease pathogen is required in order to parameterize the processes in the model. Such models have been used for the prediction and estimation of climate change impacts on malaria because of the good understanding of the disease through years of studies. For example, the Liverpool Malaria Model (LMM) (Emert et al., 2013; Hoshen and Morse, 2004) and that of dengue fever (Jetten and Focks, 1997).

The statistical approach essentially involves explaining the predictand (e.g., meningitis cases) based upon predictor(s) such as temperature and humidity, and additional potential risk factors such as vaccination (Basu and Samet, 2002). Statistical models are the mostly widely used approach in investigating relationships between climate and infectious diseases (see Table 2.1 for examples of techniques used).

Several studies have been carried out using various analytical techniques with the objectives of identifying, quantifying and assessing the roles of climate and the environment in the risk factors of infectious diseases. Statistical techniques that have been widely used in climate-disease modelling are the linear and non-linear models; these techniques are used for predicting the occurrence of disease epidemics. Chaves and Pascual (2007) investigated the suitability of both linear and non-linear methods for disease prediction in a study they conducted using historical data of monthly leishmaniasis diseases time series from Costa Rica between 1991 and 2001. Performances of all models were assessed based on their R^2 coefficient and fit based on independent data that was not included during models fit. Seasonal Autoregressive (SAR) models that incorporate climate covariates appeared to produce the most accurate forecasts.

Several studies have used linear regression models (e.g., Besancenot et al., 1997; Thomson et al., 2006; Stocco et al., 2010; Yaka et al., 2008) using different data resolutions and span (see Table 2.1 for techniques used, and 2.3 for summary of findings). For example, Molesworth et al. (2003), using gridded-base environmental variables, developed a spatial forecasting model for epidemics of meningitis in Africa. 3,281 districts were identified and grouped into similar seasonal profiles; logistic regression was used to identify the association within districts; and then stepwise multiple regressions were used for the modelling. All variables appeared to be independently associated with epidemic locations, but humidity and land cover profiles came out to be the best predictors in the final model. In what is seemingly a similar but more statistically robust study, Thomson et al. (2006) explored the potential of environmental and climatic factors in predicting the probability of meningitis epidemic occurrences. Separate land cover models were developed using stepwise multiple regression: savannah areas showed the strongest correlation. Other studies adopt the use of Poisson and logistic regression techniques for their investigations (e.g., Chou et al., 2010; Lindsay et al., 2002; Mueller et al., 2008; Paz, 2009). For example Lindsay et al. (2002) used the Poisson regression technique, taking account of population increase and the disease incubation period, to model the relationship between climatic variables and meningitis notification in Auckland, New Zealand during a disease epidemic. Temperature was the best predictor in the final model.

Artificial neural network is another option for modelling climate-disease relationships, this technique is applicable in almost every condition in which relationship between independent and dependents variables exist. This technique can be used to perform nonlinear statistical modelling and provide a new alternative to logistic regression, and is commonly used method for developing predictive models for dichotomous outcomes. Neural networks offer a number of advantages because of its ability to implicitly detect complex nonlinear relationships between dependent and independent variables; ability to detect all possible interactions between predictor variables; and the availability of multiple training algorithms. Although the method has the disadvantage of being “black box” in nature (Tu, 1996), and can have a proneness to over fitting, the method could be used in study of this nature when the predictive outcomes are dichotomous.

Table 2.1: Examples of statistical techniques used in quantifying relationships between infectious disease and climatic/environmental variables

S/N	Reference	Study Area	Method	Resolution
Meningitis				
1	Stocco et al. (2010)	Ponta Grossa-PR, Brazil	Multivariate linear regression analysis	Monthly
2	Mueller et al. (2008)	Burkina Faso	Logistic regression model	Weekly
3	Yaka et al. (2008)	Burkina Faso and Niger	Composite analysis and Multivariate linear regression	Monthly and Annual
4	Thomson et al. (2006)	Africa	Univariate and stepwise Multivariate linear regression	Monthly
5	Forgor et al. (2007)	Northern Ghana	Negative binomial regression and autoregressive term (AR) order 1 model	Weekly
6	Sultan et al. (2005)	West Africa	Mann-Whitney-Pettitt test for change detection and correlation analysis	Weekly
7	Lindsay et al. (2002)	Auckland, New Zealand	Descriptive epidemiology and Poisson regression	Weekly and Monthly
8	Besancenot et al. (1997)	Gulf of Guinea	Time series simple linear regression analysis	Monthly
9	Cheesbrough et al. (1995)	Western Zaire	By using absolute humidity map (Isohyets) of the zone and delineating the hypoendemic zone	Monthly
10	Greenwood et al. (1984)	Nigeria	Simple Correlation analysis	Monthly
Cholera				
1	Rajendran et al. (2011)	Kolkata	Seasonal Autoregressive Integrated Moving Average	Monthly
2	Hashizume et al. (2011)	Bangladesh	Time-series regression and Negative binomial models	Monthly
3	Hashizume et al. (2010)	Bangladesh	Poisson Regression Model	Weekly
4	Chou et al. (2010)	Taiwan	Time-series Poisson Regression	Monthly
5	Traerup et al. (2010)	Tanzania	Poisson Regression Model	Monthly
6	Fernandez et al. (2009)	Lusaka, Zambia	Poisson Autoregressive Model	Weekly
7	Paz (2009)	South-eastern Africa	Poisson Regression Model	Annual
8	Islam et al. (2009)	Matlab, Bangladesh	Classification and Regression Tree (CART) and Principal Component Analysis (PCA)	Monthly
9	De Magnay et al. (2007)	West Africa	Wavelet analysis	Monthly
10	De Magnay et al. (2006)	Ghana	Wavelet and Cross-analysis	Monthly

Different techniques have different advantages, so the choice of a technique should be based on the intent of the study and the expected outcome. For example, an optimal result for disease prediction could be achieved using linear regression models when both the dependent and independent variables have a linear relationship. However, this method may not be suitable for modelling data with non-linear relationships, and can only be used for predicting numerical outputs. Logistic regression and other techniques of predicting binary outcomes may be best used for the prediction of the likelihood of a disease epidemic. For predicting the magnitude of future epidemics, linear and non-linear regression, or the more sophisticated Autoregressive-Moving Averages (ARIMA) method that incorporates trends and temporal autocorrelation, might be the best option. Normal linear models might not be suitable for modelling disease data with a distribution that is skewed (Cameron and Trivedi, 1998), particularly count data, which applies to most disease data. In such cases, Poisson regression, which is part of the Generalised Liner Models (GLMs) family, has the advantage (e.g., Kinlin et al., 2009) in handling such data (Grenfell and Dobson, 1995). Compared to other normal linear models, Poisson models usually give a better estimate of data with count output, and have fewer problems of under- or over-estimation (Cameron and Trivedi, 1998). The main disadvantage of this modelling method is the assumption that the mean is equal to the variance, while in reality most distribution has a high tendency to be skewed, contrary to the Poisson assumption (Mitra and Washington, 2007). Finally, in any statistical method used, the size of the sample involved will largely determine the robustness of and confidence in the results (Knofczynski and Mundfrom, 2008). As such, climate-disease relationship studies require long and qualitative time series data in order to allow for a meaningful investigation of statistical relationships.

2.2.2 Availability and quality of data

Data quality, span, and resolution are some of the most important issues in determining the outcome of a statistical model aimed at quantifying climate-disease relationships. Basically, three types of data are involved in this kind of study: meteorological data, such as rainfall and temperature; disease data, such as surveillance data or hospitals' reported cases; and socioeconomic data that are related to the disease, such as poverty and immunity.

Meteorological data is often readily available for time series spanning several years. This is because of the availability of synoptic weather stations located in cities across the world for direct ground-based measurement. The data may have the advantage of being quality checked, but will only be representative of a small area in the vicinity of the station itself. If the targeted area has no meteorological stations, the use of this data will depend on suitable extrapolation methods. The availability of reanalysis (climate data reproduced using a systematic approach) data obviates the need for interpolation, as data can be modelled to provide proxies for standard meteorological variables (Hay and Lennon, 1999). Yet the quality of the station data needs to be checked to filter out possible human or instrumental errors, while reanalysis data have to be evaluated with available respective station data to ascertain its fidelity, most especially in areas like the West African regions where climate models are not well simulating some climatic variables like precipitation (Sylla et al., 2013).

In most cases historical epidemiological data are not readily available (McMichael, 2006) and can be expensive to compile, most especially in developing countries where national data might be totally absent, inconsistently collected, or poorly structured, due to poor surveillance systems (Alexander et al., 2013). Despite the availability of the WHO data, it worth the cost and effort to extract data from the archives of hospitals where infectious diseases cases have long being reported (e.g., Besancenot et al., 1997; Chou et al., 2010; Fernandez et al., 2009;

Hashizume et al., 2011; Islam et al., 2009), to reduce issues of uncertainties in the data due to underreporting cases for political or cultural reasons.

Climate is not the only factor that influences the spread of infectious diseases (Hay et al., 2002; Koelle et al., 2005a); as such, the climate-disease relationship needs to be assessed while taking into account multiple social data (Giorgi, 2005). The quality and availability of social data is also an issue of concern in developing countries. Some of these data might be available but not necessarily at the desired spatial and temporal resolution. For example, it is difficult to obtain detailed vaccination data, even from countries in the so called ‘meningitis belt’. Very few studies that have investigated the climate-disease relationship considered socioeconomic information in their modelling framework (Lafferty, 2009). The need to include social data alongside climate data has been emphasised (e.g., Thomson et al., 2006; Palmgren, 2009) in order to produce a more realistic result.

2.3 The relationship between climate and infectious diseases

Human understanding of the relationship between climate and diseases dates back to 384-322 BC, but the in-depth understanding of the interaction was only achieved through the fast progression of modern technology, and also the ability of man to understand the weather and climate system to the extent of forecasting and predicting the future weather and climate (WHO, 2003). Before the emergence of anthropogenic climate change, both epidemiologists and climatologists paid little attention to climate-disease relationships (WHO, 2005a). Most studies have focused mainly on investigating the risk factors for infectious diseases in individuals, not populations.

According to published research (e.g., Pascual et al., 2002; Koella et al., 2005) climate is playing a vital role in the spread of many infectious diseases. Some of these diseases include those that are capable of causing high morbidity and mortality rates. Some infectious diseases usually occur as epidemics, which are triggered by changes in climatic conditions so as to favour a higher transmission rate (Patz and Lindsay, 1999; WHO, 2003). Infectious diseases have remained the main cause of death in lower-income countries, with half of the mortality coming from countries in Africa (Murray et al., 2012). Climate has been established as a key and important player in determining the transmission, trend, and distribution (e.g., Hay et al., 2002; Koella et al., 2005; Patz, 2005) of infectious diseases. The influence and role of climate on the interannual variability, outbreak, and epidemics are discussed extensively by WHO (2005a) in their report on using climate to predict infectious diseases.

This emphasises the importance of climate information in explaining the dynamics of some infectious diseases (Connor et al., 2006) that exhibit a distinct seasonal pattern (Kelly-Hope and Thomson, 2008), and encourages the investigation of the link between some infectious diseases, such as malaria (e.g., Ceccato et al., 2007), cholera (e.g., Cash et al., 2009), and meningitis (e.g., Dukic et al., 2012). Most of these studies aim to predict diseases on different time-scales (seasonal to interannual): however, it is essential to start by investigating the influences of climate on the interannual variability of these diseases as recommended by Thomson et al. (2004). A detailed review of studies on the relationship between climate and selected infectious diseases is presented in the subsequent sections of this chapter

In the past, several studies have investigated the relationship between climatic conditions and infectious disease. Most of these have taken place in Asia, but a number of studies have been conducted in West Africa (e.g., de Magney et al., 2006). Despite these efforts to understand the climate-disease relationship, there is still a scientific need to study the driving factors behind these diseases in specific regions (Grasso et al., 2012), most especially those which experience the greatest burdens due to these diseases. Understanding the specific climatic and social risk factors that are driving the transmission and outbreak of these diseases is of great importance, because this will help authorities in the allocation of both human and financial resources in their efforts to control outbreaks (Mabaso et al., 2007).

2.4 Relationships between climatic and socioeconomic conditions for meningitis

2.4.1 Meningitis and its epidemiology

A strictly human pathogen, *Neisseria meningitidis* is a gram-negative *diplococcus* that mainly causes meningitis (Rosenstein et al., 2001; Schuchat et al., 1997). Despite the existence of several bacteria that can cause meningitis, this bacterium can cause large epidemics (WHO, 2012a). The associated symptoms of meningitis may include headache, fever, vomiting and a stiff neck.

Bacterial meningitis is a communicable disease that has high rates of fatality; it is contagious between people via the respiratory droplets of an infected person. *Neisseria meningitidis* is a common inhabitant of the mucosal membrane of the nose and throat. Up to 5-10% of a population may be asymptomatic carriers (WHO, 2011b). The occurrence of the disease in both epidemic and endemic cases causes a lot of illness and death; it may also result in persistent neurological defects, particularly deafness, paralysis, loss of limbs, and possibly mental retardation (WHO, 2010).

The disease mostly affects children (Hodgson et al., 2001), but during epidemic periods adults are also affected. The incubation period is about 2–10 days, (but normally 3 days). Meningitis was considered globally to be a fatal disease from the time it was first explained by Vieusseux in 1860 up to the early 20th century, when penicillin and sulphonamides made the disease curable (WHO, 2010). Despite this treatment and controlling strategy, the mortality and morbidity caused by the disease still remain high (Schuchat et al., 1997).

Meningitis usually shows a highly seasonal and epidemic pattern in sub-Saharan Africa. The disease is a major public health burden in several countries around the world (Peltola, 1983), but its magnitude is more profound in Africa, mainly in the Sahelian region (Figure 2.1). This is recognised as the meningitis belt by Lapeyssonnie (1963: see also Greenwood, 2006; Harrison et al., 2009; Molesworth et al., 2002). Excluding epidemics, the WHO estimates that at least 1.2 million cases of bacterial meningitis occur every year, of which 135,000 are fatal. Approximately 500,000 of these cases, 60,000 disabilities and 50,000 deaths are due to *Neisseria meningitidis.* Of these figures, 250,000 cases, 27,000 deaths and 16,000 disabilities are from Africa (Tikhomirov et al., 1997; Hodgson et al., 2001). In the meningitis belt, the disease usually occurs in a seasonal cycle between November and June, varying according to the location and climate of the country; it then subsides rapidly with the start of the rainy season. The disease has a distinct seasonal pattern, signalling that certain environmental and meteorological factors may be playing an important role (Cheesbrough et al., 1995; Greenwood, 1999; Molesworth et al., 2003).

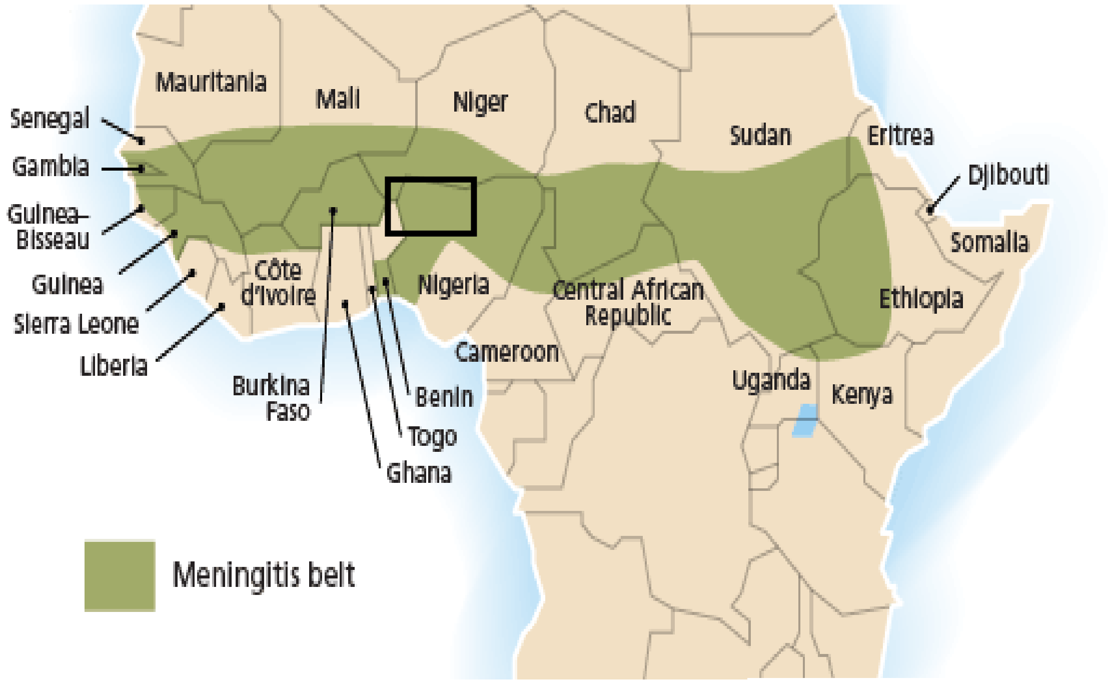

Figure 2.1: Map of Africa showing the Meningitis Belt. Adapted from: (WHO Working Group 1998)

2.4.2 Meningitis and climate

In sub-Saharan Africa, where major epidemics of meningococcal meningitis have been regularly occurring since the beginning of the century, nearly all outbreaks start during the dry season, and subside with the increase of humidity and the onset of rainfall. Several studies have revealed the relationship between climatic variables and the incidence of meningitis (Cheesbrough et al., 1995; Sultan et al., 2005; Thomson et al., 2006; Yaka et al., 2008; Palmgren, 2009): see table 2.2 for a summary of findings. Molesworth (2003) reported that dust, land-cover, absolute humidity, rainfall profiles, and population densities are individually correlated with the geographical location of the epidemics. Sultan et al. (2005) found similarity in the seasonal patterns of both Harmattan wind and the disease cases, with a strong association between the onset of an epidemic and the week of winter maximum. Mueller et al. (2008) established correlation with humid climate, and Thomson et al. (2009) noted a correlation with dust. Besancenot et al. (1997) agree with the popular view that meningococcal meningitis has a strong relationship with climate, but disputed the earlier findings that meningitis is reported entirely in the wake of the Harmattan wind, for the reason that the major peaks of the disease generally occur after and not during the main Harmattan season. Instead, in March, when the dry wind blows with a lower regularity, absolute humidity increases and temperatures are high both day and night. Harmattan is a dry and dusty West African trade wind. This north-easterly wind blows from the Sahara into the Gulf of Guinea between the end of November and the mid of March. The wind is strengthened by a low-pressure centre over the north coast of the Gulf of Guinea and a high-pressure centre located over north-western Africa in winter and over the adjacent Atlantic Ocean during other seasons. In some countries in West Africa, the heavy amount of dust in the air can severely limit visibility and block the sun for several days and risks public health by increasing the risk of lung-related diseases such as asthma. During the period of Harmattan, humidity drops to as low as 15 percent, causing spontaneous nosebleeds for some people, which consequently may aid in increasing the risk of transmission of meningitis and becoming invasive.

The peak of meningitis incidence has been found to correlate significantly with the highest mean temperatures, and to correlate inversely with absolute humidity and rainfall (Greenwood, 1984 and 1999; Moore, 1992), a finding consistent with Forgor et al. (2007) and Dukic et al. (2012). The latter projects studied Northern Ghana, and their models showed a concurrent weekly increase in maximum temperature and concurrent weekly decrease in total rainfall both significantly influencing the risk of meningococcal meningitis.

Table 2.2: Summary of findings from some studies that relate climatic variables to the epidemic or incidence of meningitis diseases. Almost all the findings show strong relationships.

S/N	Reference	Study Area	Variables	Summary of findings
1	Stocco et al. (2010)	Ponta Grossa-PR, Brazil	Temperature, Humidity, and Precipitation	Strong correlation was reported in the months of January and February (months with highest temperature and precipitation).
2	Yaka et al. (2008)	Burkina Faso and Niger	Wind velocity, Surface temperature, Sea level pressure and Relative humidity.	The relationship is clear in Niger and weak but significant in Burkina Faso.
3	Mueller et al. (2008)	Burkina Faso	Air humidity	Humid climate may favour carriage of unencapsulated meningococci.
4	Forgor et al. (2007)	Northern Ghana	Relative humidity, Temperature, number of haze days, and rainfall	Temperature and airborne dust shows a clear association. Meningitis risks are highest at the hottest time of the year, when dust exposure has already been accumulating for several weeks.
5	Thomson et al. (2006)	Africa	Soil and land cover type, aerosol index, vegetation greenness, cold cloud duration, and rainfall.	The most consistent predictants of anomalies in meningitis incidence were anomalies in rainfall and anomalies in dust.
6	Sultan et al. (2005)	West Africa	Large-scale atmospheric circulation	Strong relationship between climate and the seasonal pattern of meningitis. Strong correlation between the winter maximum and epidemic onset.
7	Lindsay et al. (2002)	Auckland, New Zealand	Temperature, rainfall, and sunshine	Occurrences varied with season, and significant relationship between the expected number of cases on a given day and season and temperature.
8	Besancenot et al. (1997)	Gulf of Guinea	Temperature, humidity, vapour pressure and dust haze (yes/no)	The risks increase in seasons and places where the absolute humidity reaches its lowest values, but they disagree with earlier findings that meningitis is completely in the Harmattan wake.
9	Cheesbrough et al. (1995)	Western Zaire	Absolute humidity, temperature, and pressure	High absolute humidity found in Congo basin appears to correlate with absolute humidity by preventing disease transmission in the zone.
10	Greenwood et al. (1984)	Nigeria	Temperature, humidity, and Harmattan dust.	A strong positive correlation with maximum temperature and a weaker, but significant, negative correlation with absolute humidity and rainfall.

Although the mechanisms by which climatic factors influence meningitis are still not well understood, it is assumed that increased concentrations of dust, high winds, elevated temperatures and low humidity may cause damage to the nasopharyngeal mucosa (WHO, 2012a), thereby increasing the risk of meningitis. In northern Nigeria, it could be hypothesised that during the prolonged dry season, the season normally starts with ‘cold dry’ months (Nov – Jan): this encourages the occurrence of diseases with meningitis risk factors such as influenza (Cartwright, 1995) and pneumonia (Dukic et al., 2012) that may aid susceptibility to meningococcal bacteria carriage and transmission through respiratory droplets. This may culminate with the development of invasive disease during the ‘hot dry’ months (Feb – May) (see Figure 2.2). It has been explained that the combination of hot, dry, and dusty weather may cause the microtrauma of the nasal mucosa (Burgess and Whitelaw, 1988) to damage. This damage may make it possible for the meningococcal bacteria to penetrate the nasopharyngeal membrane and consequently get into the bloodstream thereby causing invasive disease. This may explain why reporting of meningitis cases is high during the ‘hot dry’ period. These previous efforts to link climatic conditions to meningitis incidence suggest the possibility of predicting meningitis outbreaks using environmental information. A summary of some studies that attempt to explain incidences of meningitis as a function of climatic variables are presented in Table 2.2.

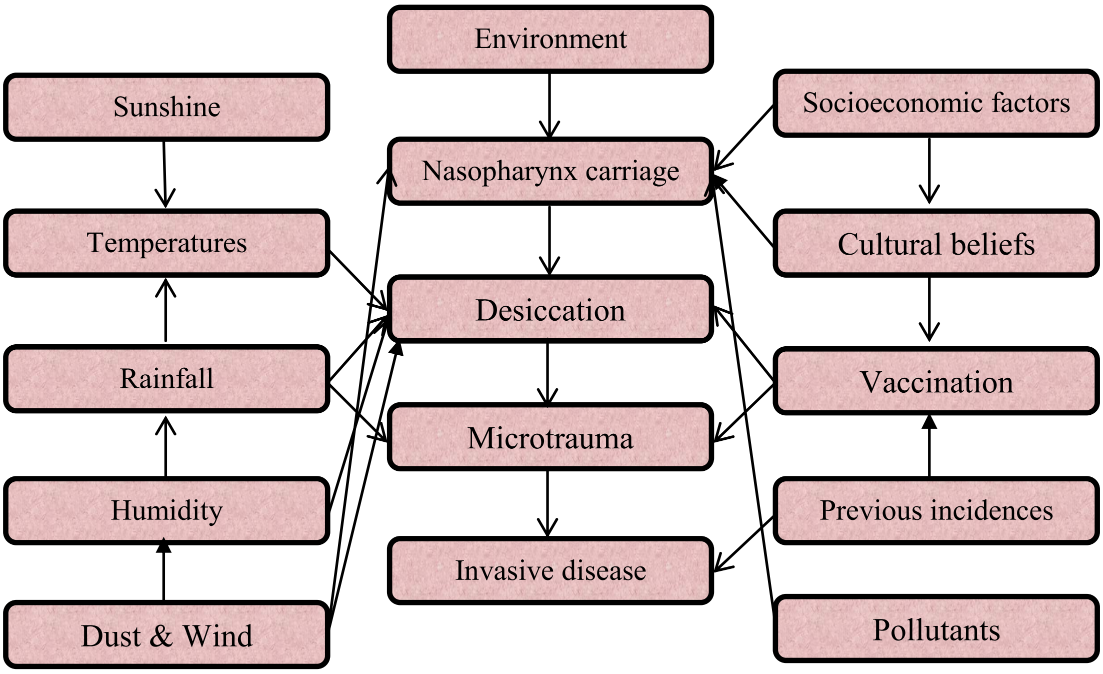

Figure 2.2: Causal web illustrating how climatic and non-climatic factors may affect the transmission and development of invasive meningitis. The arrows are showing how factors are related to each other and to each step of disease development (from the environment to becoming invasive).

Other non-climatic factors may also play important roles in the risk of meningitis transmission (Figure 2.2). Among these factors are: socioeconomic, cultural, and behavioural practices; and migration. Previous studies have established the association between non-climatic factors and meningitis risk: for example, previous incidences of other upper respiratory tract infections (URTIs) such as pneumococcal pneumonia (Moore et al., 1990), exposure to smoke from cooking fires (Hodgson et al., 2001), overcrowding (Brundage and Zollinger, 1987), disco patronage (Cookson et al., 1998), and smoking (Fischer et al., 1997). In order to attain precision in explaining and possibly predicting any kind of climate-related disease epidemic, climatic variables should where possible be jointly used with other non-climatic factors as explanatory variables (Thomson et al., 2006; Palmgren, 2009).

2.4.3 Meningitis in Nigeria

An extensive part of Nigeria lies within the meningitis belt (Figure 2.1). The first epidemic of meningitis from this country was reported by a British colonial medical officer in the British Medical Journal (McGahey et al., 1905). The disease primarily affects the country during the dry months, beginning with the Harmattan in November and continuing through May with peak incidence during the hottest months of March and April. During the 1996 epidemic, for example, Nigeria alone reported over 100,000 cases and 11,000 deaths to the WHO (Mohammed et al., 2000), which is almost half of the total cases reported from the 25 countries within the belt. 93% of these cases and deaths were reported from the northern part of the country, especially in states like Bauchi, Jigawa, Kano, Kaduna, Katsina, Kebbi, and Sokoto (NCDC, 2012), where there is a more pronounced dry season than in the south, and where the disease normally occurs each year. Meningitis in northern Nigeria is known in the native Hausa language as *"Sankarau"*, literally meaning "the disease of stiffness", obviously named because of the stiff neck often associated with the disease, caused by inflammation of tissues that surround the brain and the spinal cord (WHO, 2010). Anecdotal evidence suggests that many people in northern Nigeria believe that the disease is caused by the intense heat usually experienced during disease outbreaks. In Nigeria, meningitis transmission may be influenced by many factors apart from climate, such as socioeconomic and cultural practices. In the cities, areas mostly occupied by low-income earners are densely populated with many people per household, and most use wood as their source of cooking fuel. Based on previous studies such as, e.g., Hodgson et al. (2001), people living in these areas are likely to be at higher risk and more vulnerable to the development, carriage and transmission of invasive meningitis.

For the past thirty years meningitis in Africa and Nigeria in particular, has been occurring in sporadic cases, outbreaks, or large epidemics (Greenwood, 2006) mainly caused by serogroup A (Greenwood and Stuart, 2012; Riou et al., 1996). Until recently the only strategy for controlling the disease has been through reactive mass vaccination campaigns after a certain case threshold is crossed (WHO, 1998), using polysaccharide A vaccine; and sometimes through special campaigns intended for religious pilgrims (NPHDA, 2011). Although the efficacy of this vaccine has been established, it is expensive, and has a short period of effectiveness (Wahdan et al., 1973). The introduction of the polysaccharide protein conjugate A vaccine (Roberts, 2008) brings hope for controlling the disease. The new vaccine will not only provide longer protection, but will also prevent the disease (WHO, 2012a); i.e. a whole population can be vaccinated proactively before meningitis epidemics are detected. Another advantage of the conjugate vaccine is carriage prevention (Maiden et al., 2008; Vestrheim et al., 2010). Despite these advantages, since the conjugate vaccine is serogroup A specific (Greenwood and Stuart, 2012) other serogroups like W135 (Decosas and Koama, 2002) and C (Broome et al., 1983) might continue to circulate, increasing the risk of epidemics (Koumare et al., 1993). These other strains could be introduced by travellers from outside regions (Lingappa et al., 2003).

The new conjugate A vaccine was recently administered in Nigeria in 2011 (National Primary Health Care Development Agency (NPHCDA), unpublished report). The vaccine was administered between December 5th and 14th 2011, during Phase 1 (out of 3) of the campaign, which focused on the population group spanning 1–29 years of age in five northern Nigerian states: Bauchi, Gombe, Jigawa, Katsina, and Zamfara.

2.5 The relationship between climatic and socioeconomic conditions with cholera

2.5.1 Cholera and its epidemiology

A human pathogen bacterium (Marin, 2013), *vibrio cholarea* is a gram-negative bacillus that causes cholera disease (Charles and Ryan, 2011) depending on the amount of toxigenic ingested into the intestine (de Magney and Colwell, 2009). Despite the existence of over 200 serogroups (Marin, 2013; Morris, 2003), epidemic of this acute diarrhoeal disease is mainly caused by two; *vibrio cholarea* O1 and O139 (Charles and Ryan, 2011; Harris et al., 2012; Marin, 2013). In recent times, newly-observed strains capable of causing more intense morbidity and mortality have been found in numerous parts of Africa and Asia (WHO, 2012b). The symptoms of the disease include profuse diarrhoea, vomiting (Kanungo and Sur, 2012) and consequently progressive dehydration (Mari et al., 2012), which if not treated appropriately can be fatal within an hour (WHO, 2005b). The disease can be easily treated through oral rehydration, but severely dehydrated patients will require intravenous fluid administration and antibiotics.

Cholera is highly contagious (de Magney and Colwell, 2009). The transmission of the disease is related to sanitary conditions and environmental management. Infected patients may get rid of the organism within a few days, although if patients become asymptomatic this may take longer (Nelson et al., 2009; Weil et al., 2009). Only about 25% of people who contract *vibrio cholarae* may be asymptomatic (WHO, 2011d) but the danger of transmission remains; this is because they will transmit the bacteria back into the environment, through their faeces. Cholera transmission within households has been established (Weil et al., 2009). The organisms could be found in human stools, and where there are inadequate sanitary conditions they could be re-introduced (Harris et al., 2012) into uninfected individuals. In favourable conditions such as places with unhygienic sources of drinking water and improper sewage disposal, cholera may be transmitted easily and rapidly, which may lead to a Case Fatality Ratio (CFR) of up to 50% (WHO, 2012b). Transmission could be through the faecal-oral medium, in most cases through consumption of contaminated water and to some extent food (PHE: Public Health England), 2013). Cholera is a threat particularly in areas where sanitary conditions such as safe drinking water and proper sewage conditions are not available (Marin, 2013). Human mobility could enhance the dispersion mechanism of cholera (Righetto et al., 2011), and this can facilitate the long-distance spread of the disease pathogen away from the epidemic location (Bertuzzo et al., 2011; Chou et al., 2010; Mari et al., 2012; Tuite et al., 2011; WHO, 2012b). This dispersion could also be propagated through river channels (Akanda et al., 2009).

The use of an oral vaccine to control cholera both in endemic and epidemic conditions have been recommended (WHO, 2012c). *Dukoral* and *Shancol* are the safest and effective oral vaccines evaluated and licensed by the WHO. The first can provide protection for up to six months in all age groups, while the latter can provide longer protection for children under the age of five. The vaccines are effective for 2–3 years with up to 85% protection (Harris et al., 2012), but this immunity span could be less in children. Natural infection with *vibrio cholarae* may provide protection for up to 3 years (Kanungo and Sur, 2012).

Since the seventh pandemic, the reported number of cholera cases is on the increase (Marin et al., 2013; WHO, 2011d). According to WHO over 50 countries are currently cholera endemic (WHO, 2012c). Annually there are an estimated 3–5 million cases and over 100,000 deaths due to cholera (WHO, 2012b) with most of the cases reported (Figure 2.3) from Africa and Asia (Harris et al., 2012). In Africa, cholera cases and deaths are reported to be increasing both in severity and number, most especially in countries like Nigeria (Marin, 2013). Statistics of WHO reported cholera cases suggest that Africa is the ‘new home’ for cholera

(Gaffga et al., 2007). The endemic nature of cholera (Harris et al., 2012; Lipp et al., 2002) makes it one of the major public health threats in these countries (Emch et al., 2008), where the environmental and food hygiene tradition remains grossly insufficient. Over 90 percent of both 221,226 cases and 4,999 deaths of cholera cases reported to WHO in 2009 were from Africa. In 2010 and 2011, Nigeria alone reported over 46,700 (1840) and 23,000 (700) cases and deaths from cholera respectively.

The World Health Organisation's projection (WHO, 2011c) of the health burden attributable to diarrhoeal diseases for sub-Saharan Africa predicts an increase in the relative number of incidences. This is despite the expected socioeconomic development and improvement in the provision of safe drinking water and sanitation. New, and apparently, more virulent strains of *Vibrio cholerae* 01 have emerged and now predominate in parts of Africa and Asia (WHO, 2012b).

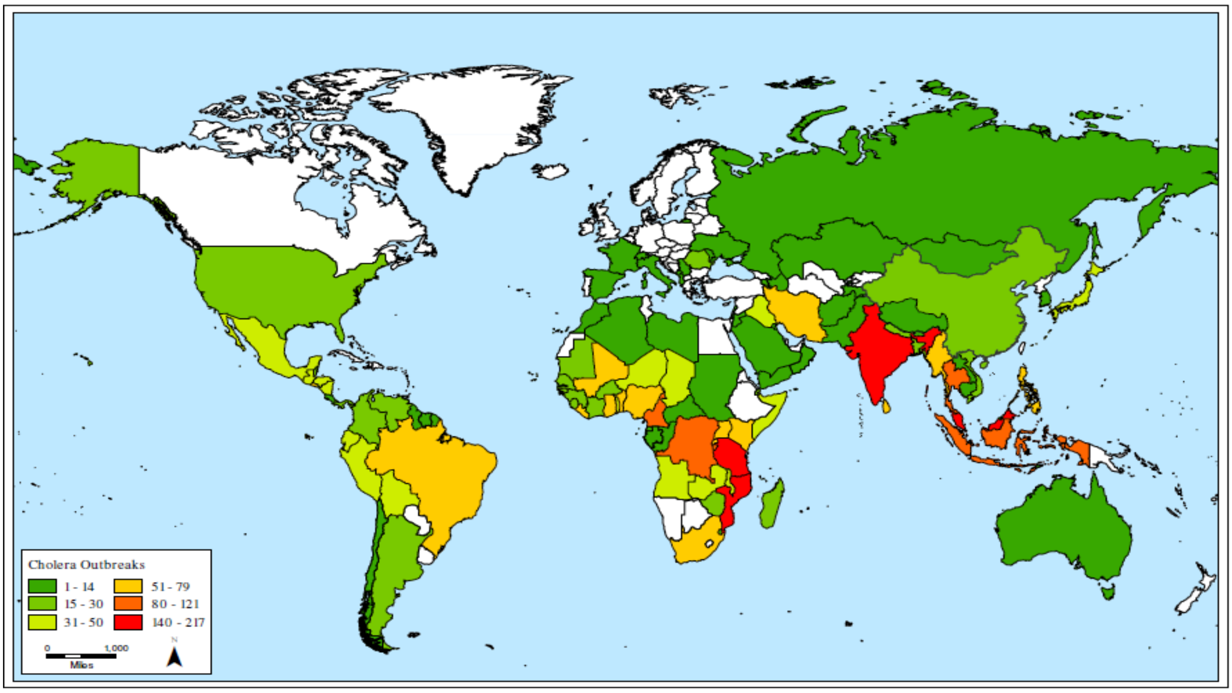

Figure 2.3: Map showing the number of cholera outbreaks reported per country between 1974 and 2005 (Source: Emch et al., 2008)

2.5.2 Cholera and climate

Cholera has a notable seasonality (Pascual et al., 2002) that is influenced by environmental factors (Harris et al., 2012; Lipp et al., 2002; Pascual et al., 2000; Rajendran et al., 2011), although these seasonal characteristics may vary with location. The annual variability (Koelle, 2009) of the disease may also be related both to variability in climate and diminishing levels of population immunity developed from preceding epidemics.

The influence of climate on the cholera dynamic has been well established in Asia (e.g., Bouma and Pascual, 2001; Pascual et al., 2000), South America (e.g., Colwell, 1996; Speelmon et al., 2000), and in Africa (e.g., de Magnay et al., 2012; Fernendez et al., 2009; Trearup, 2010). The link between temperature increase and the amplification of cholera incidence have been well reported (Colwell, 2002; de Magney et al., 2008; Lipp et al., 2002; Louis et al., 2003). Also, cholera outbreaks are characterised by strong seasonality corresponding with heavy rainfall and warm temperatures (Reyburn et al., 2011). Islam et al.

(2009) reported significance of temperature and sunshine hours to cholera outbreaks both in summer and winter seasons in Matlab, Bangladesh, while rainfall and associated river levels were found to have influence on cholera patterns in Bangladesh (Akanda et al., 2009; Hashizume et al., 2007). Cholera is also associated with regional environmental forces such as El-Nino Southern Oscillation (ENSO) (Bouma and Pascual, 2001; Cash et al., 2009; Koelle et al., 2005b; Pascual et al., 2000; Rodo et al., 2002). In Ghana, de Magnay et al. (2007) report an association between temporal patterns of cholera cases and regional climatic parameters. Paz (2009) found a significant link between cholera incidence, temperature variability and sea surface temperature (SST) both at regional and at hemispheric scales.

Table 2.3: Studies that relate climatic/environmental variables to the epidemic or incidence of cholera. Almost all the findings show strong relationships.

S/N	Reference	Study Area	Variables	Summary of findings
1	Hashizume et al. (2011)	Bangladesh	Indian Ocean Dipole	Both negative and positive dipole events are associated with an increased incidence of cholera
2	Rajendran et al. (2011)	Kolkata	Humidity, temperature and rainfall	Heavy rainfall correlate with cholera infection while temperature does not
3	Hashizume et al. (2010)	Bangladesh	Temperature and rainfall	Seasonal variation in temperature and rainfall has positive relationship with cholera incidence
4	Chou et al.(2010)	Taiwan	Relative humidity, maximum temperature and extreme rainfall.	Maximum temperature and extreme rainfall days were strongly related to diarrhoeal-associated morbidity
5	Traerup et al. (2010)	Tanzania	Temperature, rainfall and socioeconomic data	Significant relationship between temperature and cholera cases
6	Fernandez et al. (2009)	Lusaka, Zambia	Temperature and rainfall	Seasonal trend for cholera incidence was consistent with the rainy season
7	Paz (2009)	South-eastern Africa	Air and sea surface temperature (SST)	Annual mean air and sea surface temperatures had significant impact on the cholera incidence at both the local and hemispheric scales
8	Islam et al. (2009)	Matlab, Bangladesh	Temperature, humidity, and sunshine	The synergetic effect of temperature and sunshine hours provided the highest number of cholera cases.
9	De Magnay et al. (2007)	West Africa	Rainfall and the Indian Ocean index (IOI)	Large and regional scale climate variability influences both the temporal dynamics and the spatial synchrony of cholera epidemics
10	De Magnay et al. (2006)	Ghana	Sea level atmospheric pressure and the Indian Ocean index (IOI)	Strong statistical association was reported

Extreme events like flooding and drought may also increase the risk of cholera, although Carrel et al. (2010) found no significant correlation between high cholera incidence and households residing in flood control areas in Matlab, Bagledesh. Contamination of drinking water may be caused by heavy monsoon floods, on the other hand drought may help to facilitate the growth of bacteria in ponds and rivers. Natural disasters like floods, earthquakes, storms, and drought are usually related to an increasing risk of water-borne infectious diseases (Watson et al., 2007). For example, the Haitian earthquake on January 12th 2009 led to a cholera epidemic (Farmer et al., 2011). A summary of studies that attempt to explain the incidence of cholera as a function of climatic and environmental variables are presented in Table 2.3.

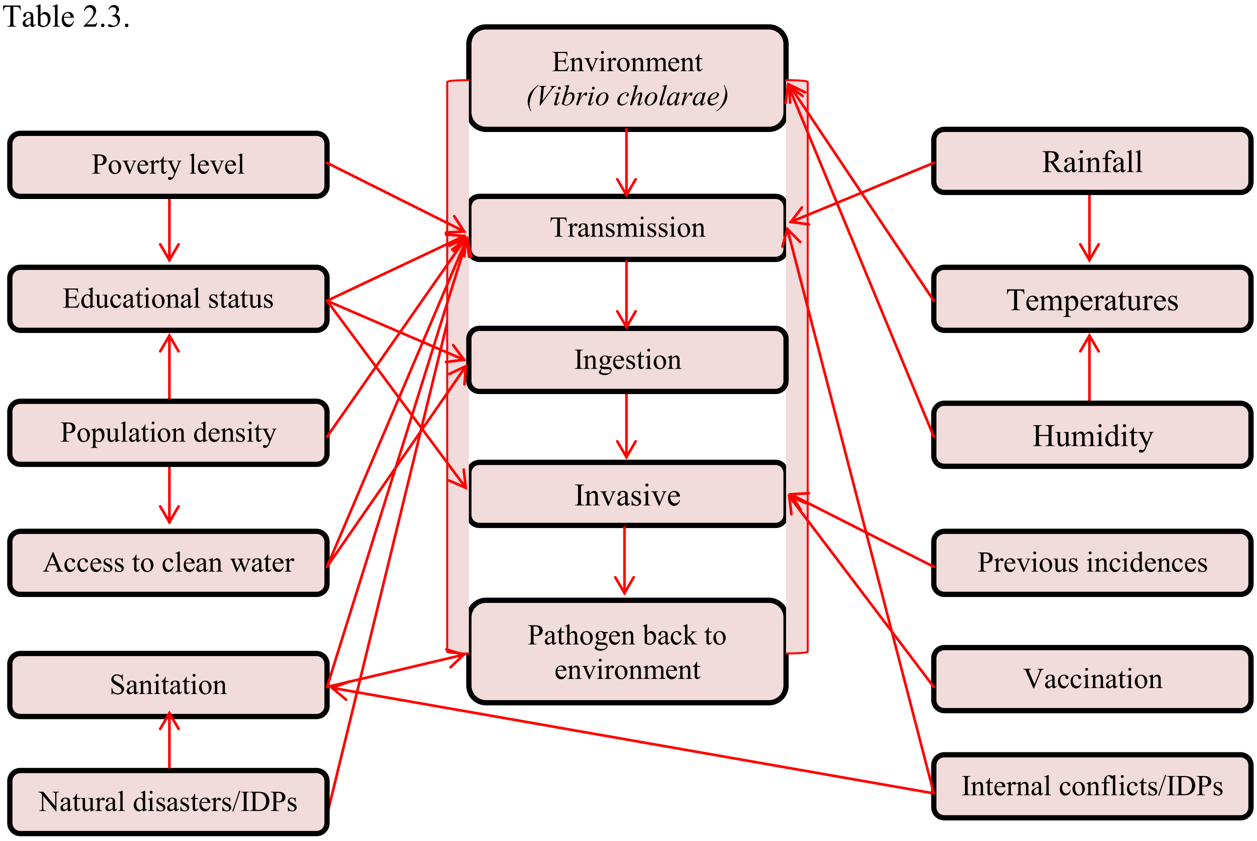

Figure 2.4: Causal web illustrating how climatic and non-climatic factors may affect the transmission of cholera pathogens. The arrows are showing how factors are related to each other, and to each step of the disease's development.

Social risk factors are also playing an important role in the transmission and outbreaks of cholera (e.g., Hashizume et al., 2007). Figure 2.4 illustrates how both climatic and non-climatic factors may affect the transmission of cholera pathogens. A study on cholera transmission in Mexico between 1991 and 1996 reveals high poverty and low level of infrastructure were the most important factors for cholera outbreak prediction (Borroto et al., 2000). Ali et al. (2002b) identify poor educational levels and population density as the most important factors in explaining the disease in Bangladesh, while in Vietnam, Kelly-Hope et al. (2007), using the multiple regression method, investigated the link between10 years of national surveillance data for cholera and some selected environmental variables. This study showed that cholera incidence is related to rainfall, urban poverty, and public well drinking water, with more cases along the coastal areas. In a closely related study, Hashizume et al. (2007), using weekly climate data and number of hospital visits, reported an increase in the number of non-cholera diarrhoeal cases alongside increases in temperature, but this increase appears to be more pronounced in people with low socioeconomic and hygiene status. Another interesting study in Dar es Salaam, Tanzania, by Penrose et al. (2010), found that risk of cholera is associated with poverty and population density. Ackers et al. (1998), using country-specific cumulative cholera incidence rates between 1991 and 1995 for Latin America, also reported an association with the Human Development Index (HDI), Gross National Product (GNP) and literacy, although the correlation is weak. Cholera has been termed the ‘disease of poverty’ (Charles and Ryan, 2011; Snowden, 2008) and associated with inadequate environmental sanitation conditions and untreated drinking water (Penrose et al., 2010; Rajendran et al., 2011; Reiner et al., 2012; Talavera and Perez, 2009).

2.5.3 Cholera in Nigeria

Nigeria has a number of infectious diseases; one that still remains a threat to public health is cholera, since the seventh pandemic reached the continent of Africa in the 1970s. The first reported cases of cholera in Nigeria were in 1971 in a village near the then capital city, Lagos, which resulted in a severe epidemic in which 22,931 cases and 2,945 deaths were recorded (WHO, 2013b). In 1991 nearly 59,478 cases and 7,645 deaths were reported (WHO 2011d). According to United Nations figures in 2010, over 1,555 have died from cholera in Nigeria and nearly 40,000 have been infected, in the country's worst outbreak for nearly two decades.

WHO data showed that Nigeria reported 393,614 cases and 22,664 deaths between 1991 and 2011 - the highest figures in Africa. The disease tends to occur in sporadic, small outbreaks, and even in large epidemics. The transmission of cholera in Nigeria might be facilitated by numerous factors such as lack of access to safe drinking water, unhygienic environment, environmental disasters, literacy levels, population congestion, and internal conflicts which lead to populations being displaced to Internally Displaced Persons (IDP) camps (see figure 2.4 for causal web, and how these factors relate with each other). Provision of safe drinking water remains a serious issue of concern: this leads people, even in cities, to buy water from street vendors, which have a high risk of being contaminated. Typical areas at risk might include populations living in urban and peri-urban slums. These areas are mostly densely populated by people on low incomes, and basic infrastructure is not readily available. Despite the availability of the oral cholera vaccines, anecdotal evidence shows that this effective control method is not yet commonly used in Nigeria. The main control method is treatment through rehydration with oral salts after infection.

2.6 Predictability of infectious diseases using climate information

Understanding the distribution and seasonality of many infectious diseases allowed the possibility of using climatic and environmental information in the development of models, with the potential to predict disease epidemics. For example, in 1923, Gill developed a statistical model for predicting malaria. He considered rainfall, economic conditions, and epidemic potential (Gill, 1923). Although the model does not define the epidemic threshold, it was used for epidemic projection until 1942 for 29 districts in Punjab, India. This study and others that followed reveal the expediency and the potential of using climatic and environmental variables to predict disease epidemics.

The improved accuracy of climate prediction and the growing understanding of the relationship between weather and infectious diseases have encouraged the academic community to develop models capable of predicting epidemic-prone infectious diseases (WHO, 2005a), using different techniques, and at various spatial and temporal scales (e.g, Connor et al., 2008). These models are usually designed to give early warning of approaching epidemics, which is extremely useful to government and health workers as it allows them to prepare well to prevent the epidemic. The main aim of disease prediction is to inform policy makers to prepare effective intervention to handle the epidemics and possibly reduce mortality and morbidity. An example of operational disease prediction exercises is that of forecasting high or low malaria incidence anomalies in Botswana and Eritrea (Ceccato et al., 2007; Connor et al., 2008). The prediction is based on a seasonal time scale using the ensemble from Global Climate Models (GCM) and historical records of clinical malaria incidences. Areas with malaria risk and temporal patterns were identified using Principal Component Analysis, stratification, and non-hierarchical clustering techniques. Although the forecasting skill was low for other seasons, however a good skill was observed in the June, July, August season in the eastern part. In a similar project, the Highland Malaria Project (HIMAL) was put in place for malaria forecasting in Kenya and Uganda (Abeku et al., 2004). This project used selected district level disease surveillance and environmental data: good prediction accuracy was also reported from this exercise.

Recently, the University Corporation for Atmospheric Research (UCAR), in conjunction with WHO, Meningitis and Environmental Risk Information Technologies (MERIT), research clusters, and some countries from sub-Saharan Africa embarked on a meningitis prediction exercise in five African countries (Chad, Burkina Faso, Nigeria, Togo, and Benin). The aim of this exercise is to use operational weather forecasts and weekly surveillance data of diseases to predict epidemics at district level, on probability of exceeding epidemic threshold over the time scale of 10–15 days, using predictive statistical models. This information is made available in real time to field health workers to help with the effective distribution and dissemination of vaccines (UCAR, 2012). The progress of this exercise was evaluated at the 6th MERIT meeting in Accra, Ghana: health workers from Benin, Chad, and Togo reported a good forecast skill in some districts. In summary, the evaluation revealed that there is no single best model, and that the modelling strategies need to be tailored to individual countries (MERIT, 2013). The importance of including other non-climatic factors was also emphasised.

There are also other small-scale attempts at disease prediction using climate information, both at national, regional, and local levels, based on records of historical diseases incidence. Examples of these studies include: cholera (Koelle et al., 2005), meningitis (Sultan et al., 2005), dengue fever (Bartley et al., 2002), in Bangladesh, Mali, and Thailand respectively. Results from these studies are encouraging, and have the advantage of being region specific (Grasso et al., 2012), based on local meteorological information.

These studies have demonstrated the possibility of predicting some infectious diseases. However, the importance of considering the effects of social risk factors in addition to meteorological conditions in predicting the dynamics of these diseases has been pointed out (e.g., Chou, 2010; Pascual et. al., 2002; Palmgren, 2009). These factors may include migration, sanitary conditions, accessibility of safe drinking water, population density, access to healthcare facilities, and herd immunity developed from previous epidemics (e.g., Ali, 2002a; Faruque, 2005). Factors such as migration, vaccination, housing conditions, prevalence of other diseases and previous exposure to infections are also thought to have a reasonable influence on diseases epidemics from small areas to wider spatial scales (WHO, 2005b). In addition, such models need to be scrutinised before bringing them into operational use, in order to ascertain their levels of confidence and accuracy. This could be achieved through evaluating and validating the models using independent data that was not included in the initial model fitting, and also by using established validation techniques. Another important issue that needs to be addressed is the quality of disease surveillance data, most especially in developing countries (Cox and Abeku, 2007).

2.7 Observed changes in climate and its potential impact on infectious diseases

Increased concentrations of greenhouse gases have affected the earth's climate in the 20th century, and will continue to modify it in the 21st century (IPCC, 2007c). Human activity is not the only key player in the observed global warming (IPCC, 2007b), but the climate system is already committed to further warming arising from physical (e.g., Meehl et al., 2005), biogeochemical (e.g., Jones et al., 2010), socio-political (e.g., Matthews and Weaver, 2010) and infrastructural (e.g., Davis et al., 2010) inertia. In the past century, not only has the global mean temperature changed, but extremes of temperature were also reported to have changed (IPCC, 2007b), with the changes in extremes exceeding those of the mean averages. The

IPCC AR4 has projected a rise of between 1.4°C to 5.8°C in global average temperature, an increase or decrease in rainfall, and a rise of up to 0.59 metres in sea level by the end of the century. Also, extreme weather events are expected to become more frequent and intense as a result of the changing climate (IPCC, 2013; Karl et al., 1995; Semenza and Menne, 2009). Despite the small carbon emissions from Africa, the negative impact of this change will be more pronounced in this continent, as Africa has been identified as vulnerable to climate change and variability by several independent studies (e.g., James and Washington, 2013; Connor and Mantilla, 2008).

Climate change is expected to impact on human health (Ebi, 2005; WHO, 2013a). These changes may aggravate local vulnerabilities in conjunction with a complex web of other numerous drivers of the diseases (Suk and Semanza, 2011). Future changes in climate variables may increase the risk of infectious diseases, because of their sensitivity to climate (WHO, 2013a), and may also change their distribution and seasonality (McMichael et al., 2003; Patz et al., 1996). For example, warmer temperatures and changes in seasonality may influence infectious diseases by enhancing pathogen survival and development (Harvell et al., 2002). Many pathogens' processes of replication are climate-sensitive (Pascual and Dobson, 2005), of which an example is cholera – it tends to proliferate quickly in higher temperatures in water (McMichael et al., 2006). Although the potential impact of future climate change on infectious diseases is still uncertain (WHO, 2003), it is nevertheless assumed that change, in particular an increase in temperature, may change the extent of the spatial and temporal distribution range of some infectious diseases, which will consequently affect their prevalence (Epstein, 2002; 2005). The infectious diseases that are likely to be affected are those that depend on vectors from transmission such as leishmaniasis, dengue, and malaria (Patz et al., 2005). There seems to be a broad agreement about the discussions that the altitudinal shift of malaria in the East African highlands is caused by the warming climate (e.g., Epstein et al., 2001; Hay et al., 2002; Patz et al., 2002; Pascual et al., 2006). Also, some mathematical models have pointed towards an increase in malaria alongside the increase in temperature (WHO, 2003). A widely cited example is the increase in malaria cases seen during the warm and wet year of 1987 in Rwanda (Loevinsohn, 1994). An analysis of a longer time series of malaria cases by Pascual et al. (2007) reveals that warming in four highland areas which leads to suitable environment for mosquitoes has increased the cases of the disease.

There is increasing evidence that, with climate change, climate extremes such as heat events will increase in frequency, intensity, and duration (Solomon et al., 2008). Extreme weather events have both direct and indirect potential impacts on health (Greenough et al., 2001). Flooding caused by extreme rainfall may provoke water-related infectious diseases like cholera and typhoid, if the flood water becomes contaminated with human and animal waste. After heavy precipitation, storm water washes human, animal, and other waste into unprotected water sources, thereby chemically or biologically polluting the water at the point of consumption. Bridgman et al. (1995) report that the outbreak of *cryptosporidiosis* in the United Kingdom was thought to have been triggered by heavy rainfall, leading to water running across the surface of a field where cattle were grazing: this washed the cattle faeces into the water supply. Outbreaks of diarrhoeal diseases associated with water contamination like cholera, typhoid, and viruses such as hepatitis A have been linked with heavy rainfall in the USA (Schwartz and Levin, 1999; Rose et al., 2000; Curriero et al., 2001). A strong relationship with about half of waterborne disease outbreaks and extreme rainfall in the United States was reported (Curriero et al., 2001). A waterborne disease outbreak of *giardiasis* in Montana was associated with heavy rainfall (Weniger et al., 1983); so as was the waterborne disease outbreak in Milwaukee, Wisconsin, in 1993, where approximately 403,000 cases of intestinal disorders and 54 deaths were recorded (Hoxie et al., 1997).

In the tropics, diarrhoeal diseases typically peak during the rainy season: several cholera outbreaks were reported following heavy rains in 1997 in east Africa. Countries like Tanzania, Kenya, Guinea-Bissau, Chad and Somalia (Kovats, 1999) were severely affected. Contamination events were found to occur when daily rainfall levels exceeded a threshold of about 5–6cm in the Great Lakes region of Africa (Patz et al., 2008).

On the other hand, drought will affect food production and increase stress on water resources, especially in the countries of southern and western Africa (Haines and Patz, 2004). Elevated temperatures will facilitate changes in water bodies' temperature, which may increase the growth of cholera pathogens and the risk of food contamination (Rabbani and Greenough, 1999). This is most true in areas where infrastructure for storage is not available and environmental hygiene is inadequate. Meningitis has also been established to have a significant positive relationship with temperatures (Abdussalam et al., 2014a; Dukic et al., 2012). For example, anecdotal information shows that extreme temperature is aggravating the incidence of meningitis in northern Nigeria (Table 2.5).

Table 2.5: Media reports of meningitis epidemic outbreaks in northern Nigeria. All dates correspond with the hottest months of the year.

Year	Date	Reporting Media
2001	28th March	AllAfrica.com, Leadership
2002	08th March	BBC News Africa
2003	04th April	VOA News
2004	01st March	Doctors Without Borders
2005	05th April	Doctors Without Borders, Vanguard
2006	02nd May	AllAfrica.com, Punch
2007	21th April	Nil
2008	20th March	AllAfrica.com, Daily Trust
2009	05th May	Reuters
2010	29th March	The Times India, CNN, SOS Children, BBC

This impact will be more in sub-Saharan Africa, especially within the most vulnerable populations with high poverty and low coping ability (Collier et al., 2008). The magnitude of these changes may exacerbate the dynamics and transmission of climate-infectious diseases in these regions; this is because the region hosts the highest burden of infectious diseases (Murray et al., 2013).

2.7.1 Observed changes in climate and infectious diseases in Nigeria

Some studies have documented that Nigeria has already been affected by adverse ecological problems, which are directly or indirectly linked to climate change (Chindo and Nyelong, 2005; Mshelia, 2005; Ayuba et al., 2007). Odjugo and Ikhuoria (2003) have showed that climate change has already led to desertification in the northern part of the country, while Ayuba et al. (2007) reported that climate change is impacting negatively on plant species composition in north-eastern Nigeria.

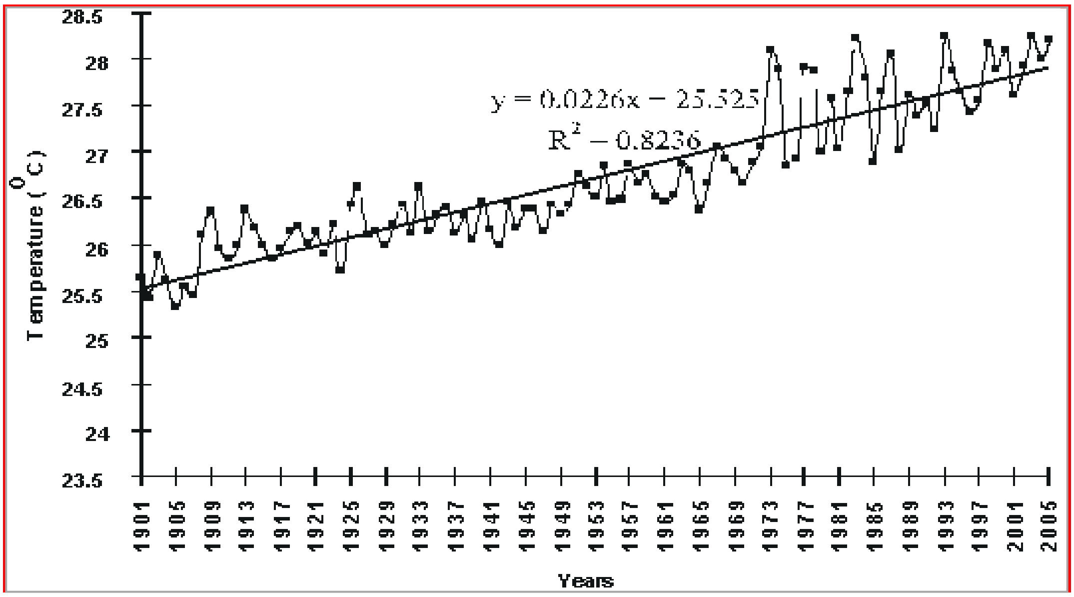

Figure 2.5: Mean annual air temperature distribution in Nigeria between 1901 and 2005. Adapted from Odjugo (2010)

In Nigeria, temperature was reported to have been on the increase since 1901 (Odjugo, 2010), with the increase higher than the global mean temperature (Figure 2.5). Many rivers and lakes in the northern part of the country have been reported to be drying up; one example is Lake Chad, which is now one-tenth of its former size (Chindo and Nylong, 2004). If this trend continues, water scarcity will lead to the concentration of users around the remaining limited sources of water. Under such circumstances, there may be increased possibility of additional contamination of the limited sources of water, and transmission of water-borne diseases like cholera, typhoid fever, guinea worm infection and river blindness will be enhanced. According to Building Nigeria Research on Climate Change (BNRCC, 2012), projected increases in heat events due to climate change may increase incidences of meningitis, which today is found to correlate positively with the highest maximum temperature (BNRCC, 2012).

Northwest Nigeria lies in one of the areas identified as more at risk of climate change (Diffenbaugh and Giorgi, 2012), and is projected to be disproportionately impacted (Suk and

Sumenza, 2011) due to the countries' large and often vulnerable populations. Northwest Nigeria may be particularly vulnerable to climate change because of its physical and socioeconomic characteristics. The region suffers badly from several critical issues of human and infrastructural development that require urgent attention: these relate to widespread poverty, desertification, ecological disruption, high population growth rate, cultural beliefs, and extreme weather events.

2.8 Potential future impact of anthropogenic climate change on infectious diseases

Anthropogenic climate change is seen by many as one of the major dangers facing human life (IPCC, 2007a). In the absence of significant mitigation and adaptation measures, the impact of climate change is projected to pose a serious threat to population health, agriculture, water resources, and economic development (Costello et al., 2009; Schellnhuber et al., 2009). Climate change is thought to have a direct impact on the dynamics of many infectious diseases: according to the WHO, at least 30 different diseases have emerged or expanded since 1975 (WHO, 2011a). Climate change and variability can further alter or disrupt natural systems in the form of ecological disruption (Sutherst, 2004), which may facilitate the prevalence of diseases or spread them to areas where they did not exist before. On the other hand, diseases may disappear because areas become less hospitable to the vector or the pathogen (WHO, 2011a). The IPCC Special Report on Regional Impacts of Climate Change (IPCC, 1997) acknowledges that climate may have an impact on vector-borne diseases. This effect could include changes in the geographical distribution and transmission of these diseases, due to changes in meteorological parameters such as humidity, rainfall, soil moisture and rising sea level.

There is a growing desire to predict the impact of climate change on major infectious diseases (Kovats et al., 2012; Patz and Reisen, 2001), as infectious diseases are expected to worsen due to the changing climate (WHO, 2013a). However, it has been argued that climate change may decrease or shift the geographic distribution of some infectious diseases (Kelly-Hope and Thomson, 2008; Lafferty, 2009). Changes in ecological, biological, and physical distribution due to human activities may lead to the absence of some infectious disease from some places even if the climate is suitable for their proliferation (Guisan and Thuiller, 2005). This is because the infectious diseases that depend on vectors may be affected if the habitat suitability of the vector has changed due to climate change. For example, by manipulating temperature and humidity in an experiment, Lowen et al. (2007) established that cold and dry conditions are responsible for facilitating the transmission of influenza from infected to non infected guinea pigs. This led them to assume that increasing temperature could directly reduce the incidence of influenza. In another example, in the Arctic region Kutz et al. (2005) found that increases in temperature in the region have favoured the faster development of lungworm in musk oxen (now one year instead of the usual two years) in their host – slugs - and this may increase the prevalence of the disease.

The potential impact of climate change has attracted the attention of researchers, who have attempted to estimate its potential burden on infectious diseases. Several studies using statistical models based on empirical weather data have concluded that climate change and variability has already impacted on diseases (Woodruff et al., 2002).

2.9 Projecting the future risk of diseases due to climate and issues of uncertainties

The probable increases in the risk of infectious diseases (IPCC, 2007b) have triggered research on the likely dimensions and extent of these changes (e.g., Abdussalam et al., 2014b;

El Fadel et al. 2012; Ermert et al., 2013; Martens et al., 1999; van Lieshout et al., 2004). This is despite the uncertainties involved in the impact assessments due to many additional factors that may influence the disease in the future. However, projecting the potential impact of climate change on infectious diseases is essential, especially for regions where the impact is likely to change the distribution, seasonality, or impact of these diseases (Murray et al., 2013; WHO, 2013a).

The major uncertainties that require attention in projecting the risk of diseases due to future changes in climate can be divided into three: uncertainties associated with (a) climate-disease relationship models, (b) climate projections, and (c) future adaptation and related issues.

Regarding climate-disease relationships, the uncertainties include data quality and statistical techniques used in modelling the present-day interaction. Uncertainties in climate models include the likely contribution of future GHGs emissions, definition of parameters and representation of processes within climate models, and downscaling climate simulation to finer scales. Finally, future adaptation may be influenced by economic and technological advancement. These uncertainties may add up to a large impact on the projection outcomes (Figure 2.6).

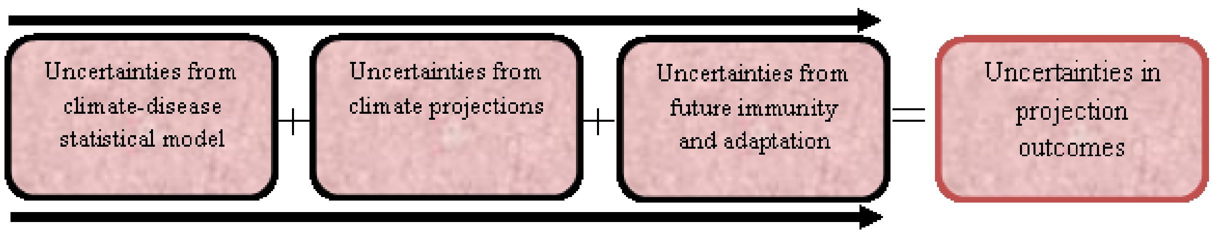

Figure 2.6: Effect of uncertainties in assessing the future impact of anthropogenic climate change on infectious diseases. The total uncertainties increase as individual uncertainties add together.

2.9.1 Uncertainties in climate-disease models

Uncertainties in modelling the present-day relationship between climatic conditions and diseases using statistical models may have a great impact on projection outcomes. The choice of statistical techniques is very important in determining the outcome of the model. For example, using a simple linear relationship may lead to large errors in projection outcomes if the actual relationship that exists is non-linear (Lafferty, 2009), and the projection may extend beyond the range of independent variables. Also, using multiple independent explanatory variables may also cause models over fitting. GAMs could be used to fit a climate-disease model, most especially when the relationship between disease and the predictors is not well understood. The advantage of using GAM is that the technique will allow the data to speak for itself. GAMs have been demonstrated to have good skill in projection studies (e.g., Astrom et al., 2012), but minimising the residual deviance, which is one of the principal features of the technique, might also introduce errors of over-fitting.

Another source of uncertainty is the epidemiological data (Ebi, 2005) used in fitting climate-disease models (as discussed in section 2.2). This will affect the assessment of the future impact of climate change. This can be caused by biases and underreporting of cases due to cultural beliefs, poor surveillance systems, or for political reasons, problems which are prevalent in developing countries.

In order to reduce these uncertainties, which both the epidemiological data and statistical techniques may introduce, disease data quality needs to be obtained from original sources and checked robustly, and statistical models need to be validated using independent data that was not initially included in the model fitting.

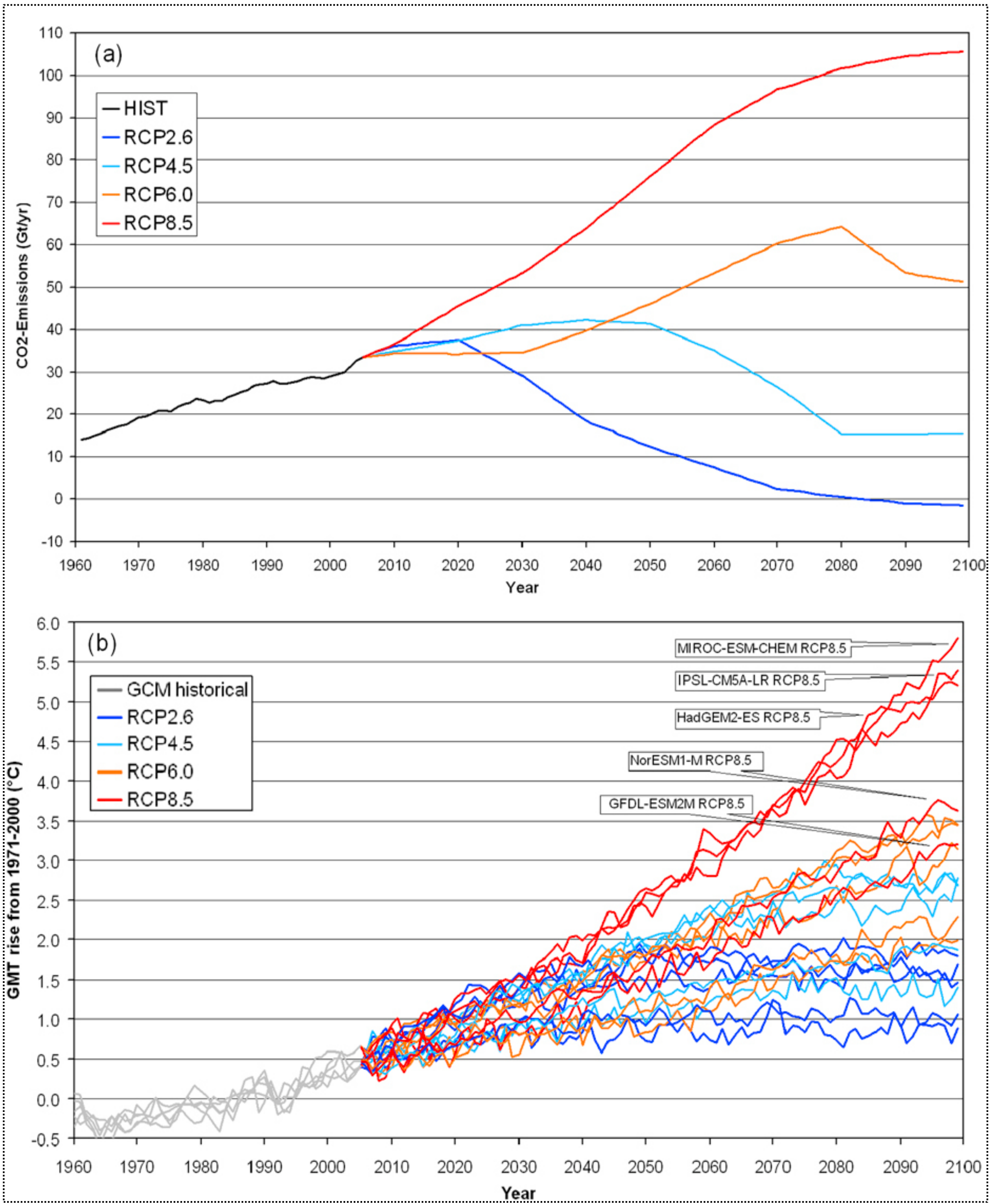

Figure 2.7: Uncertainties in climate change (a) CO_2 emissions uncertainty from anthropogenic and natural sources as a function of time (1961–2099) (b) Large scale climate modelling uncertainty. Adapted from: Portmann et al. (2013).

2.9.2 Uncertainties in climate change projections

One of the major uncertainties in estimating the future impact of climate change on diseases is uncertainty about the future emission of GHGs by human activities. This depends on so many factors in the future, such as population dynamics, economic development, and technical advancement. There are deep uncertainties about how these factors will change in the future. To minimise this problem, assessment studies must base their projection on different scenarios. For example, the CMIP5 project has produced four families of future projection scenarios that are distinguished by the values of their "Representative Concentration Pathways" (RCPs). Each RCP is based on its 2100 radiative forcing level. This is estimated according to GHG and other forcing, as developed by different modelling groups: 2.6 (Calvin et al., 2009; van Vuuren et al., 2007); 4.5 (Thomson et al., 2011); 6.0 (Masui et al., 2011); 8.5 (Riahi et al., 2011).

Despite the remarkable improvements over the years, GCMs are still a source of uncertainties (Portman et al., 2013); this is because they are designed to represent the main processes within the climate system, which are available in a variety of complexities (Petoukhov et al., 2005). These representations include that of atmosphere, ocean, land surface, and cryosphere, and biological processes and their evolution are resolved on a grid scale. Some of these processes are represented in detail, for example, the large-scale circulation, while some are simplified by parameterisation. Projections differ (Figure 2.7) between climate modelling centres because they are using different plausible representations of the climatic system (Portmann et al., 2013). Uncertainties from GCM simulations could be minimised in impact studies by using the ensemble of simulation from several models. However, this will only reduce the range of uncertainties, not address them all, because all the simulations involved might have missed out some important processes which may increase or decrease the signal of climate change in future.

Climate data from GCMs cannot be used directly in impact studies. This is because of the coarse resolutions of the models output (Wilby et al., 2012). This information is required in a finer spatial scale for disease impact studies. There are two methods available for downscaling climate models output: dynamic and statistical methods. The dynamic method is not widely used because it involves significant technical and computational resources (Wilby and Dawson, 2013), but it has the advantage of not working with the assumption (as in the case of the statistical method) that statistical relationships obtained in the present day will remain in the future. This assumption in the statistical method increases the uncertainties inherent in the climate models. However, several studies have used statistical downscaling in their impact assessments, for example in the area of health (e.g., Hayhoe et al., 2004), and water resources (e.g., Portmann et al., 2013).

2.9.3 Other uncertainties

Although population uncertainty is smaller than uncertainty associated with climate projections (O'Neill, 2004), it is important, when projecting the future risk of such diseases, to take into account the future changes that may occur in population dynamics and demographic structure. Very few impact studies have considered this in their assessment framework, while some go with the assumption that there will be no changes in the future (e.g., Donaldson et al., 2001; Hayhoe et al., 2004), although this largely depends on the nature of the historical data used in the calibration of the projection models.

There is also a considerable amount of uncertainty associated with disease projection, due to the present-day efforts of health workers and authorities to control or even eradicate the diseases. For example, the introduction of conjugate A vaccine (Roberts, 2008) in some countries in the meningitis belt is expected to give long lasting protection and may even prevent people from contracting the disease (WHO, 2012a): this will reduce the disease burden in the future. There is no available literature on how to model the future effect of vaccination; probably due to lack of data in the past (see section 2.2.2). A way to tackle this issue may be to approximately filter out the bias of the vaccination effect from the historical time series (e.g., Davis et al., 2004) before fitting the climate-disease models. This will allow modelling of the present relationship based purely on climatic influences. The limitation of this method is that the model is clearly developed in such a way that it cannot account for the uncertainty in the future projections; rather, the outcome will be solely based on objective prediction. Other uncertainties include economic and technological advances, which may prevent populations from contracting diseases in the future. For example, the provision of safe drinking water, food storage infrastructure, and accessible health care facilities may reduce the risk of cholera (Talavera and Perez, 2009) in low-income countries.

2.10 Research gaps identified

The literature review has highlighted a number of research gaps, and areas that need to be researched further. These are summarised below:

a. Until recently, most research on quantifying the relationship between climate and diseases has focused on Asia. However, there is still a scientific need to investigate these relationships in areas that have a high incidence of these diseases. Despite the status of Nigeria as one the most populous countries in Africa, the country is conspicuously neglected by such studies, apart from Greenwood in 1984 who briefly reported on meningitis.

b. A more systematic study using longer and more reliable disease time series is required, in order to robustly investigate the climate-disease relationships.
c. There is a need for more quantitative studies on climate-disease relationships that takes into account the additional effect of socioeconomic factors, in order to improve the understanding of the relationship.
d. Projecting the potential impact of future climate change on infectious diseases is essential, especially for regions where the projected climate change impacts, and infectious disease risk, are both large. Northwest Nigeria is one of these regions; and there is no known study that attempts to assess the future risk of any of these diseases in the country.

These research gaps are already highlighted in the objective sections of this thesis.

Chapter Three:

Study Area, Data, and Chosen Methodological Approaches

Chapter Three

Study Area, Data, and Chosen Methodological Approaches

3.1 Research design

As highlighted in chapter two, several studies have been conducted quantifying climate-disease relationships; however there is still a need for more systematic studies, especially those that are region specific and use longer and more reliable disease time series. This study aims to build on these previous studies by developing statistical models capable of explaining and predicting meningitis and cholera in northwest Nigeria. The structure and organisation of the research has been detailed in section 1.4. A schematic simplification of the research process and the key steps of the research and how they link to each other was provided in Figure 1.4. The study is basically divided into five main parts. The first part will give the general background to the research, review existing relevant literature, and identify gaps. The second part will discuss the reason for choosing the study area and its key characteristics, data types and quality, and the methodological approaches adopted in the study. The third part of the research will provide understanding regarding the climate system over the study area and West Africa generally. The spatial and time characteristics of the selected climate-sensitive infectious diseases will be analysed. In the fourth part, statistical models on the influences of climatic conditions on the interannual variability of both meningitis and cholera cases will be constructed and validated. Finally, models developed specifically for climate change studies will be applied to assess the impact of anthropogenic climate change on these diseases in both near and far future time periods.

This chapter presents the overall research design, characteristics of the study area, data type and sources, and methodological approaches adopted in addressing the research aim and objectives specified in section 1.3 of chapter one. Section 3.2 discusses the rationale behind choosing the study area and some of its key attributes related to the study. Data types, sources and characteristics used in the study are presented in section 3.3, while a brief description of the methodological approaches adopted is discussed in section 3.4.

3.2 The study area

3.2.1 Identifying the study area

Nigeria can be divided into four climatic regions based on the updated Köppen-Geiger's classification (Peel et al., 2007). These regions are: (a) Equatorial monsoon or Tropical rainforest, found in the most southerly part of the country, and mainly influenced by the monsoon; (b) Tropical wet and dry Savannah, which covers the west and central part of the country starting from where the Tropical rainforest ends; (c) Mountain climate, found in the highland areas of over 1,520 metres above sea level, e.g., the Plateau and Mambila areas; and (d) Sahel or Tropical dry climate, predominantly covering the northern part of the country. Politically and administratively, the country is divided into 36 states; furthermore, these states are geographically grouped into six geo-political regions: Northeast; Northwest; Northcentral; Southwest; Southeast; and Southsouth. Today in Nigeria, government policies, political appointments, sites of infrastructure and resource allocations are mostly based on these regions. Since most decisions and policies are made based on these regions, one of the most important regions in terms of vulnerability to the risk of the selected diseases and climate change was identified.

Northwest Nigeria is particularly vulnerable to the impact of climate change and variability because of its physical and socioeconomic characteristics, such as widespread poverty, desertification, ecological disruption, high population growth rate and extreme weather events. The region suffers particularly from several critical drawbacks in human and infrastructural development that require urgent attention (NBS, 2012). Northwest Nigeria was targeted for this study for the following reasons:

A. According to the WHO records, states in the region usually report the highest number of meningitis and cholera cases in the country;
B. The region lies in areas identified as "hotspots" of climate change (Collier, 2008), and which are projected to be disproportionately affected by an increasing disease burden, and extreme climate events.
C. The region has the highest population in the country (over 41 million), and a large proportion of the populace are vulnerable to flooding, desert encroachment, poverty and prevalence of infectious diseases.
D. Extreme events such as meteorological and hydrological events are common, and occur regularly (NIMET, 2012).
E. No known study of this nature has been carried out in this region apart from that of Greenwood et al. (1984).

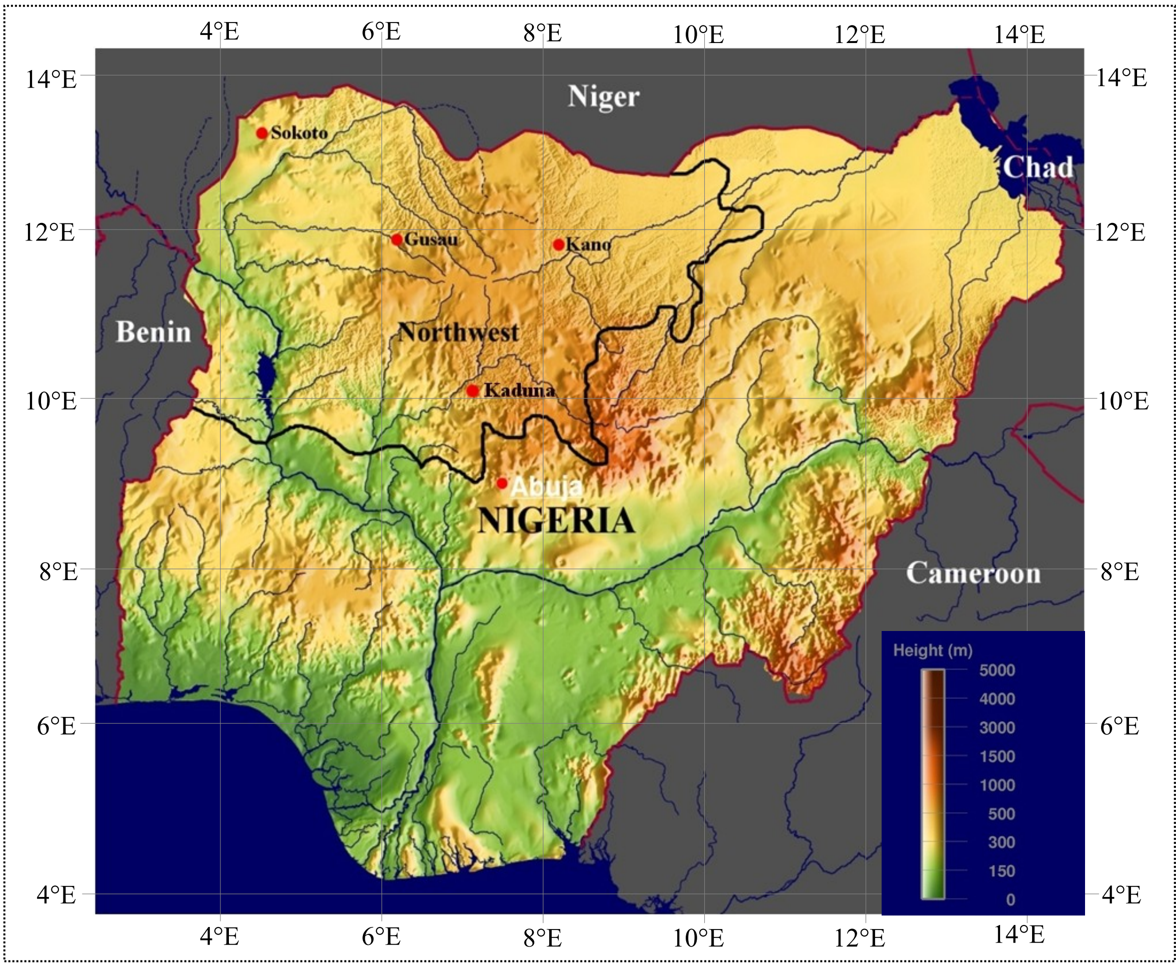

Figure 3.1: Topographic map of Nigeria showing the northwest region and the selected cities (Kano, Sokoto, Kaduna and Gusau) from which hospital and meteorological data were collected. Adapted and modified from: http://www.ginkgomaps.com/maps_nigeria.html

3.2.2 Northwest Nigeria

Nigeria is located in the West Africa region (Figure 1.3). It has an area of about 1 million square kilometres comprising 36 states and the Federal Capital Territory (FCT). Currently the population of the country is about 170m people (based on 2006 census), with an average annual growth rate of 2.5% (World Bank, 2012). According to the recent World Bank data, Nigeria has an average life expectancy of about 50 years, and a national poverty line of 54.7% out of the total population: only about 35% of its population have access to pipe-borne water.

Social statistics obtained from the Nigeria's National Bureau of Statistics (NBS) corroborate these figures, with the highest level of poverty and lower adult literacy in the northern part of the country (Figure 3.2 and 3.3).

The northwest region currently has an estimated population of over 41 million people, and comprises seven states (Kano, Kaduna, Katsina, Kebbi, Sokoto, Zamfara, and Jigawa). The regional climate is characterized by two seasons, a short wet season from June to September, and a prolonged dry season for the remainder of the year. Daytime maximum temperatures remain consistently high throughout the year with maxima during March-May (up to 47°C), while relative humidity is low during the dry season, and increases during the wet season (NIMET, 2012). These mean regional climate conditions are mainly a consequence of the West African Monsoon (WAM) system, which exhibits large spatiotemporal variability (e.g., Cornforth, 2012), especially with respect to regional rainfall distributions. The WAM is a large-scale wind system characterised by moist northward flow from the Gulf of Guinea during the wet season and a dry and dusty southward flow (Harmattan) during the dry season (details about the spatial and time characteristics of the regional climate will be discussed in chapter 4).

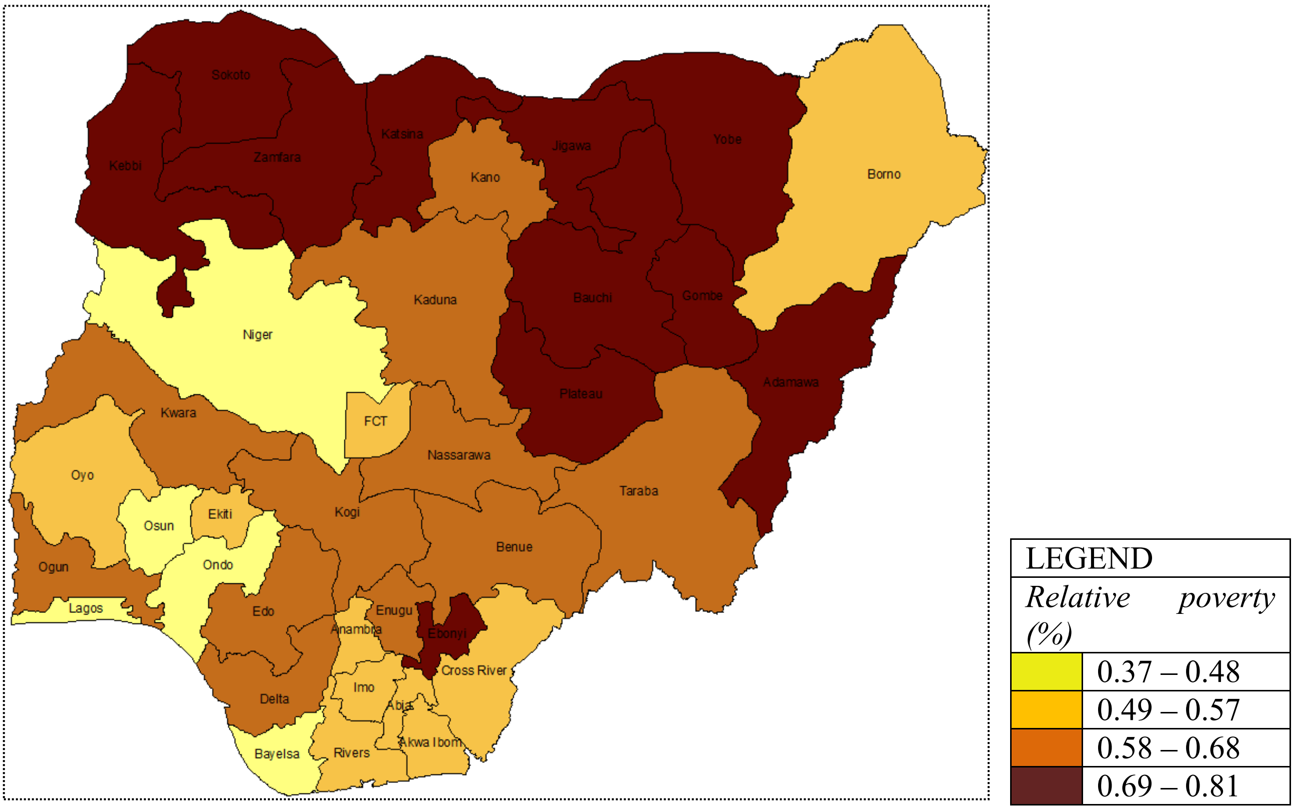

Figure 3.2: Mean percentage of population living in absolute poverty in each of the 36 states and FCT between 2000 and 2011. Absolute poverty here is defined as the percentage of the population that have an income less than some fixed proportion of median income (NBS, 2012).

3.3 Data types and sources

The relationship between disease incidence and climatic factors could be estimated using a statistical or biological model, which could subsequently form the basis for future predictions of disease outbreaks and the development of an Early Warning System (EWS) (WHO, 2005a). Before this can be achieved, however, it is necessary to ensure that both disease incidence and climate data are available at appropriate spatial and temporal resolutions and for a sufficient time period. As highlighted in section 2.2, three types of data are involved in this kind of study: meteorological data, such as rainfall, temperatures, humidity and wind speed; disease data, such as surveillance data or hospitals' reported cases; and socioeconomic data that are related to the disease, such as poverty and immunity.

In this study three categories of data at different temporal and spatial scales were obtained from different sources in order to address the specific objectives outlined for the research.

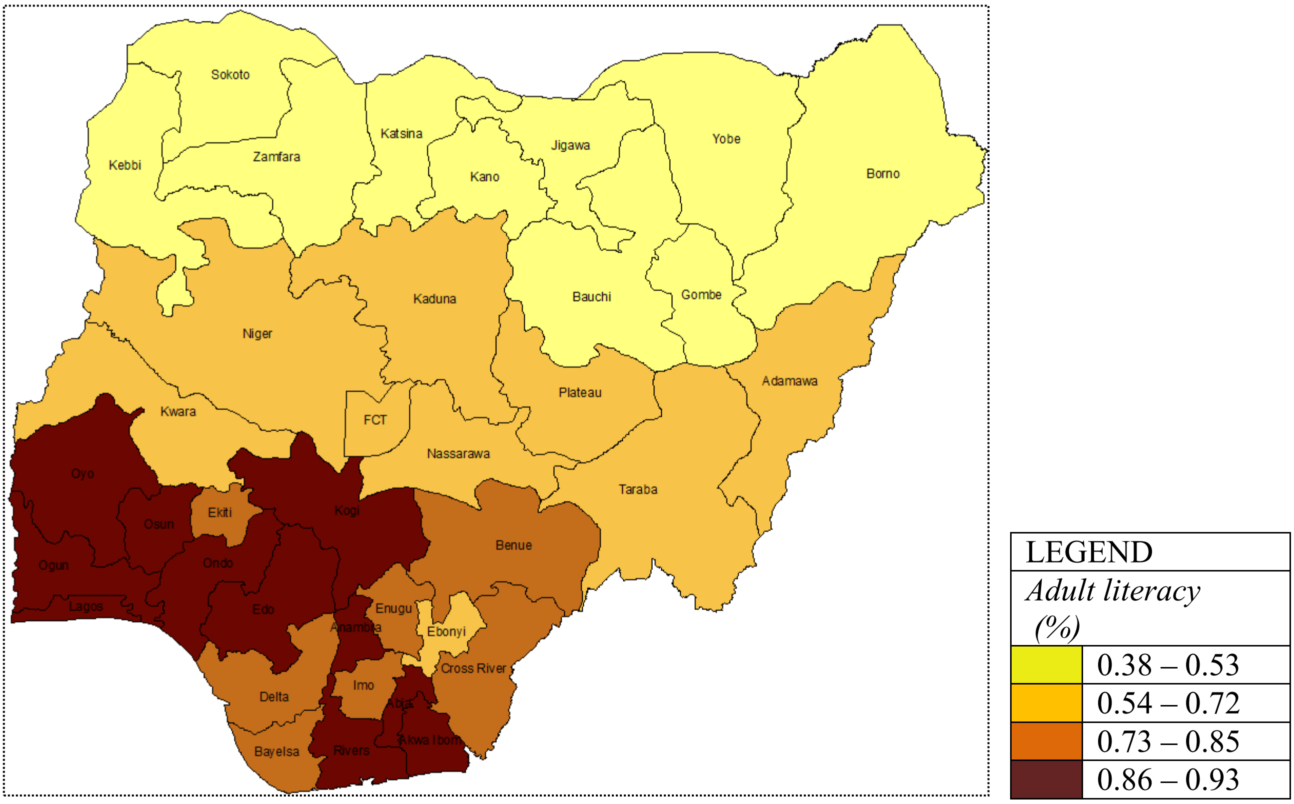

Figure 3.3: Mean percentage of population with adult literacy per state between 2000 and 2011. Adult literacy is measured by the ability to read and write with understanding, in English or in any of the Nigerian native languages (NBS, 2012).

3.3.1 Meteorological data

For the purpose of the different analysis to be carried out in this study, three types of meteorological data were obtained. These are station data, reanalysis data, and climate projections.

a. Station data

This is observational data from weather stations across the region; the study uses this data to avoid the issues of interpolation and uncertainties in modelled data. The selected stations are located in the cities closest to the targeted hospitals: the distance ranges between 4 and 9 kilometres. Digital records of meteorological variables were obtained from stations located at city airports (Figure 3.1); these stations are believed to have longer and reliable records because of their location in the aviation industry, which requires frequent and standard observations. Although the data was obtained from the Nigerian Meteorological Agency (NIMET) – a government organisation in charge of all weather stations across the country - the metadata of two of the selected stations (Kano and Kaduna) were further scrutinised by visiting them in order to ascertain the specific measurement techniques. Quality control (QC) was carried out for all variables, specifically maximum and minimum temperatures and rainfall were checked using an R-based software tool *Rclimdex.r 1.0*. This has been developed and maintained by the Climate Research Division (CRD, 2008) of the Meteorological Service of Canada on behalf of the Expert Team on Climate Change Detection and Indices (ETCCDI). This tool is capable of identifying duplicate dates, out-of-range values based on a defined threshold, outliers, coherence between maximum and minimum temperatures (Tmax > Tmin), and consecutive days with equal values. A few values of maximum temperature that were below their daily minimum counterparts were detected; also a few outliers in rainfall values were identified and corrected. Corrections were made using information from days before or after the problematic value (e.g., Aguilar et al., 2005). Other variables were manually quality controlled by removing obvious spurious values based on knowledge of the regional climate; too few values were removed to affect the overall quality and continuity of the meteorological data. Generally, less than 7% of the data was affected in this process.

b. ERA-Interim data

ERA-Interim data was used as an alternative where station data is not readily available. Specifically, this set of data was used in chapters four and seven of the thesis to investigate the spatiotemporal characteristics of meteorological conditions over West Africa and the variability of cholera over Nigeria respectively. ERA-Interim is a reanalysis product that is used by entering a wide range of observations into a data assimilation system, which is then used to drive a numerical weather prediction model with output from this as Reanalysis (Dee et al., 2011). The data is produced on a reduced Gaussian grid at a 2.5° Lat/Lon spatial resolution, which is about 79km spacing (Dee et al., 2011). It cannot be compared with point data (station data) because it is coarser. For the purpose of this study, spatial averages from grid(s) were used; the location of each grid within Nigeria is indicated on Figure 3.4. All states are uniquely associated with at least one grid cell. Modelled quantities of meteorological variables are available on a global scale between 1979 and the present day, and are accessible from the European Centre for Medium-Range Weather Forecasts (ECMWF).

Despite the advantages of the spatial coverage and range of data available in ERA-Interim, there are factors that needed to be acknowledged as sources of uncertainty (e.g., Uppala et al., 2005). Example of these uncertainties includes the temporal and spatial differences in the range of the observations data used in the assimilation process, and temporal discontinuity in the spatial coverage of observation network. Details of the uncertainties involved are discussed by, e.g., Bengtsson et al. (2004) and Uppala et al. (2005). Despite these shortcomings the data have proved to be good and are being widely used in different studies: however, the data require validation with observation data before use. Details of the validation method used can be found in section 4.2.1.

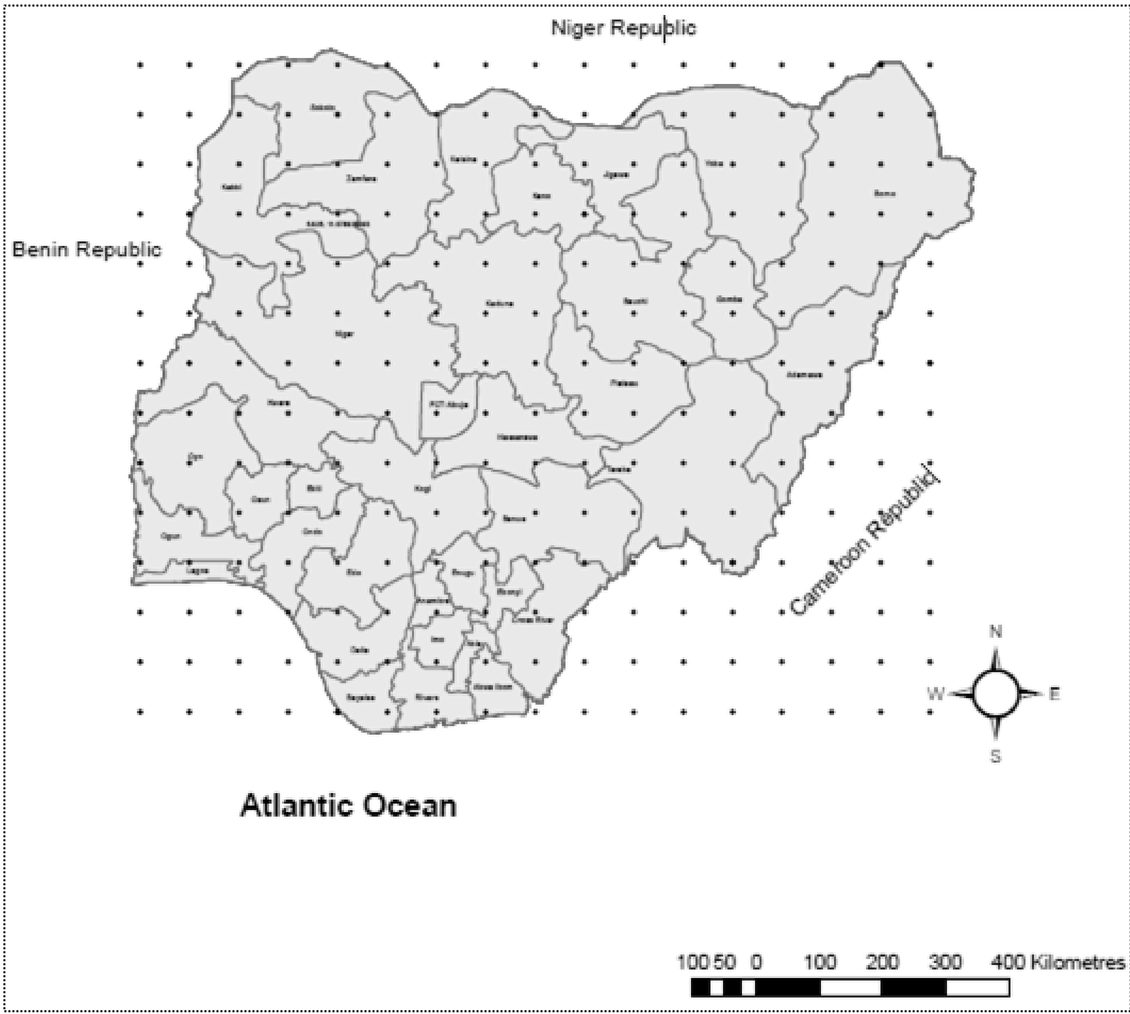

Figure 3.4: Location of ERA-Interim grid points across Nigeria.

c. Climate projections

In order to assess the impact of anthropogenic climate change on the future risk of outbreaks of the selected diseases, future climate simulations from the most recent AOGMCs that participated in CMIP5 project were downloaded. The data is available for download at the Earth System Grid - Program for Climate Model Diagnosis and Intercomparison (ESG-PCMDI) gateway at http://pcmdi3.llnl.gov/esgcet/home.htm, and the different types of interpretation of the CMIP5 framework are described in Taylor et al. (2012). The CMIP5 project has improved simulations compared with the earlier phases (IPCC, 2013). Generally the resolution is higher, and has a richer set of output fields. The spatial resolution for the atmosphere and ocean components ranges from 0.5 to 4 and 0.2 to 2 degrees. Considering the fact that simulations from the same models often exhibit similarities, this study used a wide range of simulations from different climate modelling centres, selecting one model from each centre (e.g. Monorie et al., 2012). The future projections are distinguished by the values of their RCPs. In this study the RCP2.6, RCP6.0 and RCP8.5 scenarios for 2006-2100 are used, with the numbers representing the globally-averaged top-of-the-atmosphere radiative imbalance (in W m^{-2}) in 2100 (Moss et al., 2010). Simulations were statistically downscaled to the respective locations before applying them in the study. More details of the procedure are given in section 8.2.2.

3.3.2 Epidemiological data

Three different types of epidemiological data were obtained to serve specific purposes in the study. These included disease time series from selected hospital archives; national surveillance data; and weekly records from WHO.

a. Hospital reported cases

Records of clinically-diagnosed meningitis and cholera cases were extracted in situ from the archives of four hospitals across the study area (Figure 3.1 and Table 3.1). These hospitals are: Barau Dikko Hospital, Kaduna; Specialist Hospital, Kano; Specialist Hospital, Sokoto; and General Hospital, Gusau. All hospitals are public hospitals where infectious diseases are constantly reported and treated. Monthly records of a 22-year time series for both diseases were compiled.

Table 3.1: Selected cities and hospitals where clinically confirmed cases of meningitis were collected

City	Hospital	Postcode	Status
Kaduna	Barau Dikko Specialist Hospital	800212	State/Public
Kano	Murtala Mohammed Specialist/Infectious Disease Hospitals	700212	State/Public
Sokoto	Sokoto Specialist Hospital	840212	State/Public
Gusau	General Hospital, Gusau	860211	State/Public

b. National diseases surveillance data

The Epidemiology Division at the National Centre for Disease Control (NCDC) of the Federal Ministry of Health (FMoH) in Nigeria records the number of both cases and deaths observed in all hospitals across the country. Records are reported by Disease Surveillance and Notification Officers (DSNOs) in all the 774 districts of Nigeria. These DNSOs directly or indirectly (through their local focal persons) collect data from all health facilities (both public and private) in their respective districts of the Federation. Although data exists over a longer time period, due to missing values and uncertainties in the record because of the poor surveillance system structure before 2000, annual data has been collected for only 12 years (2000–2011). This data was collected in addition to the hospital records to allow the investigation of the spatiotemporal variability of diseases over the country.

c. WHO epidemiological records

Epidemics of infectious diseases are reported to WHO by reporting countries and these are then published on its website (WHO, 2011). The data are presented in three categories: (a) annual national data on the number of cases and deaths by country; (b) Weekly Epidemiological Record (WER) of the number of cases and deaths from reporting countries by districts; and (c) data on specific epidemics. The annual national-level database dates back to 1966, and keeps track of major epidemics and endemic cases in terms of the number of cases per year per country. The WER, which is kept at district level, started at the end of 1997 and has become an important way for fast and accurate communication of epidemiological data regarding outbreaks of diseases under the International Health Regulations (IHR). The specific epidemic data is often held at district and country level.

WER could have been the most suitable disease data for model constructions because of its finer resolution (weekly) and spatial coverage. However, this data was available for Nigeria only from 2007, and only that of meningitis was made available for this study. As such this data was only used for evaluating the compiled hospital record (validation and crosscheck), and also for investigating the 'changing' patterns and shift of the meningitis belt in Nigeria.

Table 3.2: Characteristic of data types used in the study

Type	Description	Resolution/Span	Source
Meteorological data			
Station data	All the four stations are located in airports. Seven variables were collected	Data span between 1970 and 2011. Temperatures, rainfall, and relative humidity are in daily values, while sunshine hours, dustiness and wind speed are in monthly averages	Nigerian National Meteorological Agency (NIMET), Abuja
Era-interim	Reanalysis data available in both horizontal and vertical scales. Three variables were downloaded	This data is available from 1979 to date and at different temporal resolution, and a spatial resolution of 2.5°	Available from the European Centre for Medium-Range Weather Forecasts (ECMWF) at http://data-portal.ecmwf.int/data/d/interim_full_daily
CMIP5 experiments	Climate projection data for 21st century for 3 RCPs (2.6, 6.0, and 8.5). Six variables were downloaded.	Both historical and the four RCPs are available at several temporal scales, while spatial resolution ranges from 250km	Earth System Grid - Program for Climate Model Diagnosis and Intercomparison (ESG-PCMDI) gateway at Lawrence Livermore National Laboratory, http://pcmdi3.llnl.gov/esgcet/home.htm
Epidemiological data			
Hospitals	Clinically-diagnosed meningitis and cholera reported cases from four selected hospitals in the region	This data is available on monthly aggregate, collected from 1990 to 2011	Four state-level hospitals in Kano, Kaduna, Sokoto, and Gusau
Surveillance	Suspected meningitis and cholera cases	Available both at national and state levels spanning between 2000 and 2011	Epidemiology Division at the Centre for Disease Control of the Federal Ministry of Health
Weekly epidemiological records	Suspected meningitis cases	Available at weekly and at districts levels from 2007 to 2012	World Health Organisation
Social data			
Demographic	2006 national census data	Available at district levels from the 2006 national census	Nigerian National Population Commission (NPC) Abuja
Socioeconomic	Adult literacy, access to pipe-borne water, and absolute poverty profiles were collected	Available at national and state levels from 2000 to 2011	Nigerian National Bureau of Statistics (NBS) Abuja

3.3.3 Socioeconomic data

Socioeconomic and demographic data were obtained from the Nigerian National Bureau of Statistics (NBS) and the National Population Commission (NPC) respectively. The data collected include: percentage of population having access to pipe-borne water, adult literacy, absolute poverty, and population density. Apart from the population data, all data are only available at state level on an annual basis. This data is used in analysing the spatial and time characteristics of the selected diseases in chapter five, and for investigating the spatiotemporal variability of cholera in chapter seven.

3.4 The modelling approach

Relationships between infectious disease incidence and meteorological covariates could be modelled using either process-based or statistical models. As discussed in section 2.2, biological models are mostly used for vector-borne infectious diseases (Craig et al., 1999) and require the parameterization of the detailed information about the complete infection process (Pradas-Velasco et al., 2008). This information includes, for example, details on the host-pathogen relationship, transmission, habitat suitability, virulence, intra-host dynamics, and vital rates of the pathogen, and that of the vector (Jetten et al., 1997; Lafferty, 2009; Marten et al., 1999; Martin and Lefebvre, 1995; Pradas-Velasco et al., 2008).

Statistical models are considered very important tools of investigation of the climate-disease association (WHO, 2003). This tool has the advantage of being less complex, with a more transparent process if compared with process-based models (Pradas-Velasco et al., 2008). This method also theoretically allows for incorporating non-climatic factors into the investigation (Held and Paul, 2013). The approach could be used for linking disease incidence, on both spatial and temporal scales, with meteorological or socioeconomic explanatory variables (WHO, 2003). Statistical models are the most widely used approach in investigating relationships between climate and infectious diseases (see Table 2.1 for example of techniques used).

In this study, a statistical approach was adopted, because the disease data obtained were only count cases that are clinically-diagnosed. Also, the mechanism for the transmission of some infectious diseases like meningitis is still not well understood (Sultan, 2005; Thomson et al., 2006; Yaka et al., 2008). This study adopts Generalised Linear Models (GLMs), Generalised Additive Models (GAMs), and Multiple Linear Regressions (MLR) to develop models capable of explaining and predicting meningitis and cholera in northwest Nigeria.

3.5 Methods used

The study employed various and widely used methods in order to achieve the set aim and objectives.

Pearson correlation is used in chapter four to evaluate temperatures and rainfall data extracted from ERA-interim reanalysis using their counterpart from stations in northwest Nigeria. This statistical method is used to measure the degree of linear association between variables: the Pearson correlation coefficient (from +1 to -1) is the covariance of the variables divided by the product of their standard deviation. Buda and Jarynowski (2010) have discussed this technique.

Climate indices, as defined by the Climate Variability and Predictability Research Programme (CLIVAR), were computed using the *Rclimdex.r 1.0*, a software tool for daily temperatures and precipitation data from station in northwest Nigeria. Definitions of these indices and documentation for the software tool are available in Zhang (2004) and Zhang et al. (2005).

The global Moran Index statistic for spatial autocorrelation (Moran, 1950) was selected to investigate the spatial distribution of meningitis and cholera in Nigeria in chapter five. This statistic is built in ArcGIS to measure spatial autocorrelation based on feature location (e.g., district) and the feature values (e.g., meningitis cases) simultaneously. It evaluates the nature of the spatial pattern (either clustered, dispersed, or random) that exists within features based on their respective values. Moran's I is estimated by computing the mean and variance for the values of each feature. A deviation from the mean is then computed by subtracting the mean of each feature from its variance. These values are then multiplied together with a neighbouring feature within a specified distance to produce a cross-product. If higher values appear to be near each other, then Moran's I will be positive, signalling a spatial correlation pattern, and vice versa. In addition, the statistics return results in z-scores and p-values to estimate the significance of the pattern, and interpretations are made in the context of a null hypothesis. Getis and Ord (1992) and Mitchell (2005) have provided detailed information about this method.

The importance of some socioeconomic variables on the spatial risk of contracting meningitis and cholera in Nigeria was measured in chapter five using the Mantel Haenszel Chi-square test (Mantel and Haenszel, 1959). This method is used for testing groups of nominal variables if they are conditionally independent in a stratified data (Wallenstein and Wittes, 1993).

Linear regression models allow for the study of causal relationships between dependent variables, e.g. malaria cases based upon independent variable such as temperature. The technique assumes that a linear relationship exists between the variables; it then attempts to fit a line on to the data used. The nature of this fit determines the influence of the predictor variable on the predictant (Rogerson, 2001). This technique has been used extensively in modelling functional relationships between data; the outcome is an equation that could be used to predict the response variable. MLR is an extension of the simple regression model (Cook, 1977): here, more than one explanatory variable is included. MLR is a powerful statistical technique that is also based on an equation in the form of a straight line, used to predict the outcome of a dependent variable from a linear combination of independent explanatory variables. MLR was used in chapter seven in order to explain the spatiotemporal variability of cholera in Nigeria. MLR was chosen because of the availability of social data on the same spatial and temporal scale as both disease and meteorological data. Technical information regarding this statistical method can be found in Andrews (1974) and Myers (1990).

GLMs are an extension of the linear model that generalise linear regression by allowing the magnitude of the variance of each variable to be a function of its predicted value. This approach also allows the linear model to be related to the response variable via a link function (Faraway, 2005). The technique is capable of handling data that does not follow normal distribution (Dobson, 2010). Considering the fact that meningitis and cholera take the form of counts data that are close to Poisson distribution with very high and low values, this data would appropriately be analysed as Poisson random variables. Parameters of the GLM are estimated according to the family of distribution of the analysed data and a non-linear function that link the stochastic and systematic component of the model (Dobson, 2010). This method was used in chapter six for the selection of the best modelling framework of meningitis in northwest Nigeria. Technical information regarding this statistical method can be found in Dobson (2010) and MacCullagh and Nelder (1989).

GAMs are non-parametric extension of GMLs (Venables and Ripley, 2002; Faraway, 2005); and are comprehensively described by Hastie and Tibshirani (1999). Several studies have used GAM and GLM to study infectious diseases (e.g., Chou, 2010; Paz, 2009; Kinlin et al., 2009). Unlike the normal linear models, where linear forms determine the shape of the relationship between dependent and independent variables, in GAM smoothing functions, which could be far from linear, are used for such relationships. Through this additive smoothing function, the effects of other unobserved additional effect of both climatic and non-climatic factors that may be related to the diseases could be collectively accounted for (albeit not specifically) (Faraway, 2005). The flexibility and less restrictive modelling environment provided by GAM makes it suitable for this study. This is because the model can be attuned to account for the many unobserved additional climatic and non-climatic factors that may be related to the diseases using the smoothing function (Faraway, 2005). Another good reason for choosing GAM is because the model's smoothing function has the benefit of automatically dealing with both non-linear and non-monotonic associations between the outcome variable and the predictors without necessarily using variable transformation or polynomial terms (Dobson, 2010). This approach is used in modelling the relationship between meteorological variables and selected diseases in chapter six and seven. Technical information regarding this statistical method can be found in Dobson (2010), Faraway (2005), and Hastie and Tibshirani (1999).

The outcomes of the statistical models were evaluated using threefold Cross Validation Correlation (CVC) (Kohavi, 1995), the Root Mean Square Error (RMSE) (Geisser, 1993), and the Skill Score (Murphy, 1998). All three statistics were computed for observed versus predicted values for each model. Details of these are provided in the methodology section of chapter six.

In chapter eight, bias correction method was used to downscale thirteen AOGCMs simulations (e.g., Gutiérrez et al., 2012), before applying them to project potential future cases of meningits and cholera in northwest Nigeria. The details of this method are discussed in the methodology section of this chapter. An unpaired two-sample Student's t test was used to test the significance differences between the mean of the present day climate variable, meningitis, and cholera cases compared with their respective projected values in both the near and far future. This test allows for the comparison of the significance difference in the means of independent data that are identically distributed. The extent of statistical difference is determined by a p-value. Further details about this test can be found in McDonald (2008).

Most of the analyses were carried out using the R statistical software. This is a free software programming language and software environment that allows for statistical computing and graphics. It is widely used among statisticians and data miners for developing statistical software. The software provides a wide variety of statistical and graphical techniques, including linear and nonlinear modelling, classical statistical tests, time-series analysis, classification, clustering, and others. R is easily extensible through functions and extensions, and the R community is noted for its active contributions in terms of packages (R Core Team 2013). Other software packages used includes SPSS and ArcGIS.

Chapter Four:

Spatial and Time Characteristics of Meteorological Conditions over West Africa and Northwest Nigeria

Chapter Four

Spatial and Time Characteristics of Meteorological Conditions over West Africa and Northwest Nigeria

4.1 Introduction

Before investigating the relationship between the incidence of diseases and climate it is important to understand the physical processes that are driving the climate of a particular region, which in turn may drives the occurrences of these diseases. Also, with the changing climate, whether due to anthropogenic cause or natural variability, it is imperative to investigate trends and variability in observed climate data in order to understand the long terms trends and variability that exist in both time and space; this could assist in understanding its relationships and influences with the occurrence of diseases. The high variability of the West African climate and its direct and indirect impact on population, such as drought, floods and epidemic of diseases motivated projects like the West African Science Service Centre on Climate Change and Adapted Land Use (WASCAL), Integrated Approach to the Efficient Management of Scarce Water Resources in West Africa (IMPETUS), and the integrated African Multidisciplinary Monsoon Analysis (AMMA). These projects were initiated in order to improve the understanding of the mechanism of the West African climate, as well as the environmental and socioeconomic importance of its variability over West Africa. For example, one of the main objectives of the AMMA project is to study the interaction between epidemics of diseases and variability of climate on different time scales (Redelsperger et al., 2006). In particular, to ascertain the influence of WAM on the dynamics of meningitis and malaria, by determining the roles of winds, dust concentration, precipitation, temperatures and humidity on these diseases. Other objectives include improving the understanding of WAM and its associated influences on both regional and global scale, and also to facilitate the integration of the project outcome into predictions and decision making.

This chapter aims to analyse the spatial and time characteristics of meteorological conditions over northwest Nigeria and West Africa, however an overview of the physical processes that influences the climate of West Africa will be discussed first.

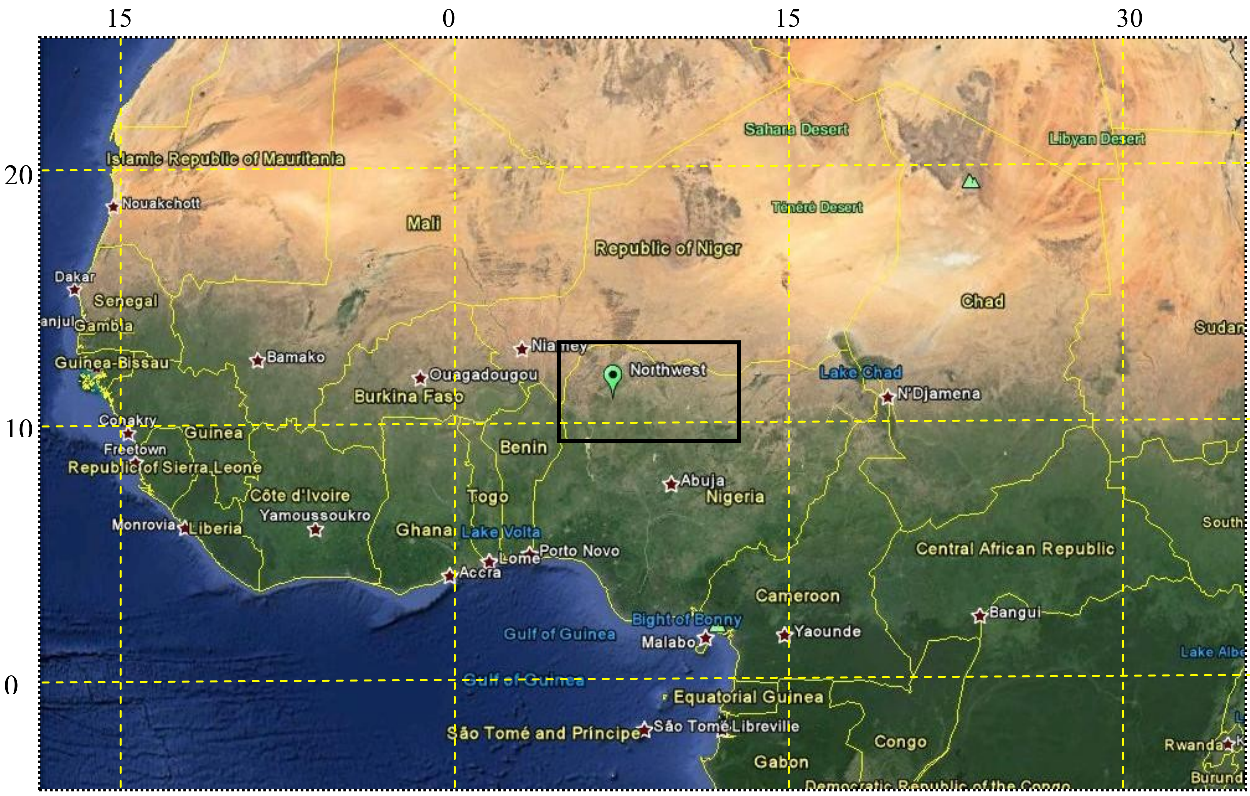

Figure 4.1: Map of West Africa, the black box is highlighting the northwest region of Nigeria. Adapted and modified from Google Earth, 2013.

4.2 Materials and Method

The main features of WAM and related influences on the West African climate will be discussed using existing literature. Also the characteristic of temperature and rainfall over the West African region and northwest Nigeria in particular will be investigated; these two climatic variables were selected because of their importance in determining the extent of change in climate and variability. Also, variability of these parameters has been documented to be strongly related to targeted infectious diseases. For example elevated temperature is correlated with high incidence of meningitis (Dukic et al., 2012) and intense rainfall is related to cholera occurrence (Reyburn et al., 2011). While other variables could have been included in this chapter, rainfall and temperature are judged as being the variables with the longest and most reliable records from stations in the region under investigation.

4.2.1 Meteorological Data

Two sets of meteorological data are used in this study. First, reanalysis data is used to examine the spatial and temporal characteristics of rainfall and temperature over the West African region (Figure 4.1), and secondly, station data are used for the same purpose, but for northwest region of Nigeria. Additionally, existing literature is used to describe the physical processes of the West African climate system associated with its dominant features – WAM.

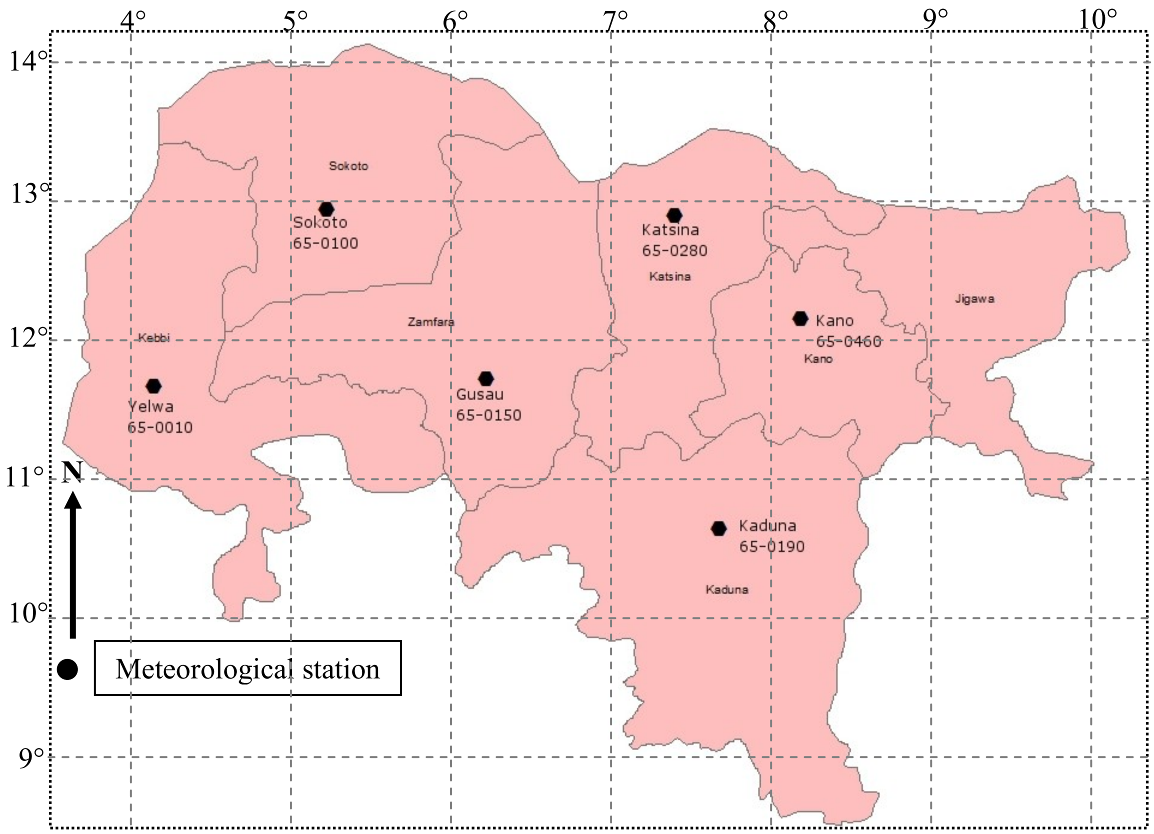

Figure 4.2: Northwest Nigeria showing the seven states and the six meteorological stations used in this study.

Monthly surface values for temperature alongside precipitation between 1979 and 2012 were extracted from the ERA-Interim reanalysis (Simmons et al., 2007), this is the most recent and one of the accurate (Decker et al., 2012) reanalysis product produced by the European Centre for Medium-Range Weather Forecasts (ECMWF) (Dee et al., 2011).

Digital records of three variables from the six available meteorological stations in northwest region of Nigeria (Figure 4.2) were obtained from the Nigerian Meteorological Agency between 1971 and 2010. Daily maximum and minimum temperatures and precipitation were quality controlled (see section 3.3.1). In order to evaluate ERA interim data used in this study, monthly time series extracted from grid points that are representing individual states were evaluated using *in-situ* data from the six stations in northwest Nigeria where data is available between 1971 and 2010. Pearson correlation coefficient is used to determine the association between the two time series in two different ways. First, monthly time series is evaluated to investigate how well the seasonal cycle is represented in the reanalysis, and secondly simple annual averages were compared to see the similarities in terms of interannual variability.

Table 4.1: List of the ETCCDI indices used in this study

ID	Indicator name	Definitions	UNITS
TXx	Max Tmax	Monthly maximum value of daily maximum temp	ºC
TNx	Max Tmin	Monthly maximum value of daily minimum temp	ºC
TN90p	Warm nights	Percentage of days when TN>90th percentile	days
TX90p	Warm days	Percentage of days when TX>90th percentile	days
WSDI	Warm spell duration indicator	Annual count of days with at least 6 consecutive days when TX>90th percentile	days
DTR	Diurnal temperature range	Monthly mean difference between TX and TN	ºC
CDD	Consecutive dry days	Maximum number of consecutive days with RR<1mm	days
R95p	Very wet days	Annual total PRCP when RR>95th percentile	mm
R99p	Extremely wet days	Annual total PRCP when RR>99th percentile	mm
PRCPTOT	Annual total wet-day precipitation	Annual total PRCP in wet days (RR>=1mm)	mm

4.2.2 Method

The major features of West African climate system are discussed, while data from ERA-interim reanalysis was used to illustrate and describe the spatial and time characteristics of precipitation and temperature over West Africa between 1979 and 2012. Analyses were also performed with stations data in the northwest region for the period 1971 to 2010 using a widely adopted approach - a non-parametric method based on Mann-Kendall (e.g., Gadgil and Dhorde, 2005; Tomozeiu et al., 2006), to investigate the annual and monthly trends of stations data in northwest region. Two sub periods from 1971 to 1990 and 1991 to 2011 were further examined to investigate whether there is any change in temperature and rainfall trends throughout the period of investigation

Additionally, trends for ten climate indices out of the climate indices for temperature and precipitation based on CLIVAR/ETCCDI recommendations (Table 4.1) were selected to investigate extreme climate conditions for the six meteorological stations in northwest Nigeria between 1971 and 2010. A detailed description of the complete list and definition of these indices can be found in Zhang and Yang (2004). The *Rclimdex.r 1.0* (Zhang et al., 2005) software is used for the computation of some selected climate indices. Firstly, four percentile-based climate indices are computed, these indices includes warmer nights (TN90p) and warmer days (TX90p) for temperature, and very wet days (R95p) and extremely wet days (R99p) for precipitation. The software samples the warmest deciles from the daily maximum and minimum temperatures and reports the magnitude change in extreme, while precipitation indices returns the amount of rainfall that is within the 95th and 99th percentiles. Secondly, two absolute indices for temperature that reports the maximum and minimum values in the year were computed. These indices are monthly maximum value of daily maximum and minimum temperatures (TXx and TNx).Thirdly, two duration indices for warm spell duration index

(WSDI) and consecutive dry days (CDD) were also computed. These indices determines the period of excessive warm and dry conditions respectively. WSDI index is computed by sampling daytime temperature maxima, while CDD returns the length of the longest dry spell in a year. Finally, annual precipitation total (PRCTOT) and diurnal temperature range (DTR) are also computed.

Both trends and indices results are presented at 95% significance level.

4.3 Results

4.3.1 West African Monsoon and its associated features

The climate of West Africa is dominated by the WAM; this is characterised by a seasonal wind movement which is facilitated by the thermodynamic differences between the Sahara and the equatorial Atlantic (Peyrille et al., 2007). The main role of WAM system in West Africa is the transportation of moisture into the continent. This moisture movement is characterised by a northward propagation from the Atlantic which brings moisture into the continent and consequently brings about moisture convergence and eventually rainfall (Thorncroft et al., 2011). The intra seasonal propagation of the moisture flux is characterised by a northward and sometimes westward propagation (Couvreux et al., 2010). Latitudinal propagation of Inter Tropical Convergence Zone (ITCZ) was previously reported to be related to rainfall change (Kraus, 1977). But it is now well documented that inter annual variability of rainfall in West Africa is instead related more to the activities of higher level circulation features (Nicholson, 2013). Figure 4.3 provides a schematic diagram of the WAM system, highlighting some of its key features. Within the WAM there are number of systems that influences rainfall pattern and the climate of the region in general. The main circulation features that are influencing the variability of rainfall in West Africa both on interannual and decadal timescales are the African Easterly Jet (AEJ), Tropical Easterly Jet (TEJ), African Easterly Waves (AEWs), Inter Tropical Discontinuity (ITD), and the Saharan Heat Low (SHL).

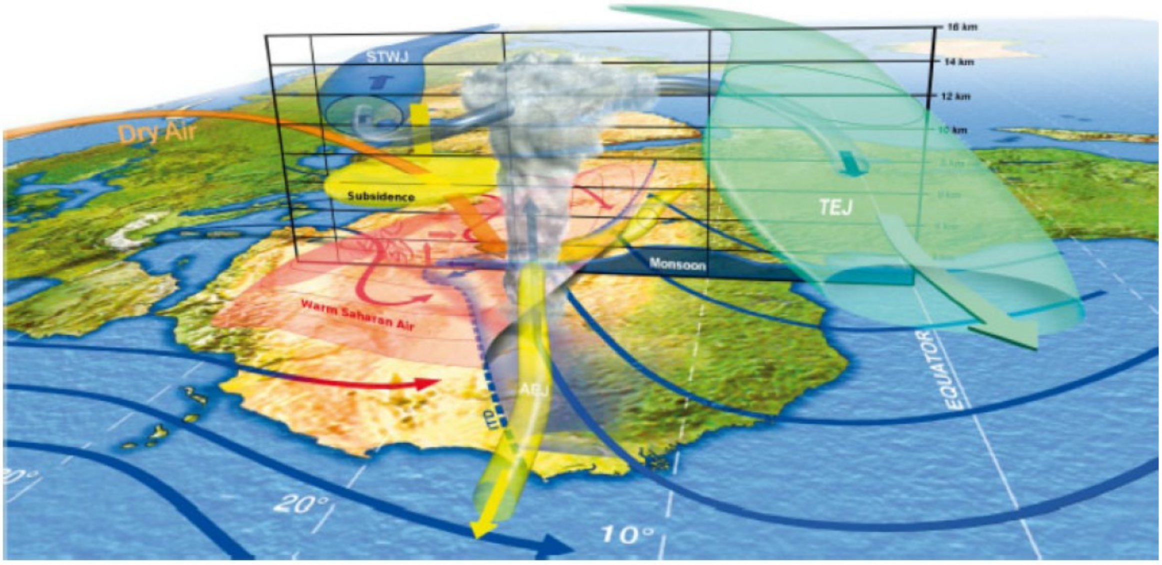

Figure 4.3: Schematic diagram of the West African Monsoon (WAM) showing some of its main features: inter-tropical discontinuity (ITD); tropical easterly jet (TEJ); and the Saharan heat low (SHL). Adapted from Lafore et al. (2010)

The Saharan heat low (SHL) is one of the major features of WAM (Parker et al., 2005; Lavaysse et al., 2009). This is a region of a shallow thermal depression below 700 hPa (Lavaysse et al., 2010a) and a remarkable high surface temperature (Lavaysse et al., 2009). This intense heat low is usually developed during the boreal summer around the Western Sahara with cyclonic inflow that includes the south-westerly wind (monsoon) and the north-easterly wind (Harmattan) (Lavaysse at al., 2010b). SHL is a very important factor in influencing the northward propagation of the monsoon (Peyrille and Lafore, 2007) and is associated with convection activities (Lavaysse et al., 2010a). A causal relationship with

Sahelian rainfall has been observed on intraseasonal, interannual, and decadal timescales (Biasutti et al., 2009; Lavaysse et al., 2010b).

The temperature differences between the continent in summer and the oceans and their development are the key driving factors for WAM seasonal migration over the continent (Sultan and Janicot, 2003). This usually results in the movement of the Inter Tropical Convergence Zone (ITCZ) towards the north. ITCZ depression is usually being reinforced by SHL thereby increasing the surface pressure gradient. The variable interplay between the SHL, its reinforcement of the seasonally migrating ITCZ, and the related propagation of the rain-bringing ITD with low level moisture flux from the Gulf of Guinea (GOG) is the main reason for modifications and changes in regional impacts on interannual as well as even longer time scales (e.g. Cornforth, 2012; Flamant et al., 2009). Especially the interaction between cold pool outflows from mesoscale convective systems and the position of the ITD can influence the monsoon onset by favouring the northward progression of the monsoon (Flamant et al., 2009). The propagation of ITCZ is characterized by series of active and recess stages (Janicot et al., 2011). Rainfall season usually begins between April and June at the coast of Guinea and then followed by the shift of the ITCZ northward over 11°N thereby bringing rainfall over the Sahel, and the gentle withdrawal gives the second rainy season over the West African coast in October and November (Fontaine et al., 2008). Thorncroft et al. (2011) have identified four phases of WAM based on the latitudinal location of rainfall peak. The first phase is the Oceanic phase which is occurring from November to the mid of April, with largest parts of the rain belt located very close to the north of the equator over the GOG. Next is the Coastal phase from the mid of June, with most of the rainfall peak situated near the coastal region around 4 - 5° north (Gu and Adler, 2004; Sultan et al., 2003). The third phase is the transition phase, which is occurring in early July. This is then followed by the

Saharan phase which prevails between the mid of July until September. During the final phase, rainfall peak is found at the south of Sahara around 10°N. The transition between 5°N and 10°N is reported to be abrupt (Barbe et al., 2002; Sultan and Janicot, 2000). Figure 4.4 shows the mean seasonal cycle of rainfall over West Africa.

The ITD separate the moist south-westerly monsoon from the dry north-easterly wind from Sahara desert (Lafore et al., 2010). The pressure minimum of the SHL which is located at its southern flank is responsible for the convergence of these two opposing low level flows. The thermal differences in convection between these flows and the resultant strong baroclinicity are the cause for the generation of the AEJ (Lafore et al., 2011), with warmer-dryer air in the north and cooler-moist air in the south. AEJ has been described as a principal driver of convection and rainfall pattern (Diedhiou et al., 1998):

AEJ is thermally produced during the boreal summer due to the steep latitudinal temperature gradient between the SHL and the GOG, in response to this temperature contrast the atmosphere produces vertical wind shear to maintain the thermal balance (Nolan et al., 2007) with its core located at the mid troposphere between 600 – 700 hPa (Nicholson, 2009). The Jet is maintained by the juxtaposition of wet and dry convections to the south and north respectively (Nolan et al., 2007; Zhang et al., 2008), and also by both the deep and shallow meridional circulations associated with the monsoon and the SHL (Cook, 1999), within which other tropical waves are formed. AEJ usually shifts northward from its southern location in January, reaching its most northerly latitude in August, and its strongest winds are experienced in September when it is shifting back towards equator (Nicholson and Grist, 2003). The system is characterised by both barotropic and baroclinic instability which is resulting in a synoptic scale westward propagation disturbances known as AEW, or tropical waves. The role of AEJ in producing AEW makes it a very important feature in determining the variability of rainfall in West Africa (Nicholson, 2013). Consequently, the AEW; is the main synoptic weather system in the WAM, this westward travelling system which is originating from 20°E are built-up through energy conversion from both barotropic and baroclinic activities. This feature has also been documented to have significant interaction with convective activities (Diedhiou et al., 1998).

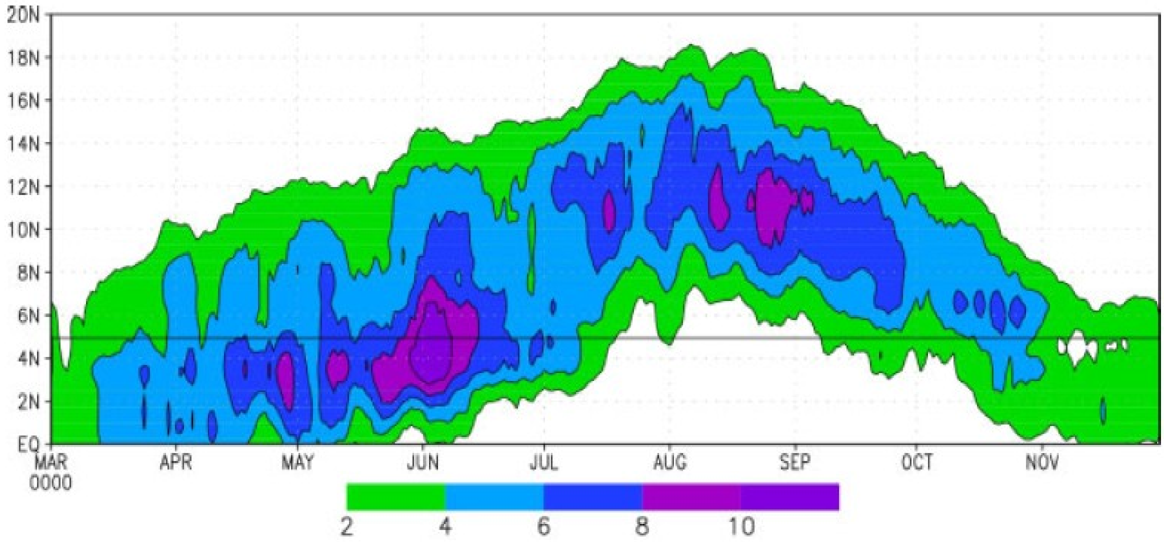

Figure 4.4: Mean seasonal cycle of rainfall over West Africa through a latitude cross section for daily precipitation averaged over 5°W - 5°E extracted from GPCP satellite estimated values between 1997 and 2006, Adapted from Janicot et al. (2011).

Another feature associated to WAM is TEJ, this is an upper troposphere jet (150 – 200 hPa), established to be developed in response to temperature differences between the Indian Ocean and the Himalayan Plateau, with is maintenance depending on the divergent circulation which is attributed with the east-west Walker circulation and north-south Hadley circulations (Nicholson, 2013). The role of TEJ on the inter annual variability has been reported by many, for example, a strong and weak TEJ has been linked with wetter and drier condition respectively in the Sahel (Grist and Nicholson, 2001; Hulme and Tosdevin, 1989; Nicholson, 2008), West equatorial Africa (Dezfuli and Nicholson, 2011; Nicholson et al., 2012), Ethiopia (Segele et al., 2009), and India (Pattanaik and Satyan, 2000).

This complex interaction between the dynamical systems of West African climate makes it difficult for Global Climate Models (GCMs) to accurately capture it (Bock et al., 2011; Druyan, 2011; Marsham et al., 2013). Despite this fact, there is recorded progress in understanding the WAM in recent times; however, there is still no agreement in terms of the future pattern and variability of the Sahelian rainfall (Christensen et al., 2007). On the other hand, the less skill representation might be attributed to the coarse grid of the GCMs (Hourdin et al., 2010; Xue et al., 2010). Other reasons that might explain why the GCMs could not simulate WAM accurately are the missing representation of cloud feedback mechanism in its parameratisation, and or the absence of dynamic vegetation and aerosol production component (Giannini et al., 2008).

4.3.2 Temperature and rainfall characteristics over West Africa

This section presents the characteristics of surface temperature and rainfall over time and space in West Africa using ERA-interim reanalysis data between 1979 and 2012. Evaluation of the reanalysis data suggests that ERA interim is able to reproduce both the seasonal cycle and interannual variability of temperatures closely to the stations data. Results suggest a statistically significant ($p<0.05$) association in both the monthly ($r = 0.7 – 0.9$) and annual ($r = 0.6 – 0.8$) time series and in all stations for maximum temperature. A lesser association is observed in the precipitation time series for some stations in both the monthly ($r= 0.5 – 0.8$) annual ($r= 0.2 – 0.5$), though not statistically significant in stations with weaker correlation (Katsina and Yelwa).

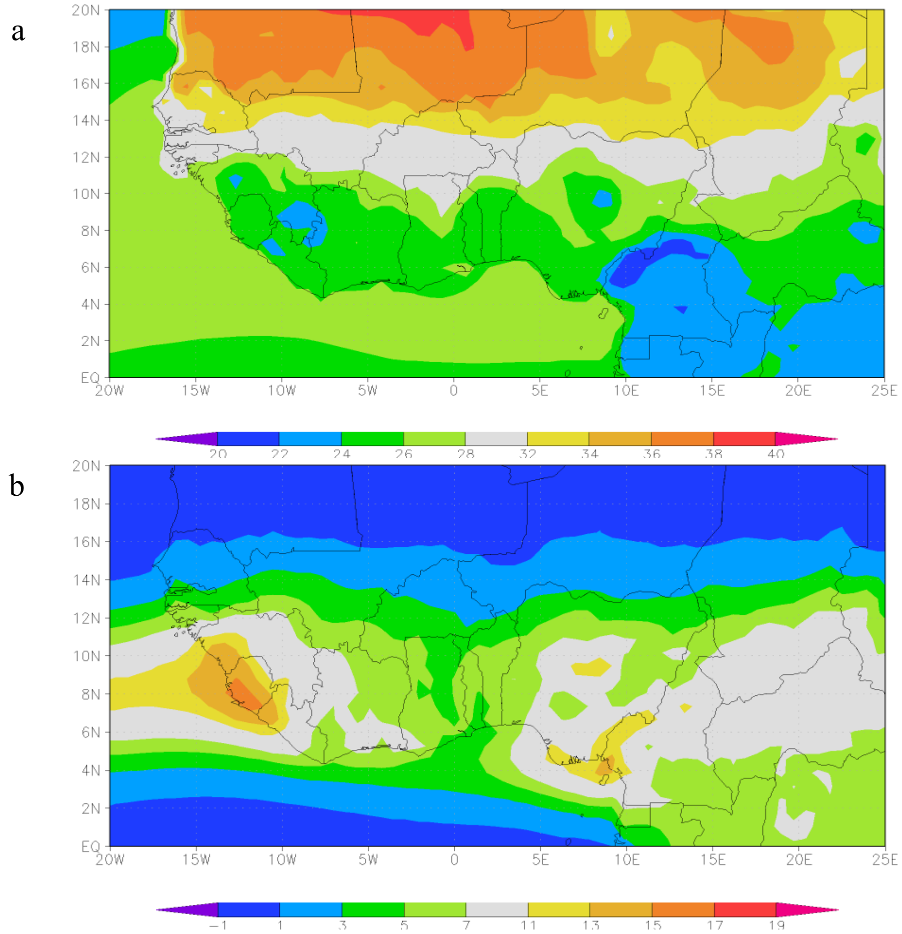

Figure 4.5: Mean Summer June-July-August (JJA) averaged ERA-interim (a) surface temperature (°C) and (b) precipitation (mm/day) between 1979 and 2012. Own figure, produced using KNMI Climate Explorer (e.g., Van Oldenborgh et al., 2009).

Figure 4.5 illustrates the mean summer June-July-August (JJA) surface temperature and rainfall from ERA-Interim reanalysis over 33-years period. Temperature shows a zonal pattern with maximum values found around the Saharan region. Minimum values of temperature are found in areas of orographic peaks and steep topography, notably the Cameroon Mountains, Guinea Highlands, and Jos Plateau. The northern part of Nigeria is much warmer (1 - 3°C higher) if compared with the southern and central part of the country. With regard to rainfall, ERA-Interim data indicates that the main summer rainfall is located in band between 4°N and 14°N, with rainfall decreasing northward from the coast. Maximum daily rainfall is also positioned in orographic regions mentioned above which also experience the coldest temperatures. Lower rainfall amounts are found in the Sahelian region.

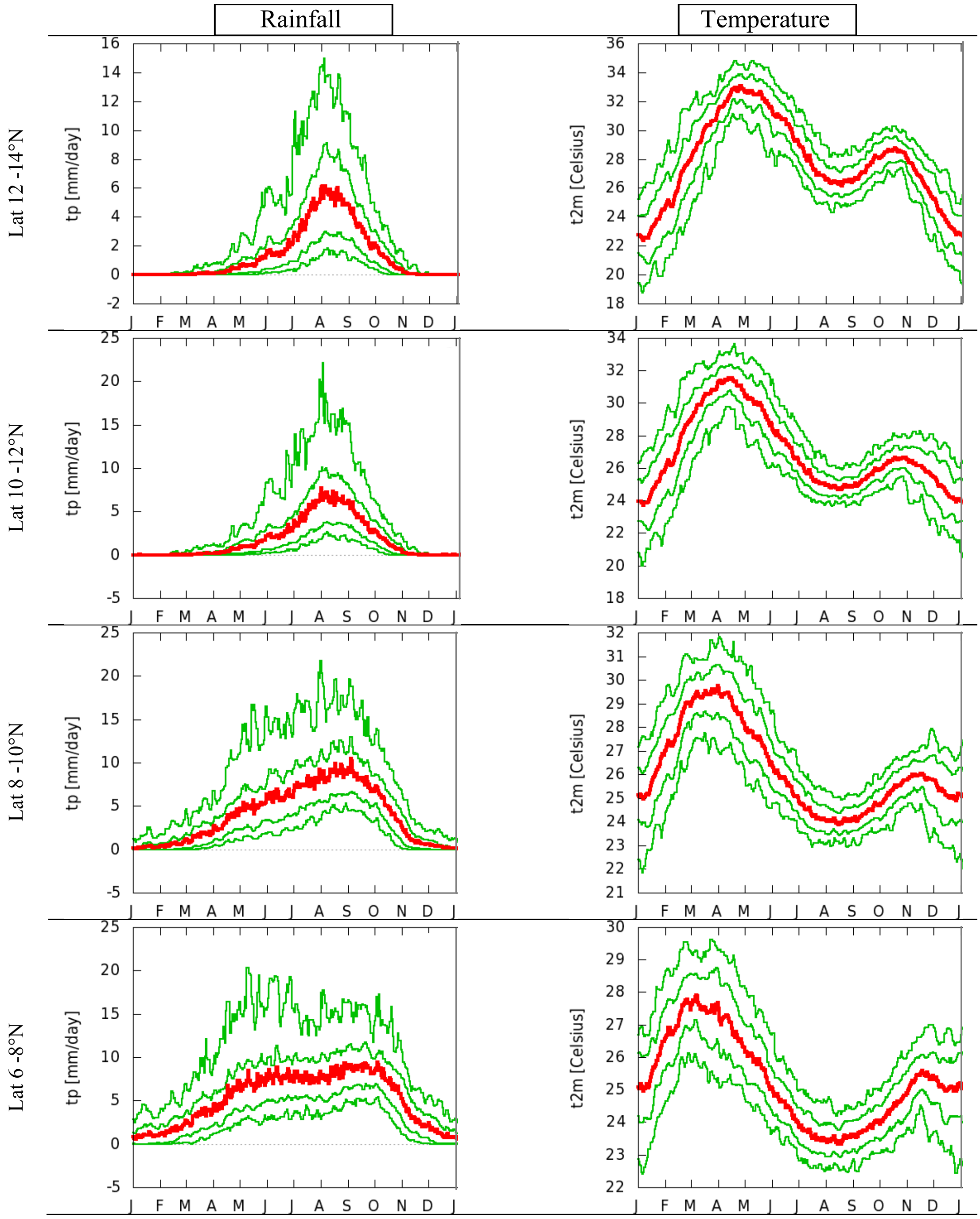

Figure 4.6: Annual cycles of precipitation (left) and surface temperature (right), computed from ERA-interim reanalysis for four latitudinal strips of West African region, each spanning two degree of latitude (-10 – 25°E, 06 - 14°N) between 1979 and 2012. The red line represents the mean index ERA-interim precipitation (left) and temperature (right), and the green lines represents the 2.5, 17, 83, and 97.5 percentiles. Own figure, produced as above

The mean annual cycle of temperature and rainfall from Era-Interim reanalysis for four latitudinal strips of West African region, each spanning two degree of latitude (06 - 14°N) between 1979 and 2012 is shown in Figure 4.6. The temporal distribution pattern for the period reveals that temperature has a double peak with the maxima in March-April-May (MAM) season, and then begins to subside with the onset of monsoon in JJA. Another peak is also observed during September-October-November (SON) season. Rainfall in the Sahel region (12°N - 14°N) usually peaks in JJA, with onset during the MAM season. There is spatial coherence of the temporal pattern of temperature in the region, although there is an increasing temperature gradient between the Coast of Guinea and the Sahara (about 4°C higher). Rainfall has a correspondence with the south-north-south fluctuation of the ITCZ, which is associated with the sequence of active and recess stages of the convective activity (Janicot et al., 2011). The data clearly reveal the three stages of the annual cycle: firstly, the onset stage in MAM, follow by the main rain season – the JJA (in the Sahel), and the final stage is the southward withdrawal of the rain belt in SON season as established by Le Barbe et al. (2002). The onset is associated with a northward propagation of the rain belt from the coast to about 4°N, this is then proceeded by an abrupt jump (Sultan and Janicot, 2003), which occurs at the beginning of June when the rain belt core shift rapidly to about 10°N. This shift brings the main rain season in Sahelian region, which on the other hand relaxes that of the Coast of Guinea. Finally, in September, a rapid southward withdrawal of the rainfall belt occurs, marking the last stage of the WAM season.

Interannual variability of both temperature and rainfall over the West African region was investigated by computing anomalies with respect to the variable's mean, derived from the full 33-year period 1979–2012. Temperatures show a positive trend from the mean in the 1990s and a continual increase to the end of the data period; this is an agreement with global temperature trends. On the other hand, rainfall also shows a relatively positive departure from the mean especially from the mid of 1990s which also continues until the end of the data. An observed positive trend in rainfall from this period has been reported by many studies in this region (e.g., Omotosho, 2008; Hagos and Cook, 2008). Investigating the interannual variation of temperature within seasons (DJF, MAM, JJA, and SON) reveals a similar temporal pattern in all the four seasons shown in Figure 4.7. Temperature is shown to be increasing more from mid 1990s most especially in JJA and SON seasons.

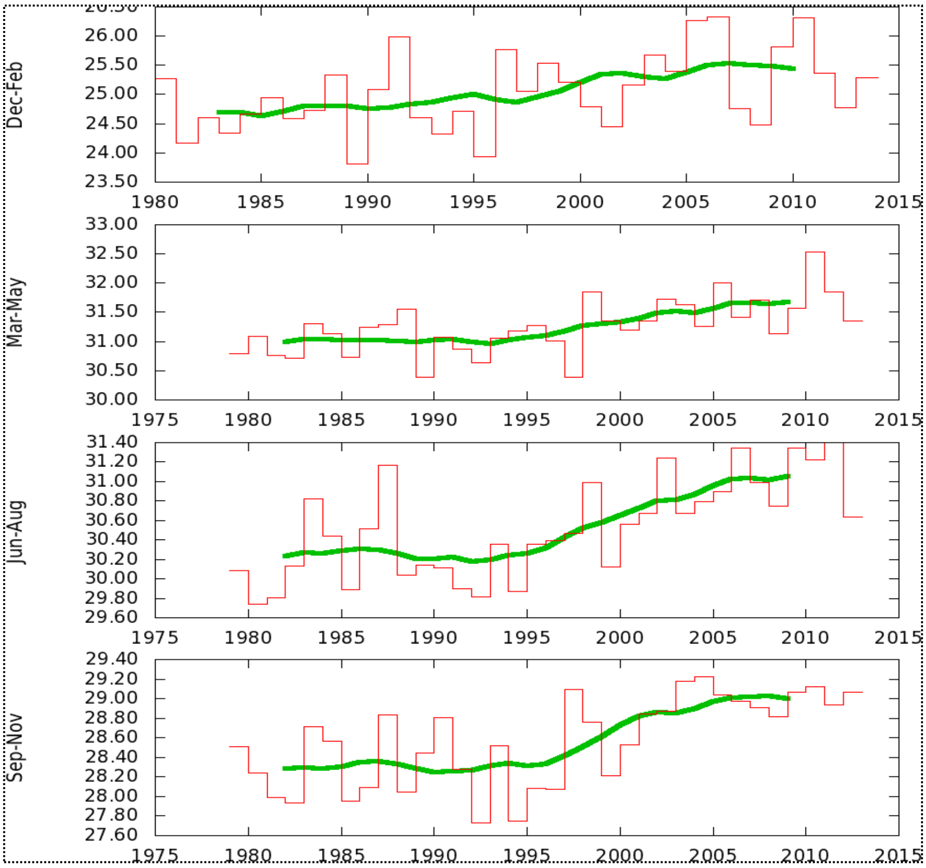

Figure 4.7: Time series (DJF, MAM, JJA, and SON) for surface temperature extracted from ERA-interim for West African region (6 – 14°N, -10 – 25°E) between 1979 and 2012. The green line is representing 10-years running average. Own figure, produced as above.

4.3.3 Temperature and rainfall characteristics over northwest Nigeria

In terms of climate, Nigeria as a whole is having a consistently high temperature throughout the year with some negligible variations across (NIMET, 2012). Rainfall is the only differentiating climatic factor both spatially and temporally, and it depends on the movement of the ITCZ north and south of the equator. A study by Odekunle (2010) reveals that the role of ITD in interannual variability of rainfall is more significant in the northern part of the country, while SST from the GOG may be playing the major role in the south. This variability in rain, produce up to four seasons in the south and two in northern part of the country with an annual average totals of 2000-4000mm and 500-1500mm respectively.

Table 4.2: Monthly maximum and minimum temperatures and rainfall variations averaged over the six stations in northwest Nigeria for the period of 40-years (1971 – 2010).

	Maximum temp.		**Minimum temp.**		**Rainfall**		
Month	Mean	SD	Mean	SD	Mean	SD	% to annual
January	31.3	1.8	14.9	1.2	0.0	0.1	0.0
February	34.4	1.7	17.7	1.5	0.3	1.2	0.0
March	38.2	1.0	23.8	1.1	3.8	6.1	0.4
April	38.8	0.7	25.7	0.8	20.5	15.1	2.4
May	36.7	1.1	24.8	0.7	71.4	28.2	8.5
June	33.9	0.7	23.2	0.5	121.4	26.3	14.4
July	31.1	0.8	22.0	0.4	192.5	40.6	22.8
August	30.3	0.7	21.5	0.4	246.9	53.5	29.3
September	31.8	0.7	21.7	0.5	154.3	39.5	18.3
October	34.2	0.8	21.0	0.9	31.7	29.0	3.8
November	34.1	1.0	17.0	1.1	0.7	2.6	0.0
December	31.8	1.3	14.9	0.9	0.5	2.1	0.0

Summaries of averaged mean monthly variations for temperatures and rainfall over the six stations in northwest Nigeria is presented in Table 4.2 for the period 1971 to 2010. The highest mean annual rainfall are occurring during the months of August (246.9mm), July (192.5mm), and September (154.3mm), with individual monthly contribution to the annual totals of 29.9%, 22.3%, and 18.3% respectively. The months of November to February contributes zero percent to the annual total. In terms of temperature, the month of April appeared to be the hottest month in both maximum and minimum temperature, with an annual mean of 38.8°C and 25.7°C respectively. The month of August have the lowest maximum temperature (30.3°C), while the months of January and December have the lowest for minimum temperature (14.9°C).

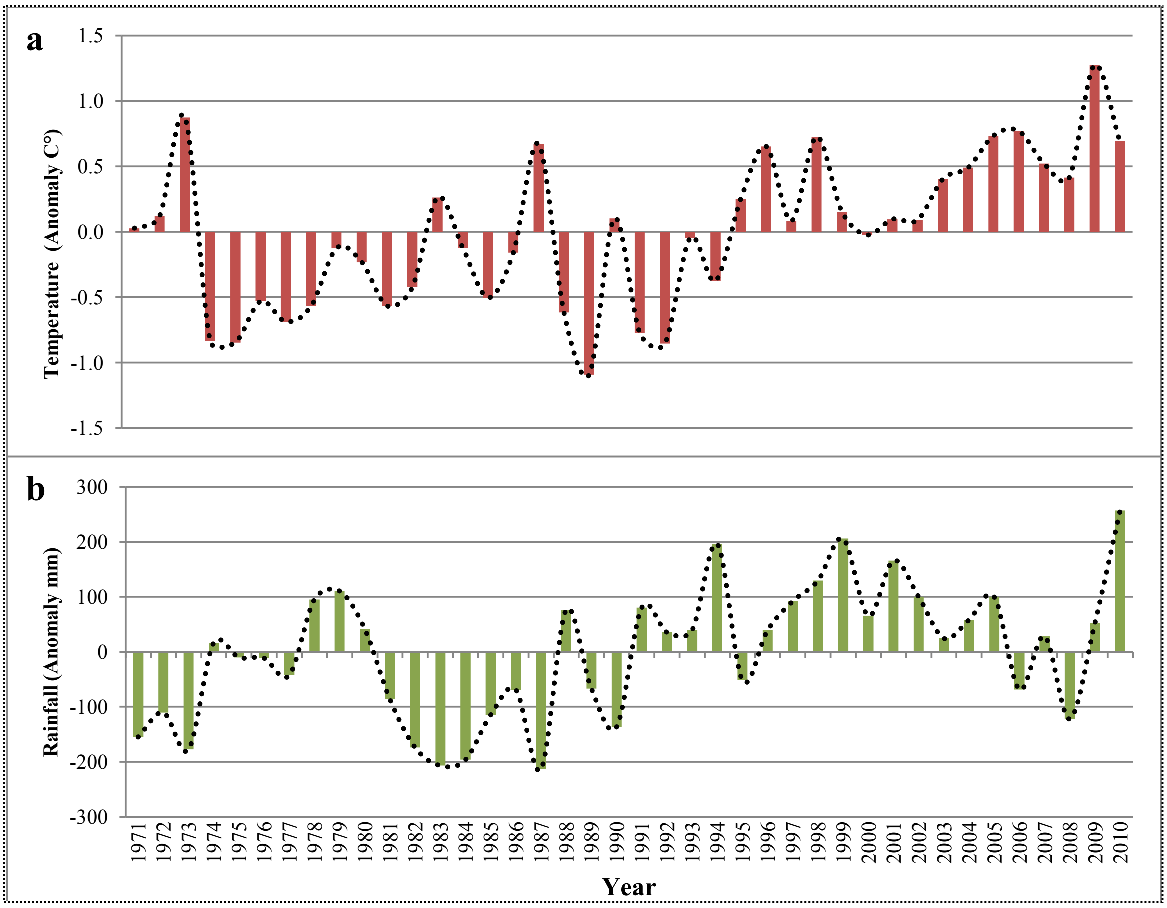

Figure 4.8: Time series (1971-2010) of averaged normalised (a) annual maximum temperature (b) annual rainfall totals used in this study for six stations (Sokoto, Kano, Kaduna, Katsina, Yelwa, and Gusau) over northwest Nigeria.

Figure 4.8 showed temperature and rainfall anomalies averaged over the northwest region of Nigeria, the anomalies were calculated with respect to the variables mean derived from the full 40-year period 1971–2010. The interannual variability of temperatures shows a positive trend from the mean in the 1990s with a continual increase to the end of the data period; this agrees very much with recent studies that reports temperature trends in regions from Nigeria (e.g., Oguntunde et al., 2012). Rainfall shows a clear positive departure from the mean from 1991 up to 2005, followed by a negative trend between 2005 and 2008, and then starts to rise again until the end of the data period. This positive trend in rainfall is also in consistent with what has been observed in the West Africa region at large. Although previous studies have reported a declining trend in the annual mean rainfall in Nigeria (e.g., Tarhule and Woo, 1998), recent studies have confirmed an increasing trend in northwest region (e.g., Obot et al., 2010; Oguntunde et al., 2012).

Table 4.3: Observed trends in annual temperatures (°C/decade) and rainfall (mm/decade) for individual stations in northwest Nigeria between 1971 and 2010, and for two sub-periods (1971-1990 and 1991-2010)

	Maximum Temp.		Minimum Temp.		Rainfall	
1971 -1990	*Slope*	*Sig.*	*Slope*	*Sig.*	*Slope*	*Sig.*
Sokoto	0.419	+	0.446	*	-1.257	***
Kano	0.422	**	0.428	**	-1.061	+
Katsina	0.374	***	0.323	*	0.566	+
Kaduna	0.410	*	0.411	*	-0.757	**
Gusau	0.385	+	0.394	**	-1.238	***
Yelwa	0.412	*	0.429	***	-2.333	+
Northwest	0.384	**	0.409	*	-1.209	**
1991 - 2010						
Sokoto	0.482	*	0.538	+	3.357	+
Kano	0.505	*	0.520	**	3.162	+
Katsina	0.448	**	0.486	**	2.215	*
Kaduna	0.481	***	0.510	***	-0.128	***
Gusau	0.414	**	0.323	+	2.643	+
Yelwa	0.395	*	0.429	*	-0.047	+
Northwest	0.456	**	0.476	**	3.217	+
1971 - 2010						
Sokoto	0.421	*	0.436	*	2.276	*
Kano	0.446	**	0.461	**	2.405	*
Katsina	0.366	*	0.363	***	2.074	+
Kaduna	0.391	*	0.403	*	-0.242	+
Gusau	0.395	***	0.411	**	1.728	***
Yelwa	0.360	*	0.381	*	3.016	+
Northwest	0.409	**	0.428	***	2.147	***

''p<0.001, '**'p<0.01, '***'p<0.05, '+'p>0.05*

Trend tests computed for temperature and rainfall for both individual stations and regional time series stations over the period 1971 to 2010 and the two sub-periods of 1971-1990 and 1991-2010 are shown in Table 4.3. For the averaged regional time series, both maximum and minimum temperatures showed a statistically significant ($p < 0.05$) positive trends. Spatially, all stations showed positive trends. However, trends seem to be higher for station in Kano 0.42(0.44) °C/decade and Sokoto 0.45(0.46) °C/decade for maximum and minimum temperatures respectively, if compared with other stations. Generally, Katsina and Yelwa showed a relatively lower trend among others. Also, all stations showed positive trends for the sub-periods which indicate an increase in temperature. In terms of rainfall, both the regional and individual station's time series reveals a negative trend during the data sub-period (1971-1990), however during the sub-period of 1990-2010, a positive trend was observed in both time series with the exception of Kaduna which consistently reveals a negative trend. Positive trends were also observed for the whole period of data for both time series with exception of Kaduna and Yelwa, though not statistically significant.

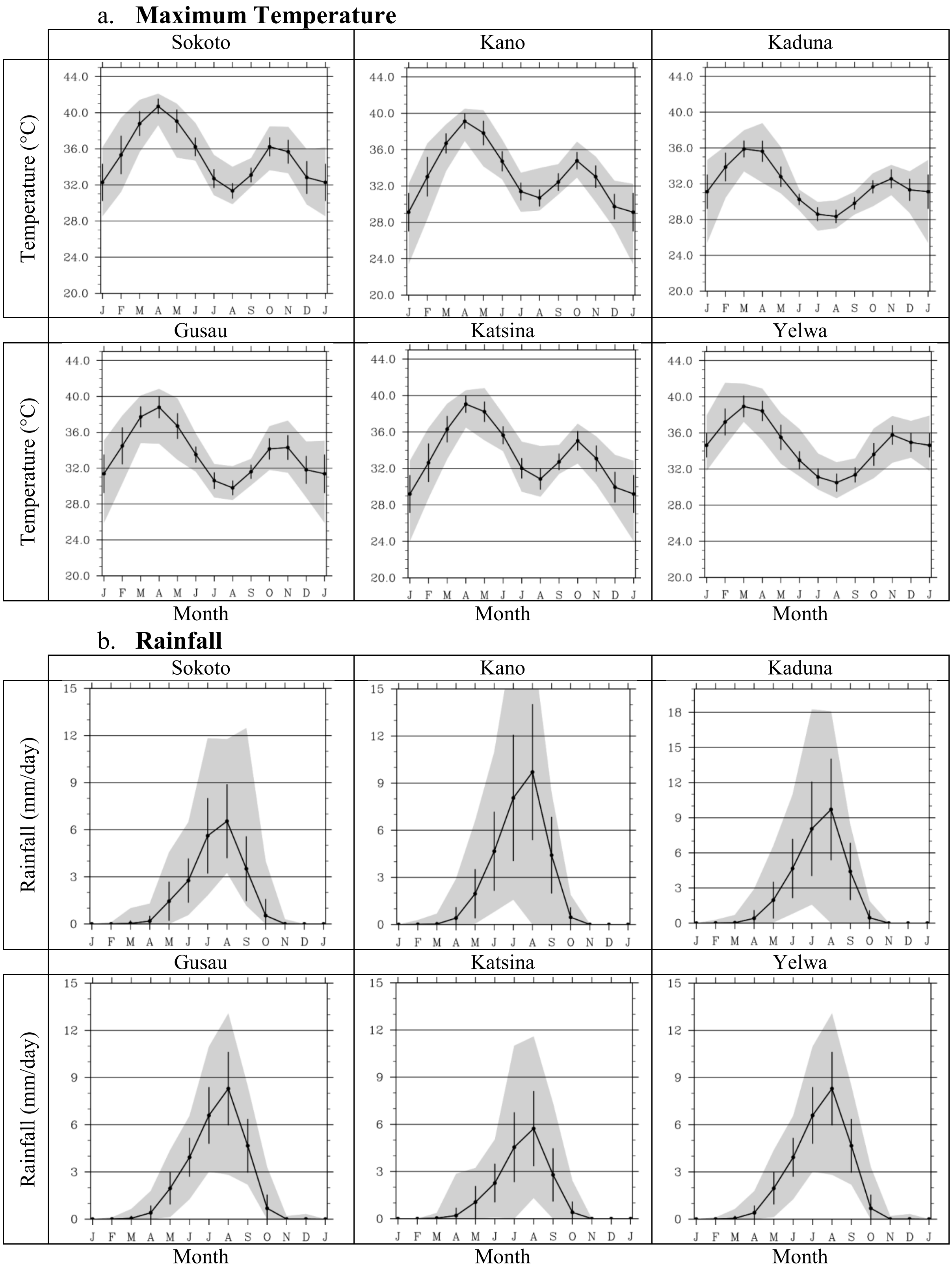

Figure 4.9: Annual cycle of monthly (a) Maximum temperature and (b) Rainfall for the six stations in the northwest region of Nigeria between 1971 and 2010. The vertical bars represent the +/- 1 standard deviation from the monthly mean, and the grey shading represents the range of monthly means over the 40-year period

In order to investigate further, analyses of monthly trends for all the stations is also performed. Trend analysis reveals spatial coherence between months of individual stations for maximum and minimum temperature. Similar monthly trend with regard to differences from month to month were found to exist between all stations. Also, monthly increases and decreases in trend, as well as months of minimum and maximum trend within stations were observed, signifying spatial coherence across the stations in the region. The highest monthly trends were observed in the sub-period (1991-2010) in February, March, May and December for maximum temperatures, and lesser trends in June, July and October for rainfall. Figure 4.9 illustrates the annual cycles of monthly maximum temperature and rainfall for the individual stations in the region, which is revealing both temporal and spatial coherence. Temperature showed double peaks in MAM and SON seasons, although the maxima are occurring in MAM.

Ten selected climate indices for temperatures and rainfall based on CLIVAR/ETCCDI definitions (Table 4.1) were computed for both regional and individual station's time series. Results from the regional time series for Diurnal Temperature Range (DTR) and Precipitation totals (PRCPTOT) are shown in Figure 4.10, from which it is evident that warmer nights have generally increased. Trends in all temperature indices for all the six stations have shown a spatial coherence with statistically significant increases ($p<0.05$). The frequencies of days and nights (Figure 4.11) that are warmer than 90^{th} percentile (TN90p and TX90p) have shown positive significant increases over the long period of data (40-years) and for the two investigated sub-periods, with Sokoto and Kano, showing the highest trend.

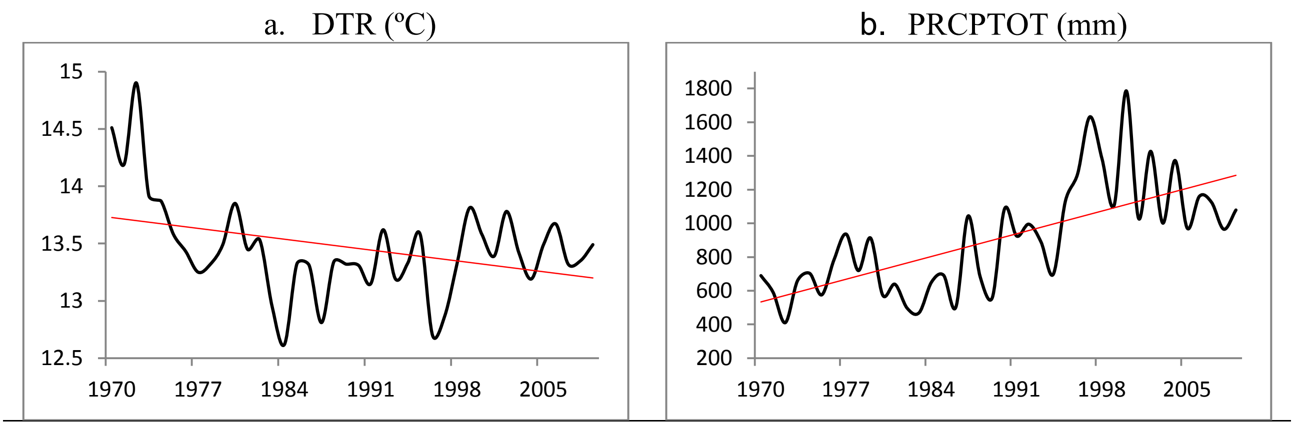

Figure 4.10: Regional time series for northwest Nigeria averaged over the six stations between1971 and 2010 for (a) diurnal temperature range (DTR), and (b) annual total wet-day precipitation (PRCPTOT).

Other computed temperature indices such as the annual count of days with at least 6 consecutive days when TX>90th percentile (WSDI) also showed statistically significant increases. In terms of diurnal temperature range (DTR) all stations time series for the full study period and for the two different sub-periods have shown a significant negative trend. This is because increase in night temperature tends to be higher than that of day time. Precipitation indices also reveal an increasing trend in all stations (though not statistically significant in Yelwa) with the exception of Kaduna that reveals a negative trend. The results from the indices calculation corroborated that obtained from the Mann-Kendall trend tests above.

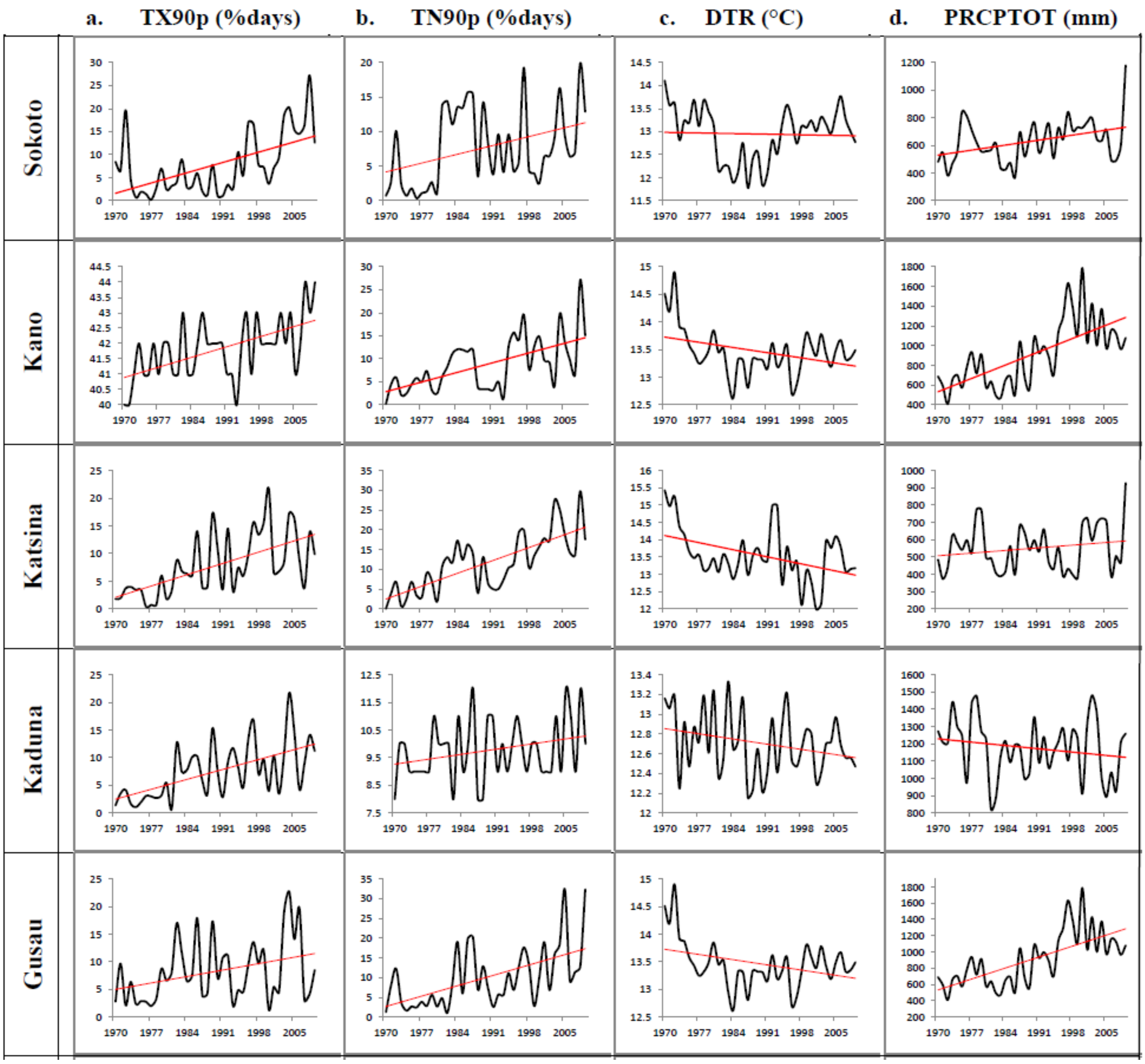

Figure 4.11: Time series of some stations in northwest Nigeria over the period of 40-years (1970 – 2010) for (a) warm days (TX90p) (b) warm nights (TN90p) (c) diurnal temperature range (DTR), and (d) annual total wet-day precipitation (PRCPTOT).

4.4 Discussion

WAM is the climatological feature dominating the West African climate system, although this system is occurring only from May to September over Sahel (Sylla et al., 2013), but it has a larger influences on several vital socioeconomic factors in this region. These factors includes but not limited to agriculture, economy, and health. The WAM brings most rainfall in West Africa (Janicot et al., 2011); in that case its variability is important in determining the length of dry season which in turns is correlated with the incidence of disease such as meningitis. For example, several studies have established significant correlation of meningitis incidence with hot, dusty, and windy weather north of the ITD (Sultan et al., 2005; Thomson et al., 2006).

The drought that occurred between 1970s and 1980s was the recent remarkable climatic event at regional scale that happened in the Sahelian region of West Africa. This event, coupled with the quest of improving the understanding WAM processes has triggered several studies on the variability of climate in West Africa. This is because of the implication of the WAM variability on the millions of people inhabiting the region, with some of their important activities like agriculture relaying solely on it. Both the West and Central Sahel and Guinea coast have been established to have similar rainfall variability on both decadal and interannual timescales (Moron, 1994). Previous studies have linked the interannual variability of the monsoon with ITCZ (e.g., Krause, 1977), however new studies have emphasizes the influence of features in the upper atmosphere, as well as the SHL (Nicholson, 2013).

Rainfall over West Africa has been characterised with variability (Fink et al., 2008). The current study also confirms this variability in the reanalysis data used over the region between 1979 and 2012. Studies in the past have reported a multidecadal dry period with notable droughts between 1970s and 1980s (Fink et al., 2008). This downward trend of rainfall has been reported to have begun in 1960s by Djomou et al. (2009), also Munemoto and Tachibana (2012) have found a declining trend in Sahelian precipitation since before the 1980s, although the driest decade was reported to be in the 1980s, for example in Nigeria (Oguntunde et al., 2011). In this current study a relatively increasing trend in rainfall has been observed in the Sahel most especially from the mid 1990s. This result is consistent with what has been observed of recovering trend in rainfall by so many studies. For example Fink et al. (2008) have reported that the last the last two decades since 1990s have been characterised by increasing trend in rainfall. Also Fall et al. (2006), Folts and Mcphaden (2008), Omotosho (2008), Hagos and Cook (2008) have observed that rainfall in West Africa including Sahel is gradually coming back to normal before the declining trend starts, although this recovery is still considered low (Label et al., 2000).

The results presented for the northwest region of Nigeria agrees to a large extent with previous similar studies of trends investigation in Nigeria (e.g., Obot et al., 2010; Oguntunde et al., 2011; Oguntunde et al., 2012). Also similar temporal variability and trends were found if compared with the West African region at large. The region is characterized by two seasons, a short wet season from June to September, and a prolonged dry season for the remainder of the year. Daytime maximum temperatures remain consistently high throughout the year with maxima during March-May (up to 47°C), while relative humidity is low during the dry season, and increases during the wet season. As meningitis and cholera are known to decrease and increase with the onset of the monsoon respectively, from a seasonal perspective, the variability of meteorological conditions should relate to the variability of incidence in specific regions such as northwest Nigeria.

Examining some selected climate indices for temperature and rainfall at or below certain threshold values, it is evident that warmer days and nights have increased, likewise the occurrence of heat events in the region. The continual increase of warm spell durations (WSDI) may have important effect on the occurrence of some infectious diseases in this region, for example the incidence of both targeted diseases in this study were established to have correlation with elevated temperature. Trends in diurnal temperature range also show for northwest Nigeria also coincides with the general global trends, which are negative over the last century (Easterling et al., 2000), due to relatively high minimum temperature. Positive trends in rainfall were observed indices for the whole period and the two sub-periods 1990-2011 of data with the exception of Kaduna which shows a negative trend.

Many regions in Africa are classified as vulnerable to climate change and variability (Diffenbaugh and Giorgi, 2012), this may have a substantial negative impacts on several aspects of human endeavours, such as change in the ecology and dynamics of some important infectious diseases. Several efforts have been made to investigate the future changes of climate in Africa (Christensen et al., 2007; Giannini et al., 2008); the Sahel where northern Nigeria lies reveals more uncertainty in the future (Biasutti and Giannini, 2006) relatively due to the poor representation of the complex WAM system. Despite these uncertainties, temperature in Africa is projected to increase in the future more than the global average (James and Washington, 2013) particularly in arid regions. While CMIP5 models are suggesting rainfall increase in central Sahel and deficit in western areas (Fontaine et al., 2011; Monerie et al., 2012).

4.5 Conclusion

WAM is the dominating climatic feature in West Africa; as such it determines the climate of the region. It is noteworthy to mention here that the variability observed in the climatic variables from stations data used for northwest Nigerian regions does not come from the stations, rather is been steered by large scale variability of the WAM features such as the ITCZ and ITD positions. Since the climate of the targeted region is produced under the same atmospheric dynamical processes, as such spatial averaging of climatic variables in this region could be considered suitable.

Conclusions can be drawn that temperature trends in northwest region of Nigeria and the West African region has been on the increase most especially from the 1990s. In the case of rainfall, ERA-interim reanalysis data showed a relatively positive departure from the mean in the mid of 1990s for West African region. Also stations data indicates an increase in rainfall with the exception of Kaduna which consistently reveals a negative trend in both the full data and the two sub-periods investigated. All computed temperature indices for the northwest region agreed with the global trends, indicating increases in warming and warming event at statistically significant levels ($p<0.05$). Rainfall indices also showed increasing trends in the regional time series, and in all stations except Kaduna for precipitation total.

This chapter addresses objective two of this study by analysing the spatial and time characteristics of climate over West African region and northwest Nigeria in particular (the target region). Mean annual and monthly trends, interannual variability, and selected climate indices were investigated and discussed.

Chapter Five:

Spatial and Time Characteristics of Meningitis and Cholera Diseases in Nigeria

Chapter Five

Spatial and Time Characteristics of Meningitis and Cholera Diseases in Nigeria

5.1 Introduction

The outbreaks and epidemics of meningitis and cholera are occurring throughout the world, but are most severe in African countries. For several decades these climate-sensitive infectious diseases have remained a major health and social problems in Nigeria, and continue to afflict the nation both in epidemic magnitude and small outbreaks. According to WHO records between 1991 and 2011, Nigeria alone reported over 393,614 (380,698) cases and 22,664 (28,898) deaths of meningitis and cholera respectively. The first documented cases of meningitis was reported from the north eastern state of Bauchi in 1905, while cholera reached West Africa and Nigeria during the seventh pandemic in 1971 (Barua and Cvjetanovic, 1970; Cvjetanovic and Barua, 1972; Goodgame and Greenough, 1975). The first reported cases of cholera was in a village near the then capital city – Lagos, and resulted to a severe epidemic of which 22,931 cases and 2,945 death. As in the case of other countries in West Africa, the human pathogen bacteria *Neisseria meningitidis* A (WHO, 2013a), and vibro *cholarae* O1 and O139 (Marin, 2013) are responsible for most of the meningitis and cholera epidemics and outbreaks in Nigeria. The diseases have notable seasonality (e.g., Pascual et al., 2002) and varies both spatially and temporally across the globe, and they are well documented to have been influenced by climatic, environmental, and social factors (Abdussalam et al., 2014a; Dukic et al., 2012; Greenwood, 2006; Harris et al., 2012; Sultan et al., 2005; Rajendran et al., 2011). Details of the characteristics, epidemiology, and the documented relationships between these diseases and meteorological and socioeconomic conditions were discussed in the literature review chapter.

Exploring and analysing long term surveillance epidemiological data is important for understanding the nature of the spatial and temporal dynamics of infectious diseases; this is in order to improve the methods and strategies of controlling them. It will also allow for the identification of high risk areas which would help greatly in investigating the driving factors responsible for the disease outbreaks, through understanding the characteristics of the risk area. This chapter will investigate the spatial and time characteristics of meningitis and cholera, and identify the states and regions with high burden and risk; this would be achieved through exploring existing epidemiological records of the diseases using various statistical techniques.

5.2 Materials and methods

The overall analysis would be based on national epidemiological, socioeconomic, and demographic data. Descriptive statistics (e.g., Chevallier et al., 2004; Sasaki et al., 2008), and spatial statistical techniques (e.g., Borroto and Martinez-Peidra 2000; Osei and Duker, 2008) were used in explaining the spatial and time characteristic of meningitis and cholera in Nigeria.

5.2.1 Epidemiological data

Three types of epidemiological data were obtained from different sources and at different spatial and temporal resolutions. Firstly, records of annual suspected meningitis and cholera cases and deaths at state levels between 2000 and 2011 were obtained from the epidemiology unit of the NCDC of the Nigerian FMoH. These cases are reported by DSNOs in all the 774 Local Government Areas (LGAs) of Nigeria (detail description of this data is presented in section 3.3.2). Secondly, annual national level records of reported cases of both diseases' cases and deaths from 1991 to 2011were extracted from the archives of the WHO. Finally, a higher resolution data of weekly records of reported meningitis cases from the 774 districts in Nigeria between 2007 and 2011were obtained from WHO.

Cases definitions:

In Nigeria, meningitis and cholera cases are defined according to the WHO case definitions, and since all the cases in this study are suspected cases, are thus defined as follows:

A suspected meningitis case is defined: “as a person with sudden onset of fever (>38.5°c rectal or 38.0°c axillary) with one or more of following symptoms: neck stiffness, meningeal sign, or altered consciousness” (WHO, 2010). While suspected cholera case is defined: “as when a patient of 5 years or older shows symptoms or dies of acute dehydration, even in areas where the disease is not common” (WHO, 2011d).

5.2.2 Socioeconomic and population data

Annual socioeconomic data between 2000 and 2011 for individual states in the country were obtained from the Nigerian National Bureau of Statistics (NBS). Data obtained includes percentages of population living in absolute poverty and adult literacy. State’s population census (2006) was obtained from the Nigerian Population Commission (NPC), Nigeria. Annual population estimate for each state was calculated forward and backward using Nigerian population growth rate index provided by World Bank. Population density for each state was computed by dividing each state’s population with its aerial cover in square kilometres. Table 5.1 shows the name and codes of the 36 states and FCT in Nigeria and their 2012 estimated population.

Table 5.1: States name, codes, and their projected 2012 population

SN	Code	State	Population	SN	Code	State	Population
0	**AB**	Abia	3,389,144	19	**KN**	Kano	11,221,827
1	**AD**	Adamawa	3,788,692	20	**KT**	Katsina	6,927,271
2	**AK**	Akwa Ibom	4,688,127	21	**KB**	Kebbi	3,873,034
3	**AN**	Anambra	5,001,239	22	**KG**	Kogi	3,920,701
4	**BA**	Bauchi	5,592,525	23	**KW**	Kwara	2,835,555
5	**BY**	Bayelsa	2,037,024	24	**LG**	Lagos	10,779,172
6	**BN**	Benue	5,045,741	25	**NS**	Nassarawa	2,228,267
7	**BR**	Borno	4,964,359	26	**NG**	Niger	4,724,053
8	**CR**	Cross River	3,454,878	27	**OG**	Ogun	4,458,385
9	**DL**	Delta	4,901,214	28	**ON**	Ondo	4,115,077
10	**EB**	Ebonyi	2,599,262	29	**OS**	Osun	4,094,162
11	**ED**	Edo	3,848,763	30	**OY**	Oyo	6,686,911
12	**EK**	Ekiti	2,851,249	31	**PL**	Plateau	3,801,382
13	**EN**	Enugu	3,895,362	32	**RV**	Rivers	6,201,154
14	**FC**	FCT-Abuja	1,680,462	33	**SK**	Sokoto	4,421,194
15	**GM**	Gombe	2,814,974	34	**TR**	Taraba	2,751,421
16	**IM**	Imo	4,705,696	35	**YB**	Yobe	2,776,361
17	**JG**	Jigawa	5,200,494	36	**ZM**	Zamfara	3,898,409
18	**KD**	Kaduna	7,254,925	37	**NG**	Nigeria	167,428,470

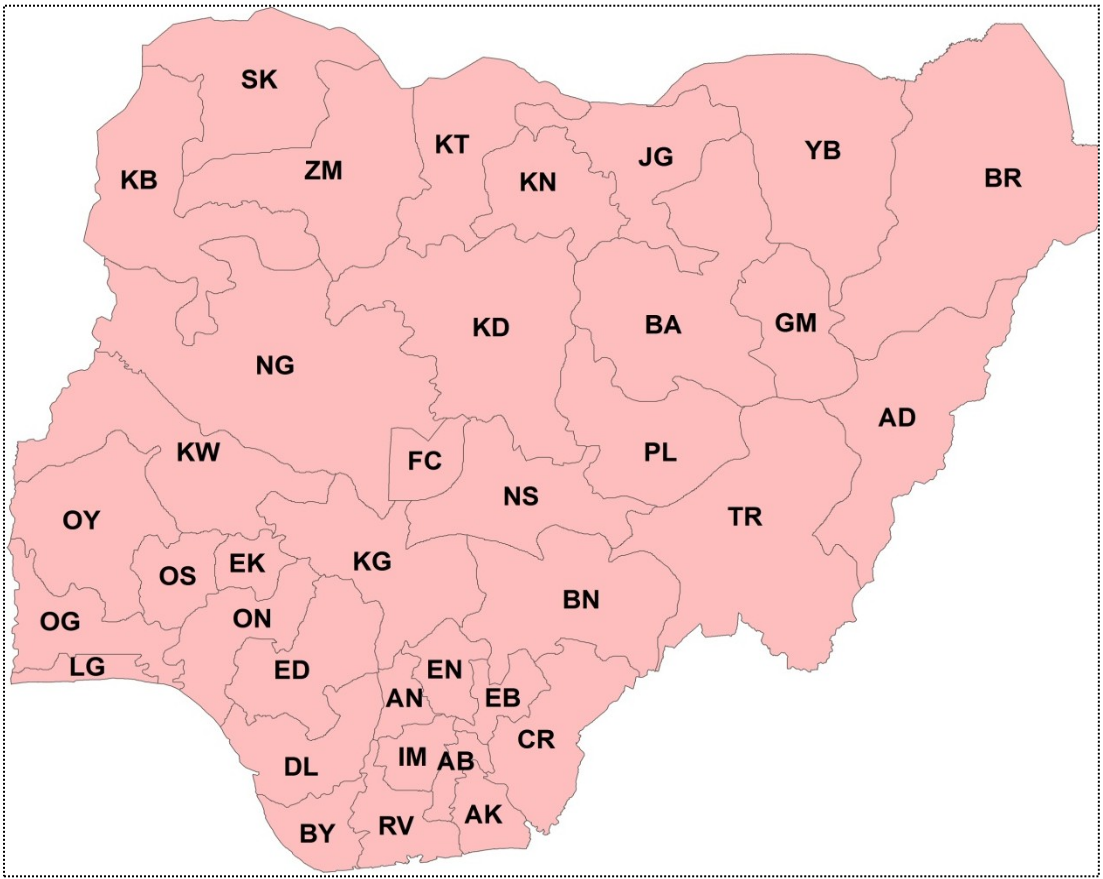

Figure 5.1: Map of Nigeria showing the 36 states and FCT.

5.2.3 Measuring the spatial and time distribution of diseases

Annual incidence rate (IR) per 100,000 of population and case fatality rate (CFR) for both meningitis and cholera were computed from the WHO national records between 1991 and 2011. IR and CFR were also calculated for each of the 36 states (Figure 5.1) in Nigeria and the Federal Capital Territory (FCT) Abuja, using the annual state levels cases and deaths reported between 2000 and 2011 obtained from NCDC.

The IR and CFR for both diseases at the states level for the 12 years of data (2000 – 2011) were classified into strata based on their respective values. ArcGIS was used to determine the cut-off point of each interval using the Jenks Natural Break method and subsequently mapped using different colours to represent each of the four intervals. This method basically classifies data by minimising and maximising the variance within and between classes respectively (Jenks, 1967). Global Moran's Index spatial autocorrelation technique is used to investigate the extent to which neighbouring values of IR are correlated and to determine meningitis and cholera demographic risk factors (see section 3.5 for more about this technique). The spatial weighing function was determined in respect to the length of the common boundaries by assuming that the states that are sharing longer boundaries are more interconnected than states sharing shorter one or no boundary at all (e.g., Borotto and Matinnez-Piedra, 2000).

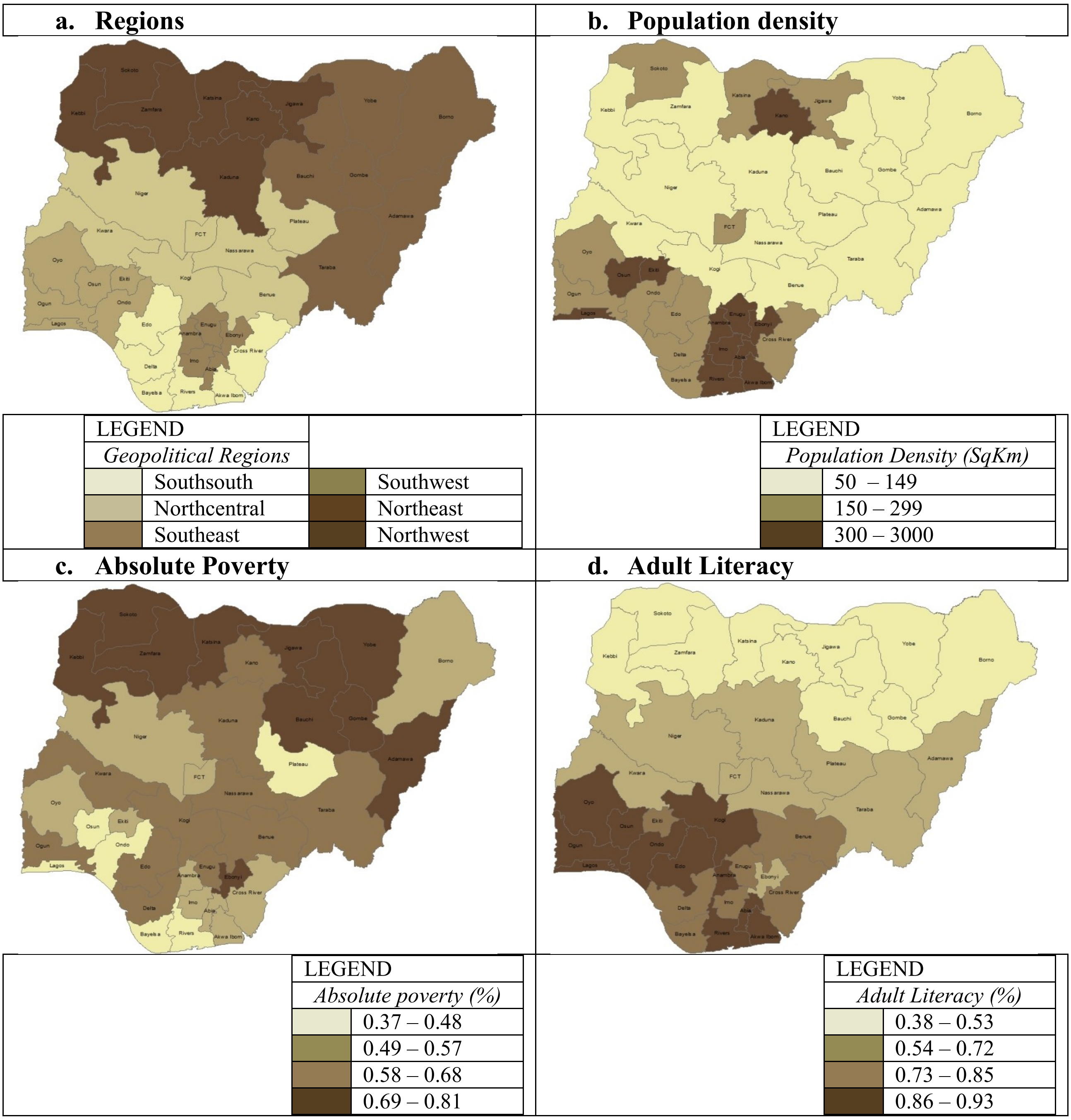

Figure 5.2: Map of Nigeria showing: **(a)** Six geopolitical regions (Northwest, Northeast, Southwest, Southeast, Northcentral, and Southsouth) grouped based on the official classification of Nigeria regions, **(b)** Three population density strata, grouped based on projected 2006 population census computed using individual state sizes in Square kilometre, **(c)** Four poverty strata, grouped based on mean percentage of population living in absolute poverty per state between 2000 and 2011. Absolute poverty here is defined as the percentage of population that have income less than the median income, and **(d)** Four literacy strata, grouped based on mean percentage of population with adult literacy per state between 2000 and 2011. Adult literacy is measured on the ability to read and write with understanding, in English or in any of the Nigerian native languages (NBS, 2012).

The states where classified into strata based on the following variables: geographic location; population density; poverty status; and adult literacy level according to diseases IR (Figure 5.2a-d). Population-based ratios were then computed for each stratum for the identification of high risk areas, using the stratum with the lowest value of IR in each of the four variables as reference point. To determine the association between these variables and diseases' IR, Mantel-Haenszel *Chi Square* test was used.

a. Geographic regions:

As highlighted in chapter three, section 3.2, Nigeria is divided into six geopolitical regions namely: northwest, northeast, northcentral, southwest, southsouth, and southeast (Figure 5.2a) consisting of 7, 6, 7, 6, 6, and 5 states respectively. For the purpose of identifying regions with the high burden and risk of the selected diseases, this official regional classification is adopted.

b. Population density:

Population density for each of the 36 states and FCT per square kilometre was computed based on projected 2006 population census. Three strata namely: high, medium, and low densely populated were identified, with each consisting of 11, 11, and 15 states (Figure 5.2b).

c. Poverty status:

Four poverty strata were identified based on the mean of the percentage of population living in absolute poverty per state between 2000 and 2011. In Nigeria, absolute poverty is defined as the percentage of population with income less than a fixed proportion of median income (NBS, 2012). Classification was made based on states with very-high, high, medium, and low poverty, with each of the stratum consisting of 11, 11, 10, and 5 states respectively (Figure 5.2c).

d. Adult literacy:

States were stratified into four, based on mean percentage of population with adult literacy per state between 2000 and 2011. In Nigeria, adult literacy is measured on the ability to read and write with understanding, in English or in any of the Nigerian native languages (NBS, 2012). Classification was made as states with very-high, high, medium, and low literate adults, with each of the stratum consisting of 10, 7, 8, and 10 states respectively (Figure 5.2d).

In order to investigate the time coherence (interannual variability) of both diseases within states in Nigeria, the state level annual cases between 2000 and 2011 were standardised for each state. An average standardised time series from the most affected states were generated for both diseases and correlated with individual states. Furthermore, the temporal and spatial distribution of a higher resolution meningitis cases was studied using the cumulative weekly district level cases districts between 2007 and 2012.

5.3 Results

5.3.1 Meningitis

The cumulated number of meningitis cases and deaths between 1991 and 2011 according to the WHO record is 380,699 and 28,898 respectively, with a cumulative IR (240.3) and CFR (7.6%). Table 5.2 shows that within this 22-year period, 62% and 65% of the total cases and deaths occurred in the epidemics years of 1996, 2003, 2006, and 2009. The highest number of cases (108,568 IR = 98.9) and deaths (11,231 CFR = 10.3%) occurred in the epidemic years of 1996, while the lowest cases (2,466 IR = 1.6) and deaths (141, CFR = 5.7%) occurred in

2011. Figure 5.3 allows for the visualisation of the disease variability between 1991 and 2011 which is characterised with three conspicuous peaks (1996, 2003, and 2006) that occurred at the intervals of eight and six years respectively.

Table 5.2: Reported meningitis cases and deaths, incidence rate per 100,000 of population, and case fatality rates for Nigeria between 1991 and 2011

Year	Cases	Deaths	IR	CFR%
1991	6992	695	7.2	9.9
1992	6418	563	6.4	8.8
1993	4209	472	4.2	11.2
1994	6014	437	5.7	7.3
1995	7376	1388	6.9	18.8
1996	108568	11231	98.9	10.3
1997	39973	965	35.5	2.4
1998	10793	797	9.4	7.4
1999	4599	222	3.9	4.8
2000	5783	509	4.8	8.8
2001	7656	691	6.2	9.0
2002	6544	655	5.2	10.0
2003	35663	4142	27.5	11.6
2004	9489	650	7.2	6.9
2005	4988	362	3.7	7.3
2006	13075	492	9.4	3.8
2007	5509	444	3.8	8.1
2008	8981	625	6.1	7.0
2009	79335	2916	52.6	3.7
2010	6268	501	4.1	8.0
2011	2466	141	1.6	5.7

The annual state level data allows for investigating the spatial distribution of meningitis across the country. Within the 12 years of data (2000 – 2011), over 98% and 94% of cases and deaths have occurred in the northern states. Specifically 78% and 77% of cases and deaths respectively that occurred within this period were reported from the northern states of Kano, Kaduna, Katsina, Kebbi, Sokoto, Zamfara, Jigawa, and Bauchi. This is suggesting that most of the cases and deaths have occurred in states from the northwest region of the country. By looking at cases occurring with respect to the population, the most affected states with the highest cumulative IR are; Kebbi (72.3), Jigawa (48.6), Kano (46.2), and Sokoto (41.7), while the least affected states comes from the southern part of the country. For example, states such as Akwa Ibom, and Imo have IR of less than 0.04 with no reported death.

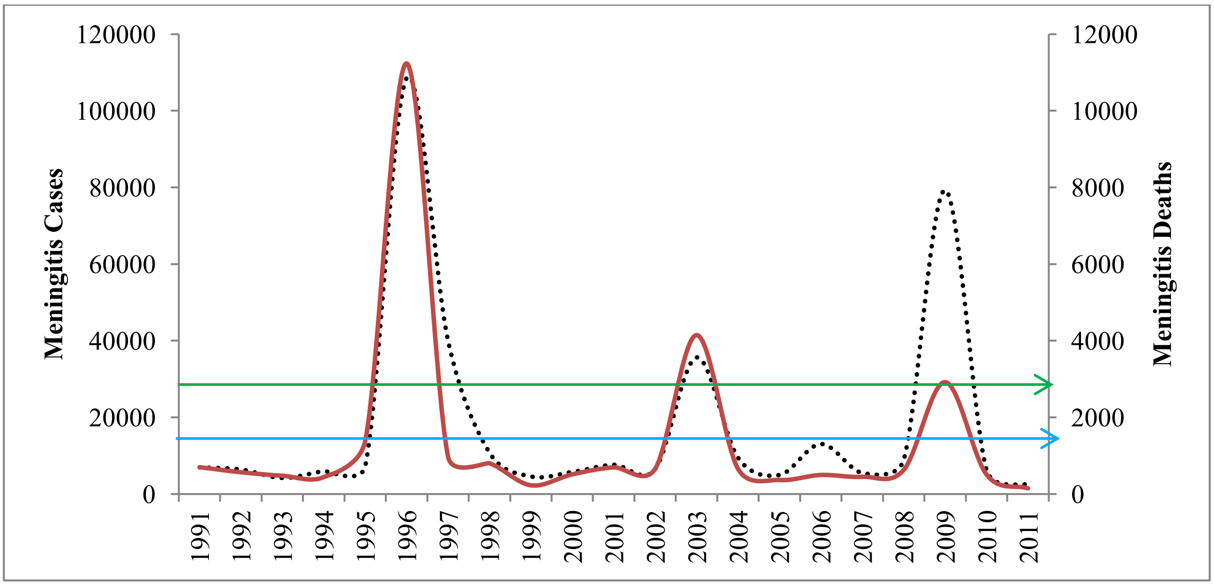

Figure 5.3: Annual meningitis reported cases (dashed-black) and deaths (red) between 1991 and 2011 in Nigeria. The blue and green arrows indicate the average and standard deviation of cases respectively.

Spatial autocorrelation was computed in order to measure the extent of neighbourhood between IR values using the Global Moran's Index. A statistically significant positive spatial autocorrelation for cumulative IR of meningitis from 2000 – 2011 (Moran's I = 0.235, z = 2.69, p = 0007) is analysed. Furthermore, spatial autocorrelation was computed for each year and were all found to be statistically significant (p = 0.000 - 0.025) (Table 5.3).

Table 5.3: Global Moran's Index spatial autocorrelation computed for cumulative meningitis incidence rate (2000 - 2011), and for each year between this period using state level data

Year	*Moran's Index*	*p-value*
2000	0.113	0.013
2001	0.023	0.003
2002	0.173	0.016
2003	0.231	0.005
2004	0.302	0.025
2005	0.122	0.001
2006	0.271	0.001
2007	0.136	0.004
2008	0.217	0.000
2009	0.191	0.003
2010	0.318	0.000
2011	0.201	0.002
2000-2011	0.235	0.007

Statistically significant clusters were detected in the cumulative IR between 2000 and 2011, reflecting a north – south steep spatial gradient with clustering of highest IR in the northern states of the country (Figure 5.4). The clustering of high rates of meningitis at the northwest and northeast was persistent in these regions in all the years (2000-2011) shown in Figure 5.4. Table 5.4a - d shows the rate-ratios computed within each stratum, IR was remarkably higher in the northwest (81.5 times), northeast (33.2 times), and northcentral (5.2 times) regions if compared with the lowest stratum – the southeast region. *Chi Square* reveals reveals a statistically significant positive relationship with poverty (p = <0.04), while a positive but not statically significant relationship was observed with population density (p = >0.05). In the case of adult literacy, an inverse but significant relationship was seen (p = <0.05). Table 5.4a – d shows that the IR of the poorest and densely populated strata are 34.8 and 2.1 times higher than that of their respective lowest stratum, while in the adult literacy stratum IR is 41.6 times higher in population with less educated literates if compared with that of the highly educated ones.

Meningitis is not evenly distributed across the country; Table 5.4 shows incidence rate being much higher in the northern states of the country most especially the northwest (336 per 100,000) and northeast (149 per 100,000) regions, followed by the central region (28 per 100,000). The southern states are having the least of IR ranging between 0.1 and 0.9 per 100,000. This steep latitudinal gradient is shown in Figure 5.4.

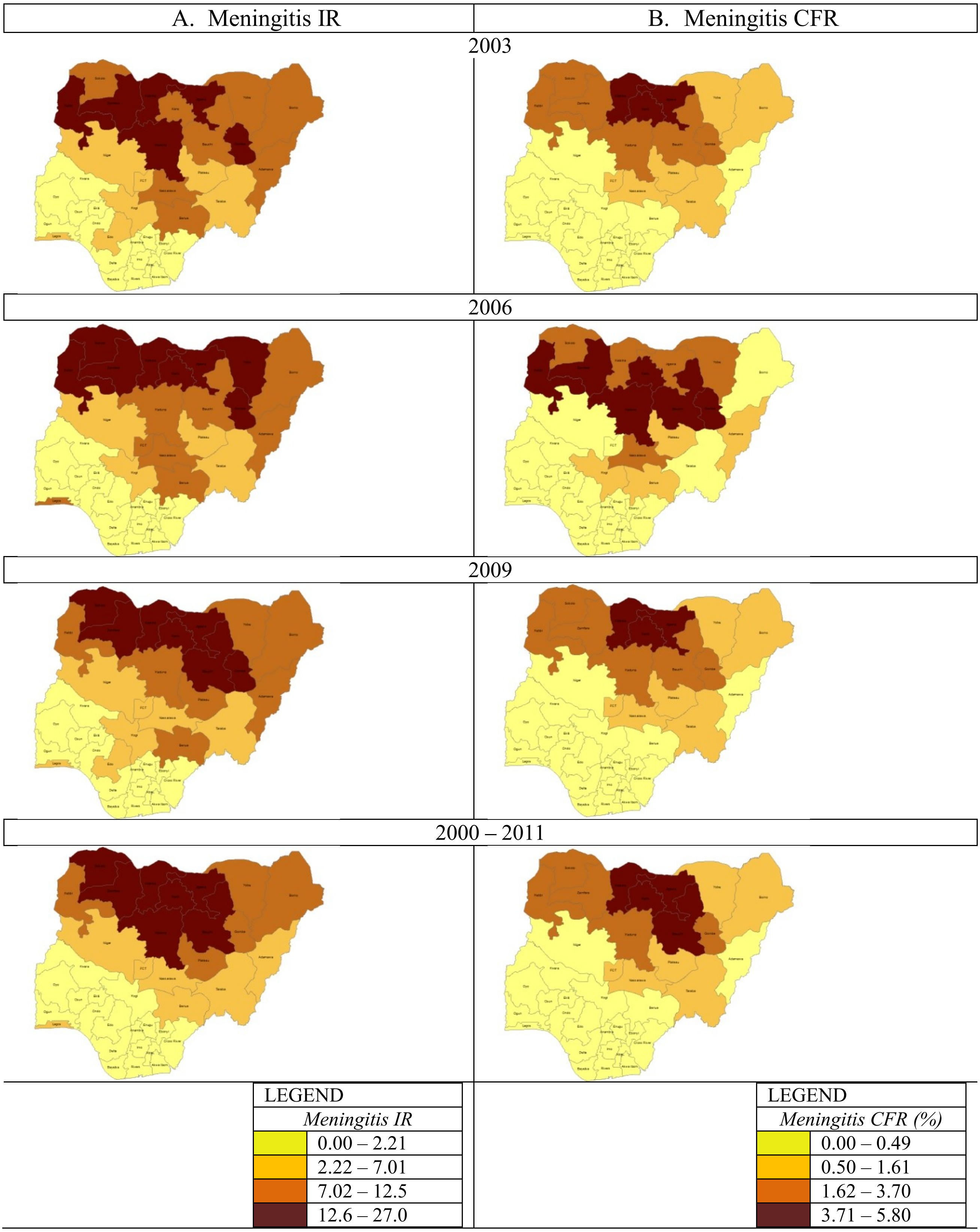

Figure 5.4: Spatial distribution of states level annual incidence rate per 100,000 for population (left) and case fatality rate (right) of meningitis for 2003, 2006, 2009 and the cumulative incidence rate between 2000 and 2011.

Table 5.4: Meningitis incidence rate and population-based rate ratio by strata of states classified based on (a) geopolitical locations, (b) population density, (c) percentage of population living in absolute poverty, and (d) percentage of literate adults between 2000 and 2011.

a.

Geopolitical region	Meningitis cases	Population	IR (per 100,000)	Rate ratio
Northwest	144086	40497542	355.8	81.5
Northeast	31088	21469225	144.8	33.2
Northcentral	5210	22933883	22.7	5.2
Southsouth	3022	23780792	12.7	2.9
Southeast	989	18538039	5.3	1.2
Southwest	1362	31212581	4.4	Reference

b.

Population density	Meningitis cases	Population	IR (per 100,000)	Rate ratio
High	90841	57031901	159.2	2.1
Medium	53157	45166916	117.7	1.6
Low	41759	56233246	74.26	Reference

c.

Absolute poverty %	Meningitis cases	Population	IR (per 100,000)	Rate ratio
Low	2278	29360751	7.8	Reference
Medium	7905	39881488	19.8	2.6
High	68642	49548594	138.5	17.9
Very high	106932	39641231	269.7	34.8

d.

Adult Literacy %	Meningitis cases	Population	IR (per 100,000)	Rate ratio
Low	149963	48912976	306.6	41.6
Medium	29280	29962622	97.7	13.3
High	2530	25446225	9.9	1.4
Very high	3984	54110240	7.4	Reference

Mapping the district levels reported meningitis cases between 2007 and 2012 allows for the visualisation of the spatial distribution of the disease outbreak (Figure 5.5). In all the seven years of data, disease cases show a consistent clustering in the northwest region of the country. Although cases have been reported from the southern districts periodically, but are recently more occurring in this part of the country, example is in year 2010 and 2011. The temporal distribution of meningitis on weekly resolution is shown in Figure 5.6 for the 6 years of available data (2007 – 2012). In all the years shown, the season has been consistently starting between week 43 and 46, peaking between week 12 and 16 and then began to subside between week 20 and 22. The disease season onset is corresponding with onset of the Harmattan and continues throughout the dry season, and then subsides with the appreciation of humidity and the onset of the rainy season. Cases were observed to have begun early in 1995 leading to one of the pronounced epidemic year in 1996. A fairly consistent interannual variability pattern was observed for meningitis in all the reporting districts between 2007 and 2012.

Correlating the standardised annual cases of meningitis from each state with an averaged time series from the most affected states allows for investigating whether there is time coherence in the interannual variability of the disease occurrence within states. As expected states from northern part of the country shows higher correlations (0.61 – 0.92) with reference time series (Figure 5.7), followed by those from the southwest and northcentral (0.29 – 0.60) with the exception Taraba state. The least correlated states are found in the south-south region of the country.

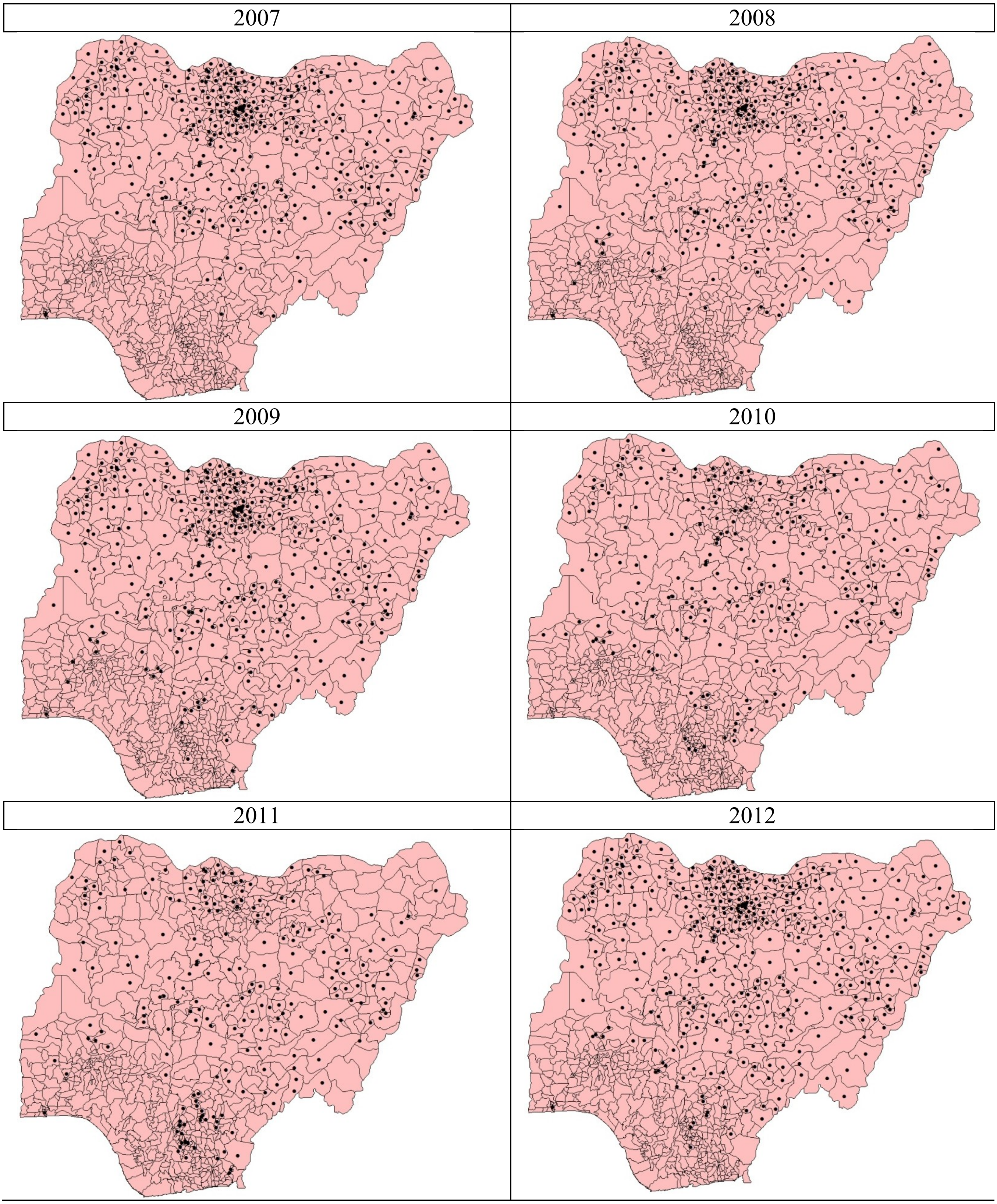

Figure 5.5: Spatial distribution of weekly reported cases of meningitis from 774 districts in Nigeria to WHO between 2007 and 2012. The black dot indicates if at least one case is reported from a particular district in the year.

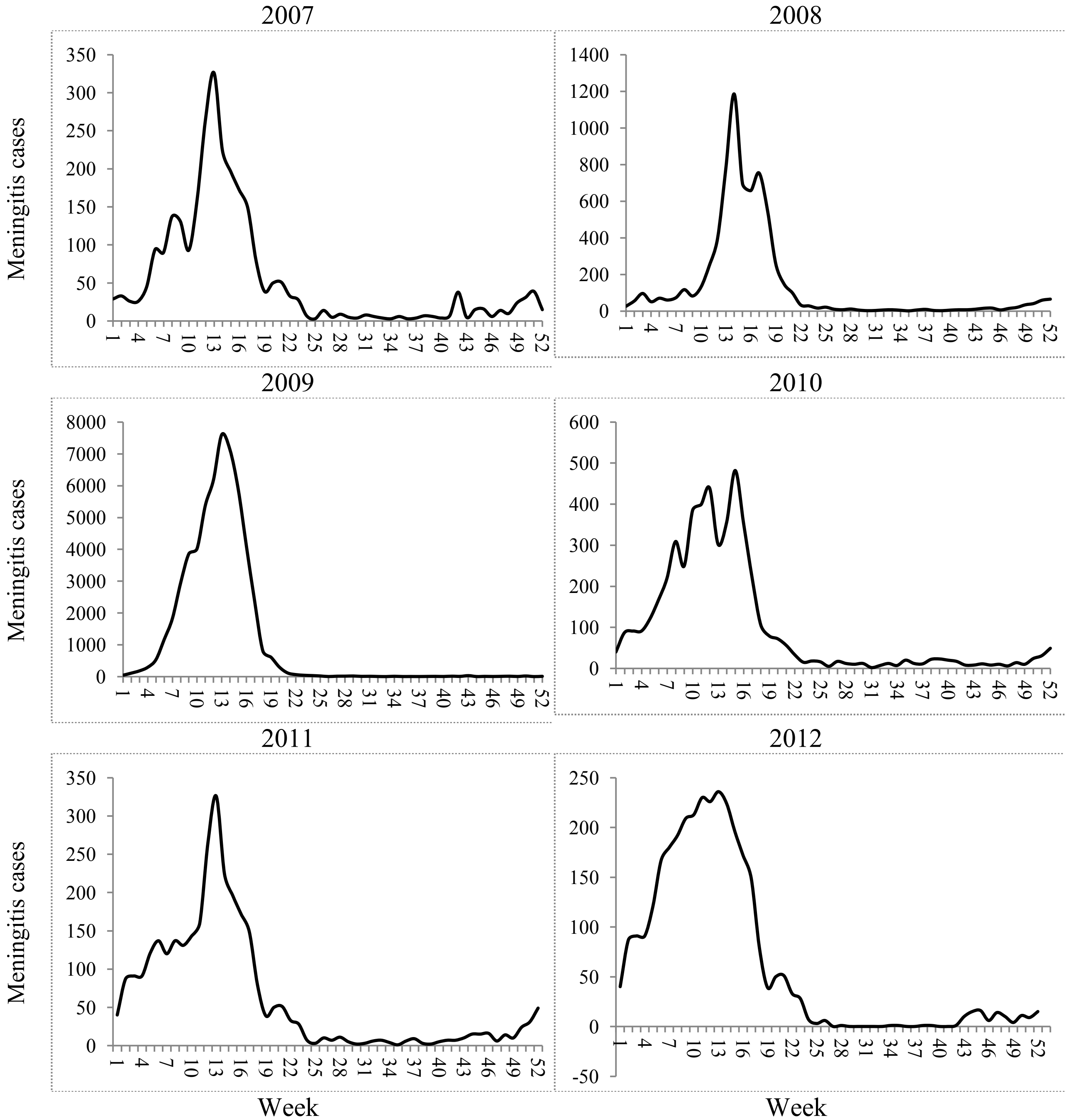

Figure 5.6: Weekly cycles of districts level meningitis cases reported to WHO from Nigeria between 2007 and 2012.

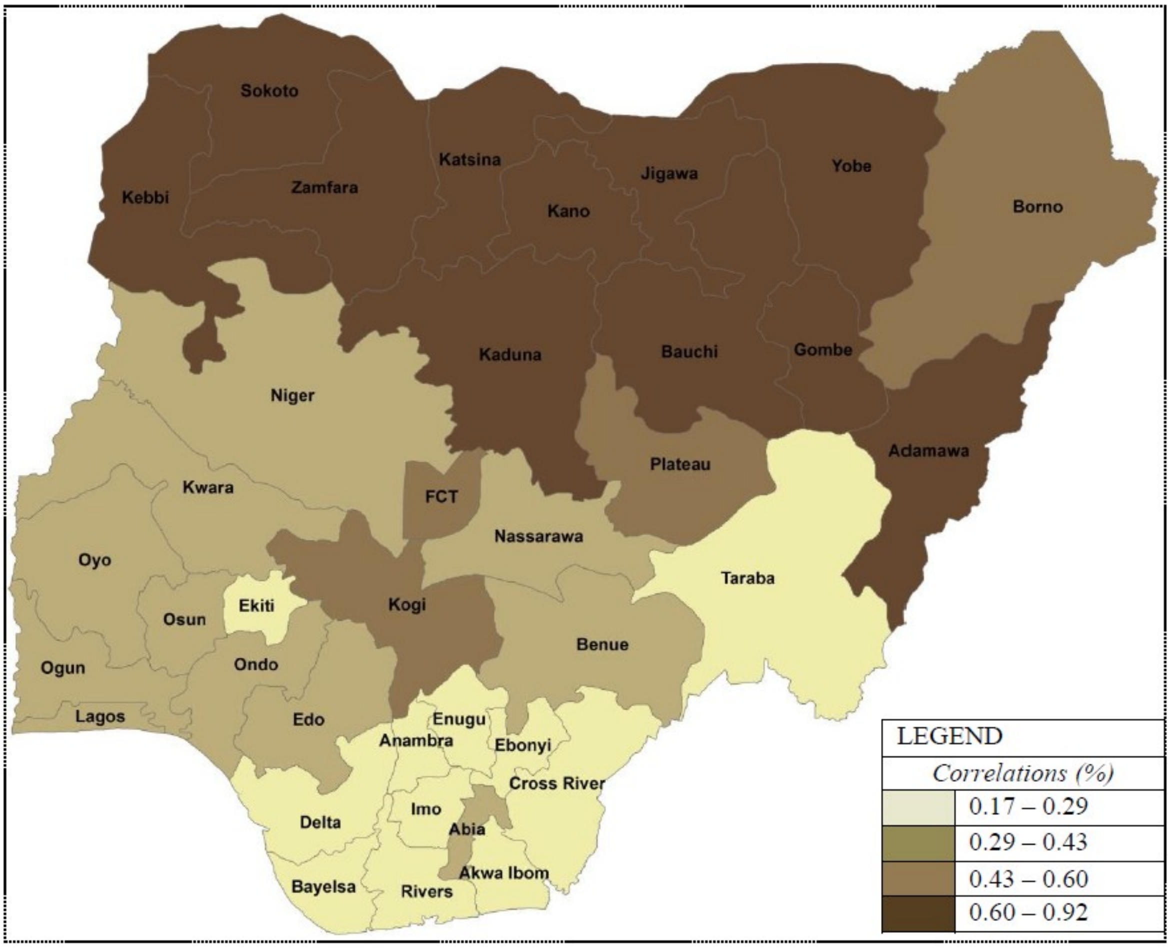

Figure 5.7: Time coherence of the interannual variability of standardised meningitis cases within states of Nigeria between 2000 and 2011.

5.3.2 Cholera

According to the WHO records between 1991 and 2011, Nigeria alone has reported over 380,699 cases of cholera and 288,898 deaths, with a cumulative IR (248.3) and CFR (5.8%). Table 5.5 shows that within this 22-year period 59.3% and 76.8% of the total cases and deaths occurred in only 7 years (1991, 1996, 1999, 2003, 2006, and 2010). The highest number of cases (61,629 IR = 63.4) and deaths (7,711 CFR = 12.5%) occurred in 1991, while the lowest cases (3,171 IR = 3.0) and death (149, CFR = 1.1%) occurred in 1994 and 2004 respectively. Figure 5.8 allows for the visualisation of the disease trend between 1991 and 2011 which is characterised with about five peaks occurring in the intervals of about three years each.

Table 5.5: Reported cholera cases and deaths, incidence rate per 100,000 of population and case fatality rates for Nigeria between 1991 and 2011.

Year	Cases	Deaths	IR	CFR%
1991	61629	7711	63.4	12.5
1992	8687	663	8.7	7.6
1993	4160	266	4.1	6.4
1994	3171	471	3.0	14.9
1995	3364	140	3.1	4.2
1996	59134	4508	53.8	7.6
1997	13411	851	11.9	6.3
1998	9254	277	8.0	3.0
1999	22335	1776	18.9	8.1
2000	6354	253	5.3	4.1
2001	7383	374	6.0	5.1
2002	23441	478	18.5	2.0
2003	9335	375	7.2	4.1
2004	13522	149	10.2	1.1
2005	10785	262	7.9	2.4
2006	20526	362	14.7	1.8
2007	12197	185	8.5	1.5
2008	17854	428	12.1	2.4
2009	16913	552	11.2	3.3
2010	46782	1841	30.3	3.9
2011	23377	742	14.8	3.2

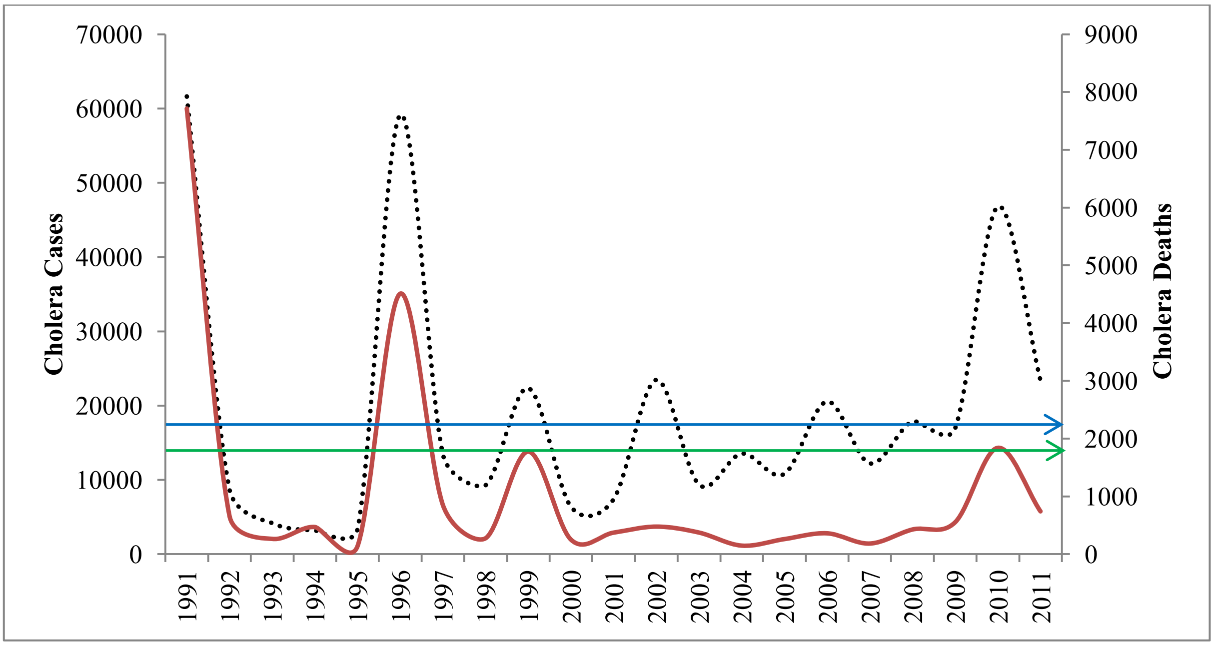

Figure 5.8: Annual cholera reported cases (dashed-black) and deaths (red) between 1991 and 2011 in Nigeria. The blue and green arrows indicate the average and standard deviation of cases respectively.

Within the 12 years of data (2000 – 2011) over 57% and 67% of cases and deaths were reported from the northern states of the country (Adamawa, Bauchi, Borno, Gombe, Jigawa, Kano, Katsina, and Sokoto). The most affected states in terms of cumulative IR are; Sokoto (38.9), Adamawa (34.2), Borno (33.4), and Gombe (28.4), while the least affected states are from the southern part of the country (Akwa Ibom (2.1), Oyo (2.1), Rivers (2.1), and Ogun (2.3).

The Global Moran's Index spatial autocorrelation reveals a statistically significant results (Moran's I = 0.211, z = 2.11, p = 0.004) which suggest a north to south gradient, with higher spatial clustering of IR occurring in the north eastern region of the country (Figure 5.6). Furthermore, spatial autocorrelation was computed for all years of available state level data and were all found to be statistically significant (p = 0.000 - 0.023) (Table 5.6).

Table 5.6: Global Moran's Index spatial autocorrelation computed for cumulative cholera incidence rate (2000 - 2011), and for each year between this period using state level data

Year	*Moran's Index*	*p-value*
2000	0.154	0.000
2001	0.234	0.002
2002	0.341	0.001
2003	0.034	0.011
2004	0.310	0.000
2005	0.072	0.013
2006	0.183	0.001
2007	0.146	0.023
2008	0.207	0.000
2009	0.173	0.012
2010	0.281	0.003
2011	0.150	0.001
2000-2011	0.211	0.004

The clustering of high rates of cholera was persistent in northeast and northwest regions in all the years shown in Figure 5.9. Table 5.7a shows that cholera incidence is 3.9 and 3.4 times higher in northeast and northwest regions respectively, if compared with the southeast region. *Chi Square* test shows cholera IR to have a direct relationship with absolute poverty ($p = <0.05$), population density ($p = <0.01$), and a negative but significant relationship with adult literacy ($p = <0.05$). Table 5.7a – d shows that the IR of the poorest and densely populated strata are 2.3 and 1.8 times higher than that of their respective lowest stratum, while in the adult literacy stratum, IR is 3.2 times higher in population with less educated literates if compared with that of the highly educated ones.

Table 5.7: Cholera incidence rate and population-based rate ratio by strata of states classified based on (a) geopolitical locations, (b) population density, (c) percentage of population living in absolute poverty, and (d) percentage of literate adults between 2000 and 2011.

a.

Geopolitical region	Cholera cases	Population	IR (per 100,000)	Rate ratio
Northwest	80357	40497542	198.4	3.4
Northeast	48494	21469225	225.9	3.9
Northcentral	29208	22933883	127.4	2.2
Southsouth	18960	23780792	79.7	1.4
Southwest	20584	31212581	65.9	1.1
Southeast	10866	18538039	58.6	Reference

b.

Population density	Cholera cases	Population	IR (per 100,000)	Rate ratio
High	98163	57031901	172.1	1.8
Medium	57425	45166916	127.1	1.4
Low	52881	56233246	94.0	Reference

c.

Absolute poverty %	Cholera cases	Population	IR (per 100,000)	Rate ratio
Low	23740	29360751	80.9	Reference
Medium	40859	39881488	102.5	1.3
High	69152	49548594	139.6	1.7
Very high	74718	39641231	188.5	2.3

d.

Adult Literacy %	Cholera cases	Population	IR (per 100,000)	Rate ratio
Low	101749	48912976	208.0	3.2
Medium	49855	29962622	166.4	2.6
High	21590	25446225	84.8	1.3
Very high	35275	54110240	65.2	Reference

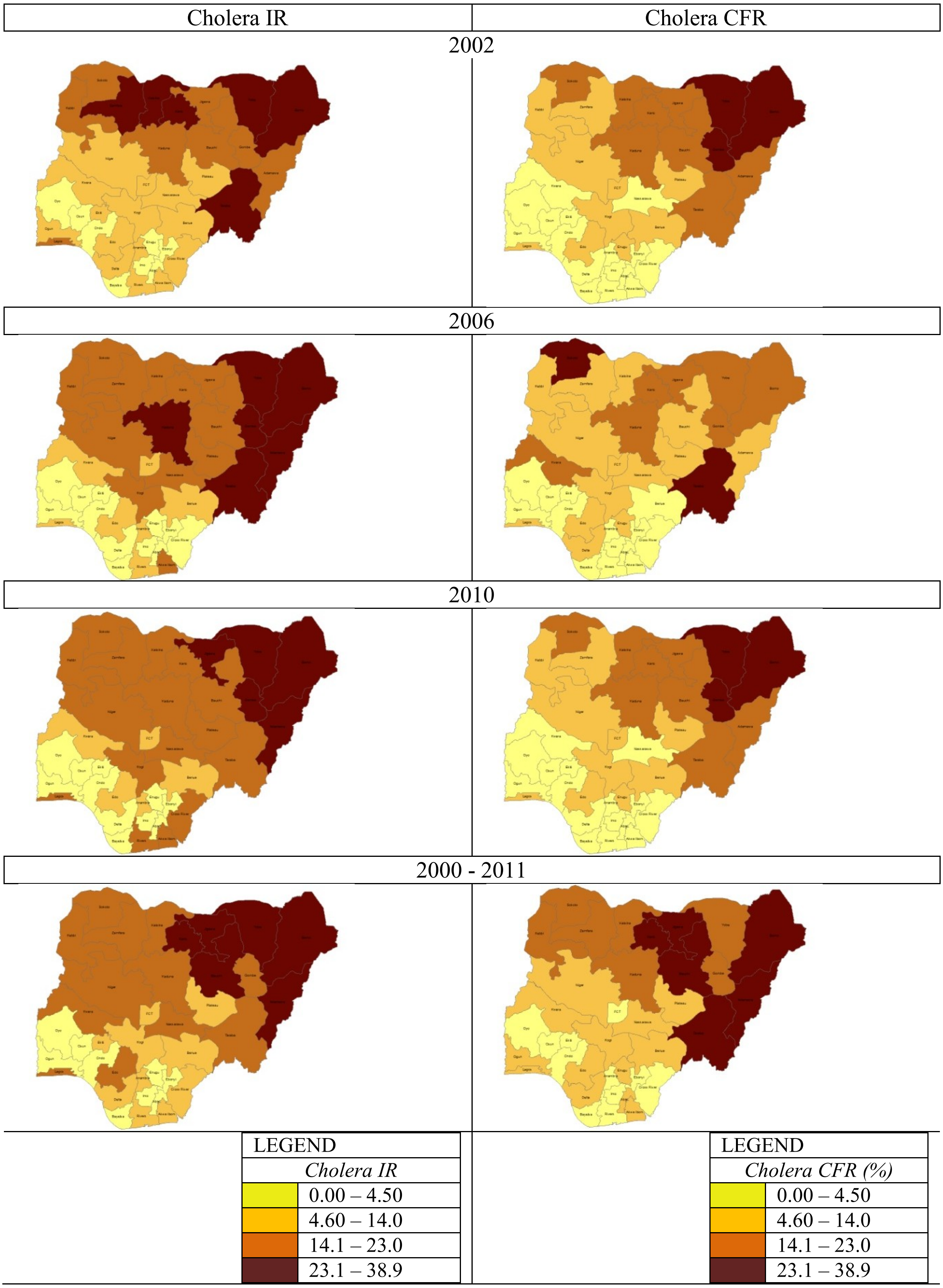

Figure 5.9: Spatial distribution of states level annual incidence rate per 100,000 for population (left) and case fatality rate (right) of cholera for 2003, 2006, 2009 and the cumulative incidence rate between 2000 and 2011.

Figure 5.10 shows the time coherence of cholera interannual variability within states in Nigeria, obviously states from the north-eastern and north-western part of the country shows higher similarities in terms of the interannual variability of the disease with the reference time series (0.37 – 0.98). In the southern part of the country only Delta, Lagos, Enugu and Cross Rivers correlated well, while states such as Oyo, Ogun, Ebonyi, Anambra, Abia, Imo, and Benue shows very low or no correlation at all (0 – 0.2).

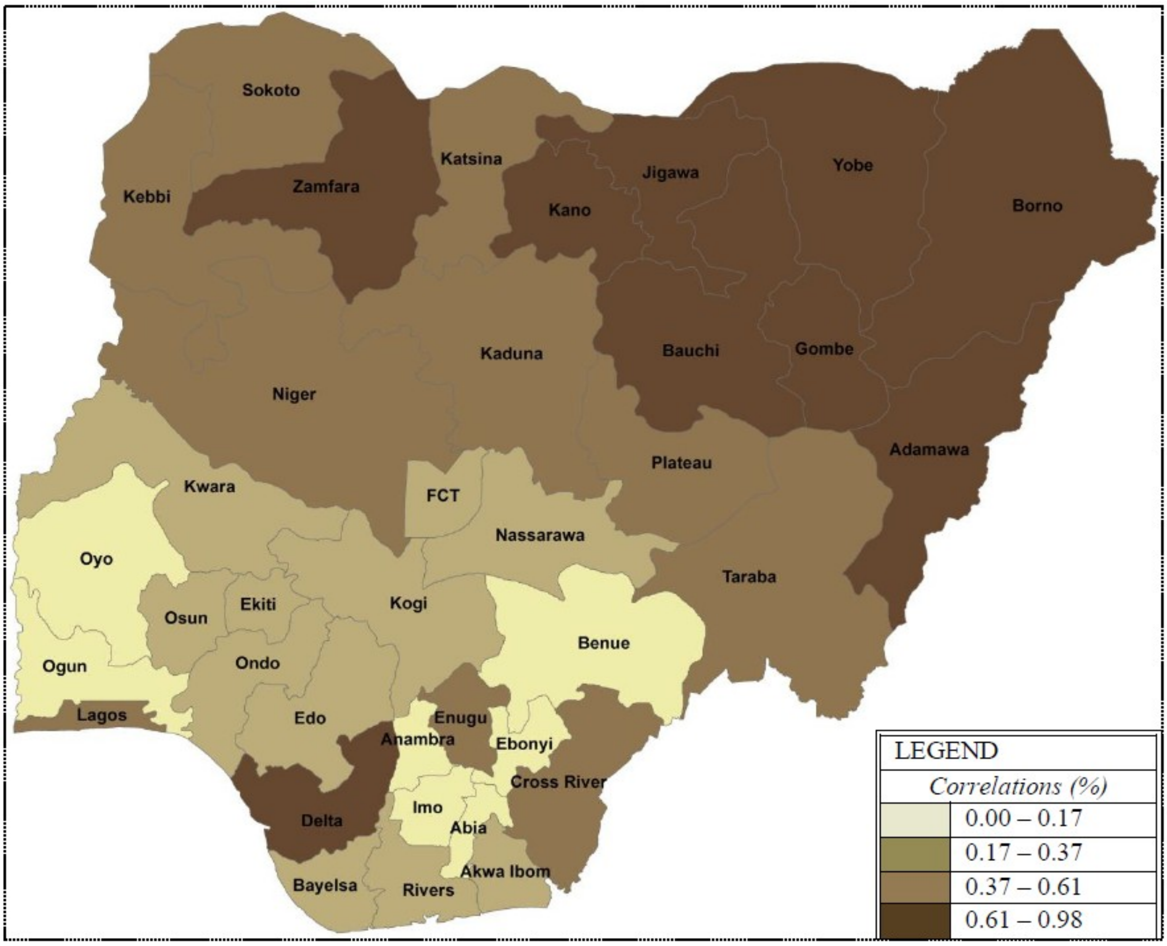

Figure 5.10: Time coherence of the interannual variability of standardised cholera cases within states of Nigeria between 2000 and 2011.

5.4 Discussions

For decades, meningitis and cholera have remained important public health and social problems in Nigeria. Both diseases have become endemic in the poorest and less educated states of northern Nigeria; notably Borno, Kano, Katsina, Sokoto, Yobe and Adamawa. However, cholera also remains endemic in some of the southern states such as Lagos, Imo, Anambra and Delta. Lower IR and CFR for both meningitis and cholera were seen in the southern part of country. Analysing the spatial autocorrelation for individual years state level data of both disease (Table 5.3 and 5.6) showed that irrespective of epidemic or non epidemic year, there is persistent significant positive clustering ($p<0.05$) of cases in the northern part of the country. Also time coherence in terms of the interannual variability of diseases occurrences is seen for both diseases most especially in the northern part of the country.

Higher incidence of meningitis in the northern regions may have been influenced by climatic, environmental, and social conditions. Firstly, in terms of socioeconomic status, northern states such as Katsina, Kebbi, Sokoto, Zamfara, Jigawa, and Bauchi are among the poorest and less educated states (Figure 5.2). Secondly, meningitis incidence has been well documented to be influenced by hot, dry, and dusty weather conditions which the northern region has favoured very well. Hypothetically, these might be the reasons why fewer cases are reported towards the coastal regions where humidity is always high round the year. Anecdotal evidence has shown that Harmattan do not usually propagate to the coast, however, recently people residing in this region of the country have been experiencing the encroachment of the dry and dusty wind. This change in weather condition might be responsible for the increasing cases being observed in this area, although are still small if compared with that of the northern regions.

Despite the fact that the high incidence of cholera is also persistently occurring in the northern part of the country, however it does not reflect the uneven distribution if compared with meningitis incidence. Table 5.7a shows the IR and rate ratio of cholera with respect to the six geopolitical regions in the country, although the northeast region has the highest IR, but is only 3.9 times higher if compared with region with the lowest incidence (southeast). Considering the spatial distribution of cholera based on poverty, population density, and adult literacy strata, the difference is not also as remarkable as in the case of meningitis (Figure 5.7c – d). The clustering of cholera as illustrated in Figure 5.9 shows a consistent occurrence in the north eastern states of Adamawa, Borno, Yobe, Gombe. The reason for this could be seen in the vicinity of Lake Chad basin which the states are neighbouring, the basin has been reported to be the most affected area in the West African region in terms of cholera incidence. Over 60% and 50% of cholera cases and deaths reported from West Africa in 2010 occurred in the countries (Nigeria, Chad, Niger, and Cameroon) surrounding the basin (IRIN, 2013). Risk of cholera from this basin might be connected to contamination from the lake, either from the water environment itself or from food contamination (Fewtrell et al., 2007). The epidemiology of cholera and risk related factors in this basin have been discussed in a collaborative study between Water, sanitation and hygiene (WASH) and UNICEF (Oger and Sudre, 2013).

Results from this study confirm that absolute poverty, adult literacy and population density are very important social factors in determining the spatial distribution of these diseases in addition to climate. For example, previous studies have linked the incidence of cholera in population with less education (e.g, Hashizume et al., 2008), population density (e.g., Penrose et al., 2010), and poverty (e.g., Traeup, 2010). Cholera is known to proliferate in population with insufficient education and careless attitudes towards hygienic conditions, lack or limited access to safe drinking water, inadequate facilities for sewage disposal and treatment (Glass et al., 1992). Higher cholera IR and CFR may not be unconnected with these social factors, because most of the states with low adult literacy and high poverty are located in this region (Figure 5.2).

During the last decade, countries located south of the meningitis belt have been reported to have experienced large epidemics, these countries includes Togo, Cameroon, Cote d'Ivoire and Benin (Cunin et al., 2003; Halperin et al., 2012; Molesworth et al., 2002). Also some countries in East Africa such as Kenya, Uganda, and Tanzania have also suffered large epidemics (Greenwood, 2006; Molesworth et al., 2002; Moore et al., 1992), suggesting the southward spread of the so called meningitis belt which is believed to have begun since the great Sahelian drought in the late 1960s (e.g., Besancenot et al., 1997). Despite this extension, these countries have a lower mean number of cases if compared with those in the belt (Savory et al., 2006). There are also observed changes into the epidemiology of serogroup, after the introduction of the MenAfric vaccine in 2010 in some countries of the belt, *Nm* W135 was observed to be largely responsible for the outbreak of meningitis in Cote d'Ivore, Ghana, Benin and Burkina Faso (MERIT, 2012)

In Nigeria, during the last decade, significant changes in the epidemiology of meningitis have been observed; cases of meningitis are now experienced in the southern part of the country, where the Harmattan is seldom experienced. Recent epidemiological data is showing increasing reported cases of meningitis in the southern states of Nigeria. Figure 5.4 illustrates the spatial distribution of weekly districts levels meningitis cases reported between 2007 and 2011, as can be seen clearly, cases are reported from southern districts most especially in 2010 and 2012 disease years. Cases occurring in that part of the country might not be unconnected with the southward annual temporary relocation of people from the northern region of the country, or possibly due to the "Saheliazation" as observed in Ivory Coast (Soro et al., 1988).

The result of the spatial autocorrelation should be treated with caution; this is because in Nigeria, national surveillance data may have been marred with uncertainties because of underreporting of cases, particularly in remote villages where access to health care facilities is difficult or totally absent. Population living in these areas tend not to report cases by resorting to traditional medication, and when death occurred they hurriedly buried the body without reporting. Another issue is the differences in sizes and shapes among the states which may affect the scales of spatial patterns that could be detected. Also the relatively small number of states (only 36 and FCT) may reduce the robustness of the spatial correlation.

5.5 Conclusion

This chapter addresses objective three (section 1.3) of this thesis by analysing the spatial and time characteristics of meningitis and cholera in Nigeria. The study has identified the hotspots of meningitis and cholera in the country, and confirms the important role of social risk factors on the spatial distribution of these infectious diseases. Geographical location, poverty, overcrowding and literacy status all appears to be linked to the spatiotemporal distribution of diseases in addition to climate. The results will help in identifying specific regions where research should be focused; it will also help in knowing where attention should be given in terms of human and resource allocation by relevant authorities.

Chapter Six:

Climate Influences on the Interannual Variability of Meningitis Incidence in Northwest Nigeria

Chapter Six

Climate Influences on the Interannual Variability of Meningitis Incidence in Northwest Nigeria.

6.1 Introduction

Meningitis remains a major public health burden in several countries around the world, but its magnitude is more profound in Africa, in an area mainly in the Sahelian region recognised as the meningitis belt by Lapeyssonnie (1963) where northwest Nigeria lies (refer to figure 2.1). Despite the physical mechanisms by which climatic factors influence meningitis are still not well understood, relationships has been established (e.g., Dukic et al., 2012; Sultan, 2005; Thomson et al., 2006; Yaka et al., 2008). Non-climatic factors may also play important roles in the risk of meningitis transmission. Among these factors are: socioeconomic, cultural, and behavioural practices; and migration. Previous studies have established the association between non-climatic factors and meningitis risk, for example previous incidences of other upper respiratory tract infections (URTIs) such as pneumococcal pneumonia (Moore et al. 1990), exposure to smoke from cooking fires (Hodgson et al., 2001), overcrowding (Brundage and Zollinger, 1987), disco patronage (Cookson et al., 1998), and smoking (Fischer et al., 1997). A more detailed overview on the disease and its relationships with climatic and social factors was discussed in chapter two.

This chapter aims to statistically model the influence of climate on the interannual variability of meningitis incidence in northwest Nigeria, while collectively accounting for the effects of all unobserved climatic and non-climatic factors that may be related to meningitis, such as social and behavioural practices, and migration. The study is the first to report a relationship between meteorological conditions (reflected by variables from station observations) and meningitis in Nigeria since the study by Greenwood et al. (1984). Since that time, a much longer case record has been established. The model development and results are based on 22-years (1990 – 2011) of clinically diagnosed hospital-reported cases of meningitis. Detailed information about the study area and its meteorological conditions are discussed in chapter three and four respectively. A part of result from this chapter has been published in the journal of Weather, Climate, and Society with contribution from six co-authors (see Appendix A attached).

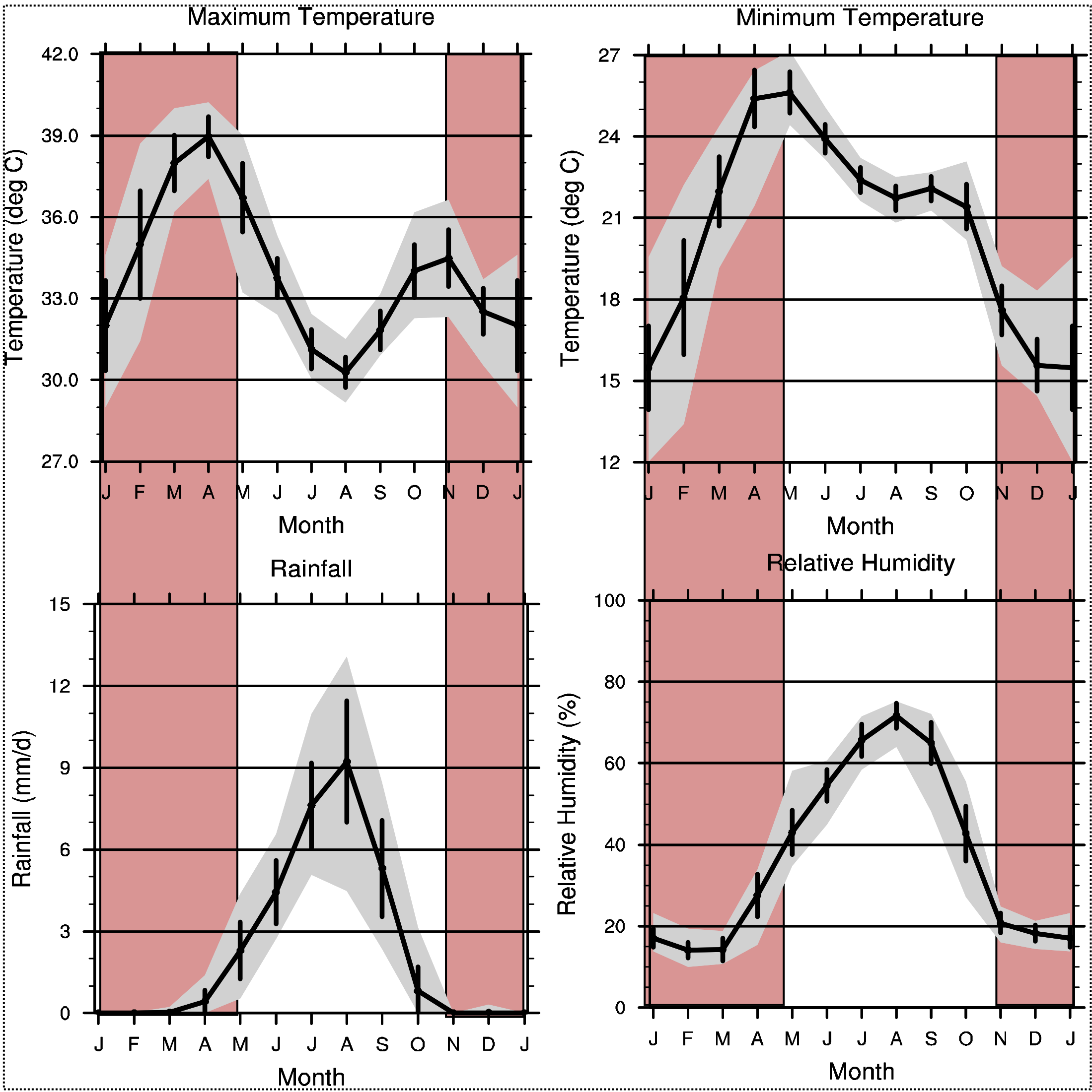

Figure 6.1: Averaged annual cycle of selected meteorological variables (monthly resolution), averaged over three stations in northwest Nigeria (Kano, Sokoto and Gusau) between 1990 and 2010. The vertical bars represent the +/- 1 standard deviation from the monthly mean, and the grey shading represents the range of monthly means over the 21-year record. The highlighted areas (red) are showing the meningitis season (Nov – May).

6.2 Materials and Methods

6.2.1 Epidemiological data

Monthly counts of clinically diagnosed meningitis cases reported between 1990 and 2011 were collected in situ from selected hospitals in the region (see Figure 3.1). The selection of hospitals was based on three criteria: (a) proximity to meteorological stations with long-term records of measurements, (b) similar climatic patterns, and (c) consistently reported records of infectious disease cases. In Nigeria, the FMoH classifies four categories of hospitals based on ownership status: federal, state and local public hospitals, and private hospitals. Personal communication with FMoH staff prior to the data collection indicated that the state-owned hospitals best suited the above criteria because most of the infectious disease cases are treated at these hospitals. Four hospitals in major regional cities met the first two requirements: Kaduna, Kano, Sokoto and Gusau. Kaduna is not included in the model because it lies further southward and differs in terms of humidity and rainfall amount, but the city was later used for testing and validating the regional model. A brief summary of the results of a separate model developed for Kaduna was presented in the discussion. In addition to the monthly case data from these three hospitals (1990-2011), weekly records of suspected meningitis cases at the district level (from all hospitals in a district) in Nigeria for the years 2007-2011 was obtained from the WHO. The proportion of cases between WHO and hospital records was rather constant across the study period, providing evidence that the records are of sufficient quality and that the hospital records are regionally representative (Figure 6.1).

6.2.2 Meteorological data

Digital records of seven variables from airport-based meteorological stations in each of the three cities were obtained from the Nigerian Meteorological Agency (Table 6.1). Daily precipitation and maximum and minimum temperatures were quality controlled (see section 4.2.1). Monthly averages, totals or percentages were then computed from the quality controlled daily values.

In addition to meteorological records, monthly total estimates of carbon monoxide (CO) emissions (Tg month^{-1}) for the sub-period from 1997-2009 were produced for northwest Nigeria by the Global Fire Emissions Database (GFEDv3.1) model (van der Werf et al. 2010). These emissions estimates are driven by satellite observations of active fires, burn area, and modelled vegetation information.

Both lag zero and one-month lagged meteorological data were included as explanatory variables in the development of the models, while CO was only used for a sensitivity test because the data spans too short a period for inclusion in the final model development.

Table 6.1 Summary of station characteristics and meteorological data at four stations in Northwest Nigeria

City	Station ID	Lat	Lon	Elev. (m)	Variables obtained from all stations
Kano	65 0460	12° 03'	08° 32'	476	Max. Temp. (°C), Min. Temp. (°C) Rain (mm), Relative Humidity (%) Wind Speed (km/hr), Dusty Days (yes/no), and Sunshine (hrs)
Sokoto	65 0100	12° 55'	05° 12'	351	
Gusau	65 0150	12° 10'	06° 42'	463	

Note: Dustiness in this study means monthly percentage of number of dry haze days (defined as relative humidity below 80% and visibility below 5km (WMO 1995)) determined by recording visibility at a given observation point.

6.2.3 Demographic and vaccination campaign data

District-level population census data as of 2006 was obtained from the National Population Commission in Abuja, Nigeria. Annual population estimates for each city were calculated forward and backward from 2006 using the Nigerian population growth rate index (World Bank, 2012). As vaccination campaigns will influence the number of meningitis cases that would occur in the absence of vaccination and thus can confound the model results, information was obtained from FMoH on the specific years that reactive mass vaccination campaigns were carried out in the selected cities. Using an established methodology described below, this information was used to estimate the expected number of meningitis cases that would have occurred had there been no vaccination campaign. An additional model was then developed using these expected cases as predictands, and compared to the models that used the actual (unadjusted) cases as predictands.

6.2.4 Model overview

For statistical model development, monthly meningitis counts for the three hospitals in Kano, Sokoto, and Gusau were aggregated, and variables of the corresponding three meteorological stations averaged. Monthly meningitis counts were aggregated in order to minimize the effect of bias in reporting to individual hospitals, and as well to have a regional perspective which is the intent of this study. Generalized additive model (GAM) and generalized linear model (GLM) approaches were used. GAMs are a flexible extension of GLMs and are comprehensively described by Hastie and Tibshirani, (1999). Because of the additive smoothing function within the GAM (cf. below), it can collectively accounted (albeit not specifically) for the effects of all unobserved climatic and non-climatic factors that may be related to meningitis.

Both GAM and simpler GLM frameworks were subsequently applied to model the influence of climatic conditions on the monthly variability of clinically diagnosed hospital-reported cases of meningitis. During model development, several predictor variables such as previous disease incidence; warm days and nights; monthly maximum values of daily maximum and minimum temperatures (above 98th percentile); and mean monthly values of meteorological variables were considered. Also different lags of meteorological variables ranging from 0 – to 2 month were tested in order to select the best combination of predictor variables that could better explain the variability of diseases. Lag zero and one month lagged meteorological variables appeared to be best and were selected for model input. Collinearity diagnostics and autocorrelation checks were performed, and explanatory variables were selected through a process of manually entering and removing variables from the model in a stepwise selection process, with a criterion of elimination being a p-value <=0.05 when testing the significance of the coefficient estimate. The explanatory variables include meteorological variables aggregated monthly between the three selected stations (Table 6.1), as well as the previous incidence of meningitis in some models. Additionally, all other unobserved seasonally-varying climatic and non-climatic factors that may influence the disease were represented in GAMs by a smooth function of time, $s(t)$, which was modelled as a low-degree cubic spline that changes monthly over the course of the annual cycle (Dukic et al., 2012). The variable $s(t)$ is the so-called "additive function" characteristic of GAMs, and captures the seasonality effect in a way that can be viewed as a smoothed analogue of the month-specific effects. It is assumed that $s(t)$ is common to all years (i.e., that there is no intercept that can be applied to adjust the function for a specific year). The assumption is that the clinically diagnosed hospital meningitis counts, y_{it} (equation 6.1) follow independent Poisson distributions (thus a log-link function was used (Cameron and Trivedi, 1998)), with mean μ_{it}, where i =1,..., 22 denotes the years, and $\mathbf{t}$ =1,...,12 denotes the month within each year. The GAM formulation is thus:

$$\log(\mu_{it}) = s(t) + X_{it}\beta \text{ ....Equation 6.1}$$

The expected meningitis count in year $_i$ in month $_t$ therefore depends upon the vector of coefficients β, which contains the effects of climate variables collected in the covariate matrix

X_{it}, and upon the effects of the unobserved seasonally-varying factors, $s(t)$. The GAM is fitted and the coefficients β and the parameters for the smooth function $s(t)$ are estimated. For the simpler GLMs, the equation is identical except that the additive function $s(t)$ is removed if compared to the GAM.

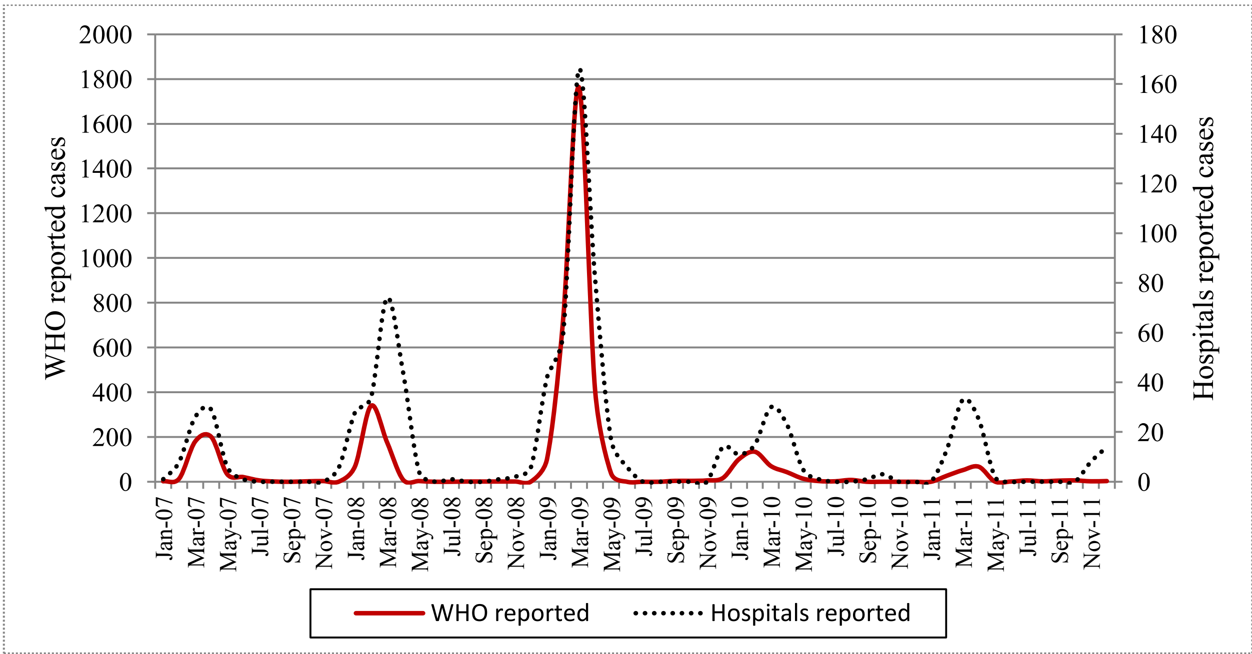

Figure 6.2: Meningitis reported cases from three hospitals in northwest Nigeria (Kano, Sokoto, and Gusau) in comparison with WHO district level reported cases from the same districts between 2007 and 2011.

6.2.5 Model fitting

In order to understand the sensitivity of models to a variety of *a priori* model choices, 3 GAMs (denoted as models A, B, C) and a simpler GLM (denoted as model D) were fitted. Model A was fitted with the combination of both 1-month lagged and non-lagged climatic variables and cases from the previous month; model B, with only the 1-month lagged explanatory climatic variables and cases from the previous month; and model C is the same as GAM A, except previous cases were excluded. All three GAMs were tested for a variety of degrees-of-freedom (DOF) for the fit of $s(t)$, but it was found that those models in which $s(t)$

has 4 DOF have the best fit. Model D, which is a GLM, has the same composition as model A without the smooth component ***s(t)***. Model A is intended to be optimal *explanatory* model of meningitis cases, whereas model B by using only lagged variables is intended to be the optimal *predictive* model (with 1-month lead time). Model C, which does not include previous cases, is intended to be used for future climate change studies (since the number of cases in the previous month is unknown in the future). Model D is meant to test whether adding a smooth function of time ***s(t)*** improves the model fit. All models were fit within R statistical software (R Core Team, 2013).

The best models were selected by minimising the Bayesian Information Criteria (BIC) (Dobson, 2010). Variable selections were made separately for each model, although the same variables were retained in all models, but variables were all lagged by 1-month in model B, while previous cases were not included in model C. The retained variables in models A and D include the current mean monthly maximum and minimum temperatures, precipitation totals, average relative humidity, sunshine and the 1-month lag of wind speed, dust and cases (i.e., cases in the previous month).

A population offset term (to account for population growth) was not included in these models because estimating the changes to the population served by a single hospital, the source of our records, is highly uncertain. For example, as population grows, new hospitals and other treatment facilities are built to accommodate more patients, so the population served by a given hospital does not fluctuate linearly with regional population growth.

6.2.6 Model validation

The robustness and accuracy of models were assessed using the cross validation correlation (CVC) (Kohavi, 1995), the root mean square error (RMSE) (Geisser, 1993), and the skill score (Murphy, 1998) techniques. All three statistics were computed for observed versus predicted values for each model. To perform the cross validation, the data was partitioned into 3 consecutive subsets of equal length. One of these subsets is then successively excluded, fitted the model on the remaining data and computed the fitted values for the excluded subset. The fitted values that were obtained were then combined into one time series for ease of comparison with the "full model" (i.e., based on all 22 years of data). The skill score provides a measure of the prediction accuracy of the models by comparing the models' predicted RMSE, $\mathbf{E_{pre}}$, with that of a reference model $\mathbf{E_{ref}}$.

$$\textbf{Skill score} = \mathbf{1 - (E_{pre} / E_{ref})} \text{................Equation 6.2}$$

In this case, $\mathbf{E_{pre}}$ represents the RMSE of the monthly model-predicted cases compared to the observed cases, while, $\mathbf{E_{ref}}$ represents the RMSE of the long term monthly mean of the observed meningitis cases, also compared to the observed cases for each month and year. The reference model is thus a persistence model: even if there is no model at all, they could predict cases for a given year and month by assuming that they will equal the long-term average of cases for that month, based on observations from other years. The skill score is the percentage of improvement or deterioration of a given model's RMSE with respect to the reference model.

To gain a perspective on the average comparative importance of each covariate for a given month, relative influence (RI) was computed by estimating the effect of each covariate with respect to all the covariates in the model, based on the long-term monthly means of each covariate over the 22 year period, as well as the monthly value of ***s(t).*** The RI for a GAM is calculated as a percentage of all terms for a given month as follows:

$$RI = 100 * \frac{\bar{X}_{t,\vartheta}\beta_{\vartheta}}{[|s(t)| + \sum_{v=1}^{n}\bar{X}_{t,v}|\beta_v|]}) \ldots\ldots\ldots\ldots\ldots.\text{Equation 6.3}$$

Where in the numerator $\bar{X}_{t,\vartheta}$ is the long term mean of X for a given month, t, and ϑ denotes a particular variable within the vector of X (e.g., Tmin), and $\beta_{\vartheta}$is the coefficient that corresponds to that particular variable. In the denominator ***s(t)*** is the month-specific additive function (which does not vary by year) and $\sum_{v=1}^{n}\bar{X}_{t,v}|\beta_v|$, is the sum of all other model terms $\bar{X}\beta$ over all variables from **v=1** to **n** (maximum and minimum temperature, relative humidity, dust, etc), for a given month t. The absolute values are taken for the coefficients, β and ***s(t)*** in the denominator, in order to omit negative terms in the equation, otherwise, the RI of a given term may be inflated due to cancellation of negative and positive terms.

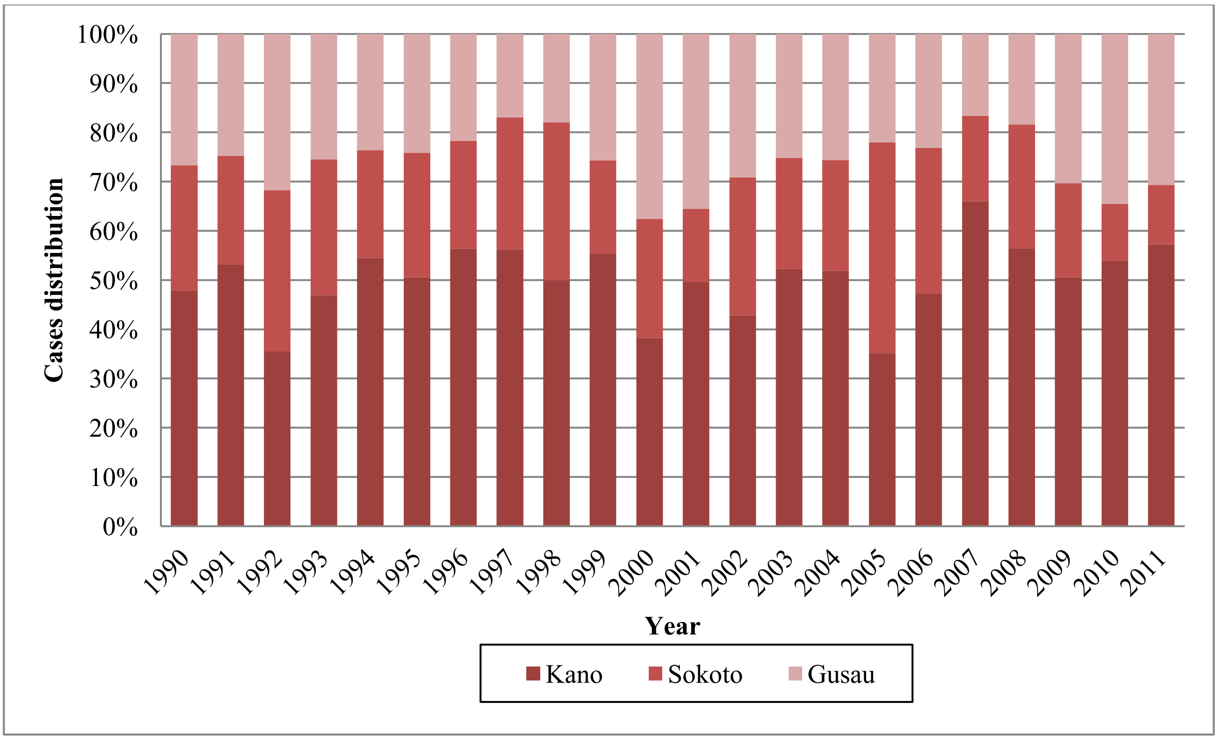

Figure 6.3: Relative distribution of meningitis reported cases from three selected hospitals (Kano, Sokoto, and Gusau) in northwest Nigeria.

6.2.7 Sensitivity tests

Three sensitivity tests were performed in order to investigate (1) the influence of accounting for vaccination campaigns in the case data, (2) the influence of including CO emissions as an explanatory variable, and (3) whether the model can be applied outside our immediate study area. The first test requires greater description here.

Information from FMoH shows that four vaccination campaigns were carried out within the study period (1990-2011). The effect of these campaigns could not be accounted directly in the models because there is no detail and reliable record of the number of people vaccinated and the time of administration. However, to test the sensitivity of the model fit and accuracy to the influence of vaccination and to develop a model suitable for climate change assessment, model C was refitted to an adjusted case dataset that accounts for vaccinations. The proportion of cases assumed to be mitigated during epidemic years by the Polysaccharide A vaccine were estimated based on information collected from the FMoH indicating the years and districts in which vaccination campaigns were conducted. The month in which the vaccination campaign began was estimated to be the first month during an FMoH-indicated vaccination year in which the average case rate exceeded 20 per 100,000 persons (this was required because FMoH did not indicate the month in which vaccination was begun). The threshold of 20 cases per 100,000 in a given month was chosen because the case data was on monthly resolution, whereas the officially defined threshold for epidemics (which trigger reactive vaccination campaigns) is 10 cases per 100,000 based on weekly data. Considering the strong weekly variability of case counts it is likely that at least one week in a given month would have epidemic conditions (10 cases per 100,000) if 20 cases per 100,000 or more are reported for a given month.

The proportion of cases mitigated due to vaccination campaigns was estimated by comparing the number of actual cases occurring in a given month with a projection of the number that may have occurred supposing polysaccharide vaccination was not administered, using the following equation (Leake et al., 2002; Pinner et al., 1992):

EC = OC/ [(1-VE)*(PV) + PNV]………………..Equation 6.4

EC is the monthly estimate of expected cases if vaccination was not carried out; **OC**, observed cases; **VE**, vaccine efficacy; **PV**, proportion of population vaccinated; **PNV**, proportion of population not vaccinated. **VE** is defined to be 85% in the month following vaccination administration (e.g., Reingold et al., 1985), and decreases linearly to zero over the next 30 months in order to simulate for the development of post-vaccination immunity and diminishing effect. The choice of 30 months was made because polysaccharide A vaccine has an efficacy of approximately 2 – 3 years or even less in children under 4 years of age (e.g., Reingold et al., 1985). Due to uncertainties about the proportion of population that was vaccinated (**PV**), **EC** was calculated for two different plausible bounds of **PV**, 40% and 60% based on anecdotal information.

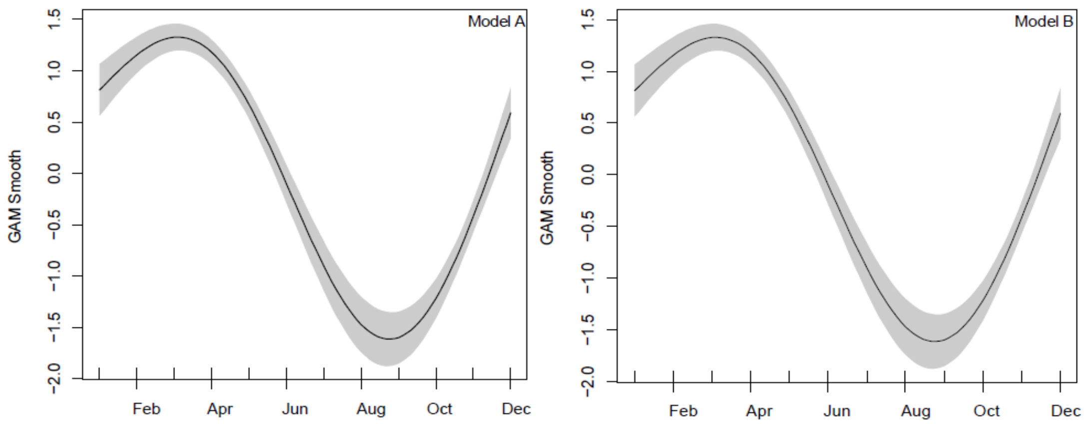

Figure 6.4: Estimated smooth function of time, ***s*(*t*)**, across 12 months, for the models **A** (with combination of both 1-month lagged and non-lagged climate variables; left) and **B** (with on 1-month lagged climate variables; right). The shaded area shows the 95% confidence interval about ***s*(*t*)**.

6.3 Results

6.3.1 Model performance

Generally, both the individual and aggregated counts of the monthly hospital-reported meningitis cases exhibit a marked annual cycle, with yearly disease onset and maxima occurring during the beginning of the dry season (November) and the peak of the hottest months (March and April) respectively. Also, as in other places in the meningitis belt, cases decrease with the increase of humidity and the onset of the rainy season. Figure 6.3 shows the individual contribution of each hospital.

The shape of the smooth function of time $\boldsymbol{s(t)}$ is shown in Figure 6.4 for models, A and B. The shape of the estimated function of both models is similar and follows the seasonality of the disease, with the months of February – April having the highest values of $\boldsymbol{s(t)}$. The model estimates and standard errors for models A and B are presented in Tables 6.2 Models C and D has similar estimates and their skill is discussed below. Current maximum and minimum temperatures, sunshine duration, and 1-month lagged dust frequency and wind speed are positively correlated with disease incidence, while relative humidity and precipitation are inversely correlated in all models. Figure 6.5 shows the 22-year time series of observed cases versus predicted cases for models A, B and D (results were similar for model C).

Table 6.2 Estimates for model **A** containing the combination of both1-month-lagged and non-lagged climate variables, models B containing only 1-month lagged climate variables

Predictors	Model A		
	coef.	*std. error*	*P-value*
Monthly mean Tmax (C°)	0.085	0.007	<0.001
Monthly mean Tmin (C°)	0.055	0.008	<0.001
Rain (mm)	-0.008	0.001	<0.010
Relative humidity (%)	-0.036	0.003	<0.001
Dusty days (%)[a]	0.016	0.001	<0.001
Wind speed (km/hr) [a]	0.010	0.005	<0.010
Sun shine (hrs)	0.047	0.015	<0.001
Previous month cases	0.004	0.001	<0.001
Predictors	**Model B**		
	coef.	*std. error*	*P-value*
Monthly mean Tmax (C°)	0.048	0.006	<0.001
Monthly mean Tmin (C°)	0.025	0.008	<0.050
Rain (mm)	-0.003	0.001	<0.001
Relative humidity (%)	-0.015	0.003	<0.010
Dusty days (%)	0.012	0.000	<0.001
Wind speed (km/hr)	0.010	0.004	<0.001
Sun shine (hrs)	0.035	0.014	<0.001
Previous month cases	0.0024	0.002	<0.001

Abbreviations: coef, coefficient; std error, standard error
[a]*Variables lagged by 1-month*

The three-fold cross validation technique enable for the verification of the results (Table 6.3), as well as an indication of how sensitive the model fits are to the period selected for development; for example, if the model fits were substantially different in the early 1990s versus the late 2000s, the "Full" versus cross validated statistics would be notably different. As Table 6.3 shows, the fit between the observations and both the “Full” and the cross validated model statistics are remarkably good and almost similar, indicating that the meningitis case dynamics were similar throughout the 22-year period. As expected, model A is the best model as measured by CVC and skill score (0.75 and 0.52). The skill score indicates that the RMSE of model A is 52% lower than if one assumes the number of cases in a given year and month are equal to the long-term monthly average of observed cases for that month; thus, model A exhibits substantial skill compared to doing no modelling at all. The 1-month lag model B also has similar CVC and skill score statistics (0.73 and 0.45), suggesting its potential for short-term prediction of cases. Likewise, model C has similar statistics, suggesting it may be useful for exploring how cases may change in the future as a function of climate change. Model D (the GLM) has a lower CVC and skill score (0.62 and 0.40) compared to the GAMs, suggesting that the GAM additive function ***s(t)*** is effective in capturing some of the unobserved seasonally-varying factors that may affect meningitis.

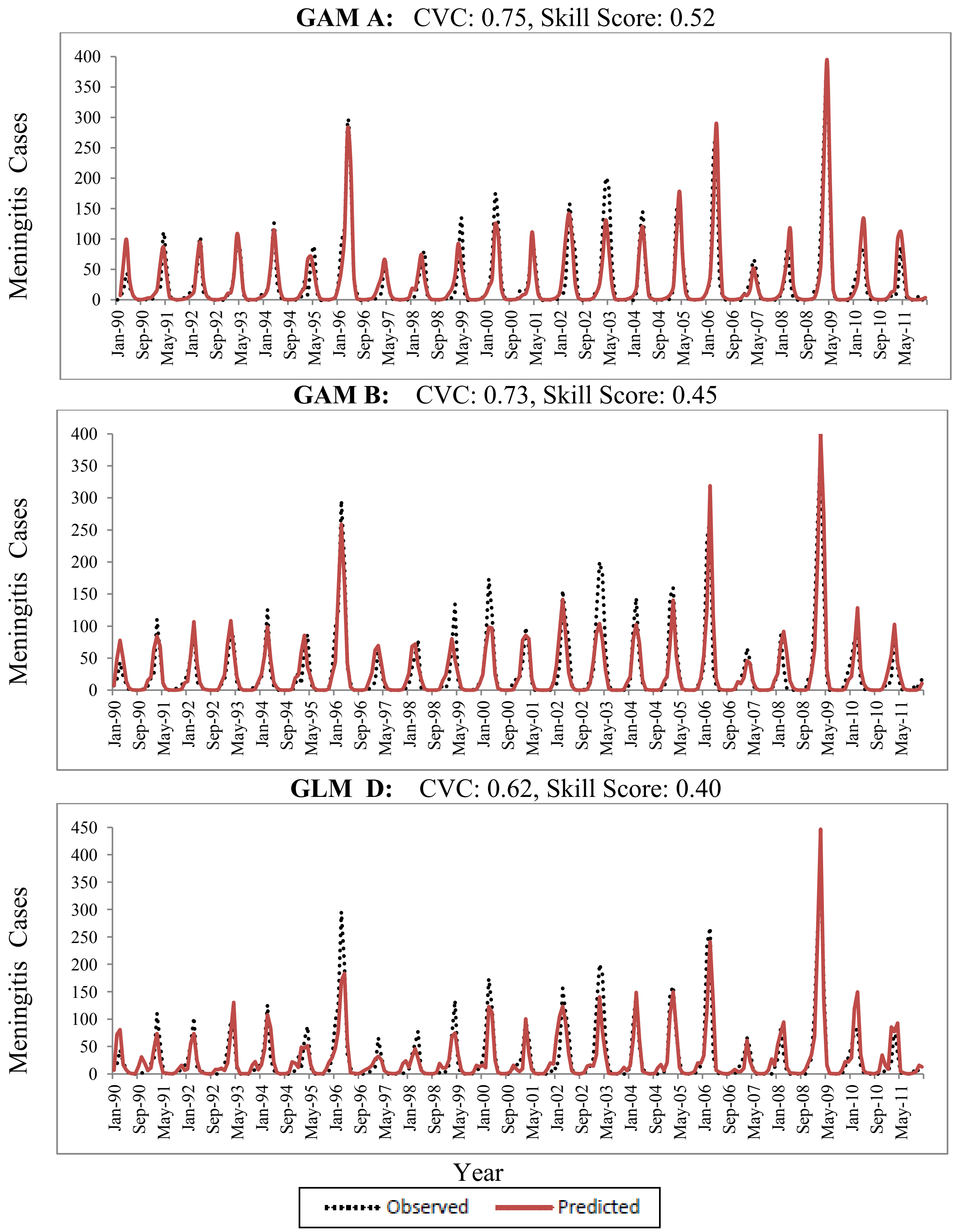

Figure 6.5: The fit for models A, B and D ("observed"; dashed "predicted"; non-dashed). Models A and D are fitted with a combination of both lagged and non-lagged climate covariates, while model B is fitted with only 1-month lagged climate covariates. Models A and B are GAMs, while D is a simpler GLM.

The relative influence of each explanatory variable for the four months in which meningitis incidence is generally high is shown in Figure 6.6. Overall, the maximum temperature shows a comparatively important influence on the fitted meningitis cases for models A and B. Regardless of the model, the relative influence of maximum temperature increases from about 30% in January to over 35% in April during the peak of meningitis incidence. The influence of average relative humidity remains almost the same across the months, having an important negative influence of about -15%; this is because humidity usually remains consistently low throughout the dry season. As expected, the dust and wind speed influence is higher in the "cold dry" months in which the Harmattan is strongest. Rainfall plays a negligible role throughout these months because it rarely rains (Figure 6.1). The number of cases in the previous month provides a comparatively modest influence of up to about 10%. The function ***s(t)*** which accounts for unobserved seasonally-varying explanatory variables, varies in influence from about 6-15%, suggesting that unexplained factors are important drivers of meningitis incidence, especially during the annual peak of cases.

Table 6.3 Model validation results, given by correlation and skill score.

	Kendall Correlation		Skill Score	
Models	**Full**[a]	**CV**[b]	**Full**[a]	**CV**[b]
A	0.762	0.746	0.527	0.515
B	0.740	0.732	0.458	0.449
C	0.750	0.736	0.489	0.476
D	0.634	0.616	0.419	0.401

[a]'Full' and [b]'CV' stands for full and 3-fold cross validated models respectively.

6.3.2 Model sensitivity

Experiment 1: As described in section 6.2.3, to investigate the influence of the four vaccination campaigns that occurred between 1990 and 2011, the expected cases that would have occurred in the absence of the campaigns were estimated. A model was fit using the expected cases as predictands, and retaining all of the explanatory variables used in model A, except the previous month's cases. Previous cases were omitted because its intended to employ this model in chapter eight to investigate the impacts of climate change on meningitis in the absence of vaccination (because it is impossible to know what vaccine advancements will occur in the future). The new model is therefore identical to model C, except it is trained on the expected case data rather than the actual case data. The new model (with **PV** = 40%) has a higher CVC and skill score of 0.75 and 0.52, respectively, compared to model C (0.74 and 0.48, respectively). The slightly higher skill score of the new model compared to model C is perhaps expected, since the additional effects of vaccination are at least partially removed, and therefore the explanatory climate variables are targeting a largely expected number of meningitis cases without vaccination. Since the choice of **PV** is somewhat arbitrary, another model was fitted assuming a different proportion of the population was vaccinated, **PV** = 60%, and found that the values and significance of the model coefficients in the GAM are relatively insensitive to the choice of **PV** (Table 6.4), although the best model fit is for the case of **PV**=40%.

Table 6.4 Experiment 1: showing models' estimates for two bounds of **PV**

Predictors	PV = 40%			PV = 60%		
	coef.	*std. error*	*P-value*	*coef.*	*std. error*	*P-value*
Monthly mean Tmax (C°)	0.0827	0.0069	<0.001	0.0821	0.0067	<0.001
Monthly mean Tmin (C°)	0.0576	0.0078	<0.001	0.0565	0.0076	<0.001
Rain (mm)	-0.0039	0.0006	<0.001	-0.0035	0.0005	<0.001
Relative humidity (%)	-0.0403	0.0024	<0.001	-0.0431	0.0023	<0.001
Wind speed (km/hr) [a]	0.0143	0.0048	<0.001	0.0165	0.0047	<0.001
Sun shine (hrs)	0.0494	0.0124	<0.001	0.0476	0.0120	<0.001
Dusty days (%)[a]	0.0166	0.0007	<0.001	0.0176	0.0007	<0.001

Abbreviations: coef, coefficient; std error, standard error
[a]Variables lagged by 1-month

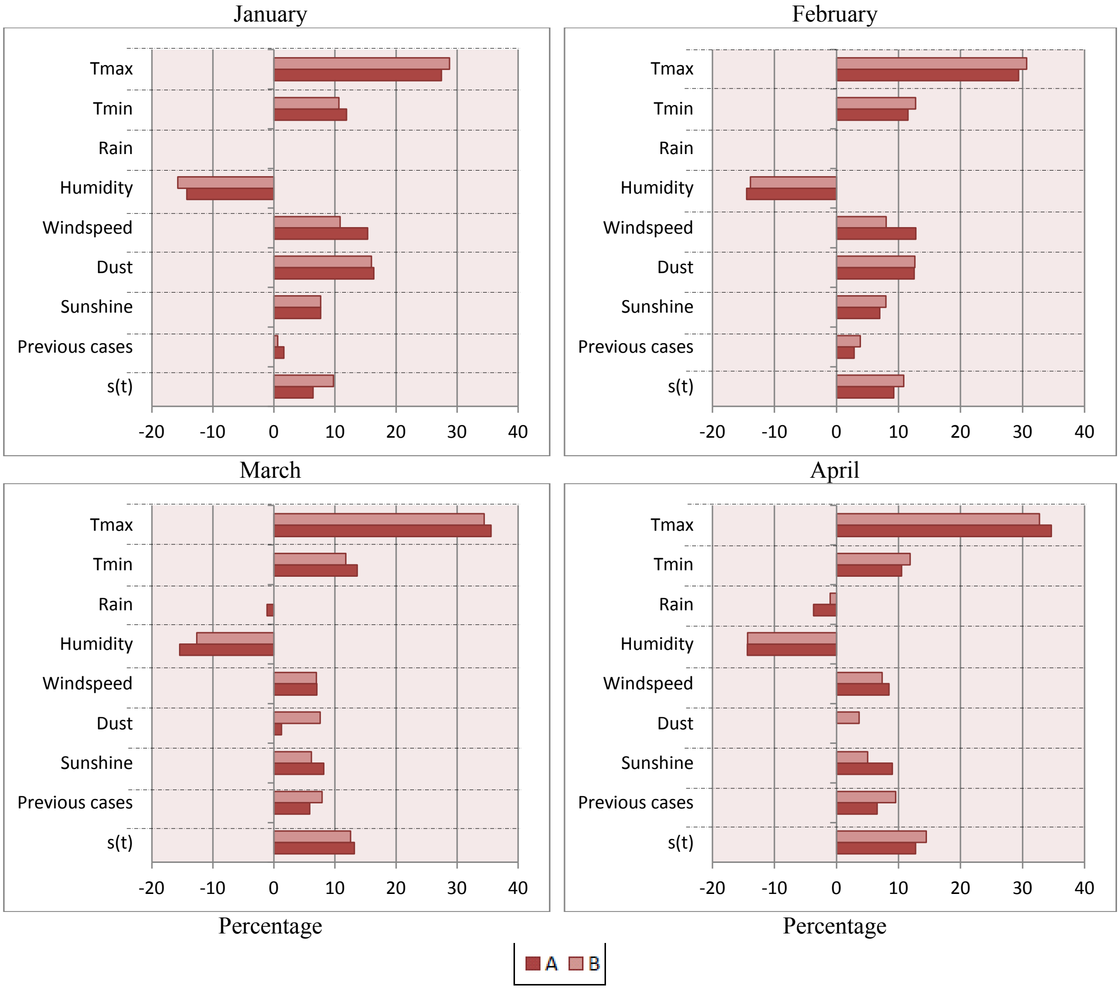

Figure 6.6: The relative influence of explanatory variables on meningitis in northwest Nigeria for models A and B for the dry-season months in which the meningitis burden is typically highest: January, February, March, and April.

Experiment 2: Air quality contributes to the risk and incidence of meningitis in northern Ghana (e.g. Hodgson et al., 2001), as such this was investigated in northwest Nigeria by refitting model A keeping all of the variables in the model, but now including the total regional carbon monoxide (CO) from biomass burning emission estimates (for the 15-year period from 1997-2009 for which CO data are available). Although the previous month's CO emissions are significant in the model, it does not substantially change the model estimates for other explanatory variables, and it does not appreciably change the model fit (see Table 6.5). Therefore, biomass burning CO emissions, and presumably other air pollutants released in conjunction with the CO, do not appear to exert much influence on meningitis incidence in northwest Nigeria compared to the other meteorological variables in the model.

Experiment 3: For the purpose of testing the model elsewhere, the estimated coefficient of model A was used to predict cases for Kaduna, and then compare the predicted time series with that observed from Kaduna hospital. Although the fit is not as good as that of model A (CVC, 0.57 and skill score, 0.39), the monthly variability of cases is reasonably captured. Another completely new GAM with 4 DOF was fitted specifically for Kaduna city, employing the same variables as for model A. The estimates of this model are also shown in Table 6.5. The only difference of this model with model A is that the rain variable is less significant, but the model remains qualitatively similar in terms of predictive power. This suggests that the explanatory variables employed in the models may be relevant for simulating meningitis incidence in other regions of Nigeria, and perhaps the broader Sahelian region (this is supported by the fact that Dukic et al. (2012) found similar explanatory variables when modelling meningitis incidence in northern Ghana).

Table 6.5 Experiment 2 and 3: showing estimates for model with carbon emission (CO), and that of Kaduna respectively

Experiment 2			
Predictors	*coef.*	*std. error*	*P-value*
Monthly mean Tmax (C°)	0.0841	0.0072	<0.001
Monthly mean Tmin (C°)	0.0532	0.0018	<0.001
Rain (mm)	-0.0103	0.0021	<0.010
Relative humidity (%)	-0.0415	0.0032	<0.001
Dusty days (%)[a]	0.0163	0.0014	<0.001
Wind speed (km/hr)[a]	0.0106	0.0005	<0.010
Sun shine (hrs)	0.0334	0.0105	<0.001
Previous month cases	0.0065	0.0042	<0.001
Carbon emission[a]	0.0096	0.0122	<0.010
Experiment 3			
Predictors	***coef.***	***std. error***	***P-value***
Monthly mean Tmax (C°)	0.0872	0.0042	<0.001
Monthly mean Tmin (C°)	0.0613	0.0023	<0.001
Rain (mm)	-0.0054	0.0031	<0.050
Relative humidity (%)	-0.0462	0.0034	<0.001
Dusty days (%)[a]	0.0285	0.0016	<0.001
Wind speed (km/hr)[a]	0.0166	0.0040	<0.010
Sun shine (hrs)	0.0327	0.0150	<0.001
Previous month cases	0.0116	0.012 3	<0.001

Abbreviations: coef, coefficient; std error, standard error
[a]Variables lagged by 1-month

6.4 Discussion

In this chapter, the use of both GAMs and GLMs was employed to model the influence of meteorological conditions on the monthly meningitis incidence from three hospitals in northwest Nigeria, using monthly aggregate counts of clinically diagnosed hospital-reported meningitis cases for 1990-2011. The case data exhibit a marked annual cycle, with yearly disease maxima occurring during the peak of the “hot dry” season in March and April. Explanatory variables in the models include meteorological variables, cases from the previous month, and *s(t)* in the GAMs. Model performance was estimated by three-fold cross validation, RMSE, and skill score.

The results indicated that both *explanatory* (fitted with the combination of lagged and non-lagged climatic variables) and *predictive* (fitted with only 1-month lagged climatic variables) models showed similar capabilities to fit values of meningitis incidence. The best explanatory model (A) had a CVC of 0.75 with the observations, and a skill score of 0.52 out of 1.0. Additionally, the cross-validation version of model A (that was developed by systematically omitting the first, middle and last 7 years of case data) exhibited nearly identical statistics to the "full" model that was fit using all 22-years of case data, indicating that the model performance is not sensitive to the period chosen for development. Although the best *predictive* model B was not as powerful as the best *explanatory* model A in terms of fitting performance, it has strong potential for short-term disease prediction, having a CVC of 0.73 and a skill score of 0.45. It is noteworthy that all of the most successful models were GAMs, suggesting that model fit is substantially improved by employing the monthly-varying smoothing function ***s(t)***. Despite the fact that reliable vaccination data are difficult to obtain, the expected number of cases that would have occurred assuming the vaccination campaigns were not carried out were estimated using established methods. A model was the fit to these expected cases and found that the model fit and accuracy changed very little, suggesting the results are reasonably insensitive to whether or not vaccination is accounted for. Regardless, documentation of vaccination campaigns may improve for future studies, as Nigerian authorities are now keeping detailed records of vaccination campaigns for the on-going MenAfriVac (the new conjugate A vaccine). The recent change in strategy from reactive to preventive vaccination is a welcome development in the effort of controlling the disease;

however, there is need for continual surveillance because other strains not covered by the conjugate vaccine may cause epidemics (e.g., Koumare et al., 1993).

Although there is no general agreed-upon physical explanation for the role of meteorological conditions in the incidence of meningitis (e.g., Cheesbrough et al., 1995), results from this study support the hypothesis that hot, dry, dusty conditions may facilitate both the transmission and the development of invasive meningitis in northwest Nigeria. For example, these conditions might be playing important role during the “cold dry” months, aiding in initiating the meningitis season by causing microtrauma to the nasal mucosa (Burgess and Whitelaw, 1988). This damage may make it possible for the bacteria to penetrate the nasopharyngeal membrane and subsequently enter the blood stream causing invasive disease. This may explain why reported meningitis cases are highest during the “hot dry” period (February - May) that follows the “cold dry” period.

Unobserved seasonally-varying non-climatic factors such as the occurrence of URTIs, societal and behavioural practices – which are represented in a very basic sense by the function ***s(t)*** – are likely to enhance the transmission of the disease in this region. For example, during the “cold dry” period (which favours diseases like influenza) people are often overcrowded in rooms and sometimes cluster around wood fires for warming. This overcrowding (e.g., Brundage and Zollinger, 1987) might enhance transmission through respiratory droplets, while particulates from wood fires may irritate the lining of the nasal mucosa. Additionally, social gatherings like marriages and economic activities in market places tend to be more frequent and active during this season.

Until recently the only strategy for controlling the disease has been through reactive mass vaccination campaigns after crossing a certain case threshold. While a new vaccine has recently been introduced that is effective and inexpensive enough to be used more broadly and proactively, it is only effective against the strain of bacteria that causes the most common kind of bacterial meningitis. As a result, there will likely be continued epidemics caused by other serogroups as has been recently observed in some countries. As such there is still strong need for information on when and where vaccines should be administered.

6.5 Conclusion

Results indicate the role of specific meteorological conditions in explaining and predicting monthly meningitis variability in northwest Nigeria, and also emphasize the importance of additional risk factors that are not well understood but may be linked to societal and behavioural practices. With respect to the latter, its currently limited to only collectively accounting for these unobserved seasonally-varying climatic and non-climatic risk factors via functions such as ***s(t)***. Identifying and quantifying such factors, and improving disease surveillance, will likely enhance our understanding and ability to predict and reduce meningitis incidence.

This chapter addresses objective four by developing and validating suites of regional empirical statistical models capable of: (1) explaining the influences of climatic conditions on the interannual variability of meningitis taking into consideration the effect of other non-climatic confounding factors, (2) predicting meningitis with a one month time lead, and (3) estimating future risk of climate change on the disease. The model developed in this chapter with adjusted cases of meningitis will be applied for assessing the potential of climate change on the disease in chapter 8.

Chapter Seven:

Climate and Socioeconomic Influences on the Interannual Variability of Cholera in Nigeria

Chapter Seven

Climate and Socioeconomic Influences on the Interannual Variability of Cholera in Nigeria

7.1 Introduction

One of the meteorologically-sensitive infectious diseases that remain a major health burden in Nigeria for several decades is cholera. The influence of climate on cholera dynamic has been well documented in literature, for example, in Asia (e.g., Bouma and Pascual., 2001; Pascual et al., 2000), South America (e.g., Colwell, 1996; Speelmon et al., 2000), and in Africa (e.g., de Magnay et al., 2012; Fernendez et al., 2009; Trearup, 2010). Social risk factors are also playing important roles in the transmission and outbreak of cholera, for example, the disease has been termed the 'disease of poverty' (Charles and Ryan, 2011; Snowden, 2008) and is associated with inadequate environmental sanitation conditions and untreated drinking water (e.g., Ali et al., 2002a; Hashizume et al., 2007; Penrose et al., 2010; Rajendran et al., 2011; Reiner et al., 2012; Talavera and Perez, 2009). Previous studies have demonstrated the possibility of predicting cholera epidemics (e.g., Reybourn et al., 2011), with few that considered the effects of social risk factors in addition to meteorological condition (e.g., Pascual et. al., 2002; Chou, 2010). Details of these relationships have been discussed in the literature review chapter.

In Nigeria, cholera is one of the primary causes of morbidity and mortality, with incidence occurring in both small outbreaks and large epidemics. The transmission of cholera in Nigeria might be facilitated by numerous factors such as lack of access to safe drinking water, unhygienic environment, environmental disasters, literacy level, population congestion, and internal conflicts which may results to population displacement to Internally Displaced Persons (IDP) camps. The United Nation Refugee Agency (UNHCR) has alerted the increasing number of the IDPs in the country due to Boko Haram security challenges that the country is facing in the north and flooding events (UNHCR, 2014). According to the Nigerian National Emergency Management Agency (NEMA), over 2.3 million people where displaced during the 2012 flood disaster that is occurring annually (This day, 2014). Provision of safe drinking water remains a serious issue of concern and this necessitate people even in cities to buy street vended water which has the high risk of being contaminated. Typical areas at risk might include population living in urban and peri-urban slums, these areas are mostly densely populated by low income earners and basic infrastructures are not readily available. Despite the availability of the oral cholera vaccines, anecdotal evidence reveals that this effective control method is not yet commonly used in Nigeria. The main control method is mainly treatment through rehydration with oral salts after infection.

This part of the study aims to statistically model the influences of meteorological and socioeconomic factors on the interannual variability of cholera disease in Nigeria. Despite the fact Nigeria is reporting the largest number of cholera cases and deaths to WHO, this study is the first to report this type of relationship. The model development and results are based on 22-years (1990 – 2011) of clinically diagnosed cases of cholera from three selected hospitals in northwest Nigeria, and also for 12-years (2000 – 2011) annual cholera cases and deaths from the 36 states of the federation and FCT. The chapter will provide new data by using a longer disease records and by taking into account some important socioeconomic factors that were previously discussed in the literature to have relations with the disease. A good understanding of the meteorological and socioeconomic drivers of cholera outbreak could help to a larger degree in the epidemic prediction, thereby allowing authorities to effectively prepare and respond in good time to prevent outbreaks through measures such as vaccinating the vulnerable population.

7.2 Materials and methods

Two statistical modelling approaches were adopted for this study in order to take the advantage of the two different set of disease data obtained. The choices of explanatory variables included were based on results from chapter five and previous studies that have already documented the importance of these variables. These includes meteorological variables such maximum and minimum temperatures, rainfall, and relative humidity (e.g., Hashizume et al., 2007; Rajendran et al., 2011; Reybourn et al., 2011), and social factors like absolute poverty (e.g., Traerup, 2010) adult literacy (e.g., Hashizume et at., 2007) access to safe drinking water (e.g., Penrose et al., 2010) and population density (Ali et al., 2002a).

7.2.1 Epidemiological data

Two different set of epidemiological records of suspected cholera cases were obtained. Firstly, monthly counts of clinically diagnosed cholera cases reported between 1990 and 2011 were collected from the same hospitals using the same criteria as described in section 6.2.1. Secondly, annual count of cholera cases and deaths for the entire country from the 36 states and FCT (see Figure 5.1) were obtained from the Nigeria Canter for Disease Control (NCDC) - a unit of the Federal Ministry of Health, this is a disease surveillance data across the country compiled by the NCDC spanning between 2000 and 2011.

7.2.2 Meteorological data

Based on the epidemiological data obtained, two sets of meteorological data were used; firstly, digital records of four variables from stations were obtained and quality-controlled as described in section 4.2.1. Secondly, due to non-availability of meteorological station data to represent individual states in the country, this study employs the use of ERA-interim reanalysis data (see details of data description in section 3.4.1 and 4.2.1). Almost each state is represented by at least one grid cell with the exception of very few because of their small sizes; (location of ERA interim grid within Nigeria is indicated on Figure 7.1). Daily time series of surface values for maximum and minimum temperatures alongside precipitation were extracted from each grid cell between 2000 and 2011. These variables were validated using the available station data from the six stations in the northwest (see section 4.2.1). Seasonal averages of maximum and minimum temperatures for the hottest months (from March to June) and annual rainfall totals were computed from the extracted daily time series.

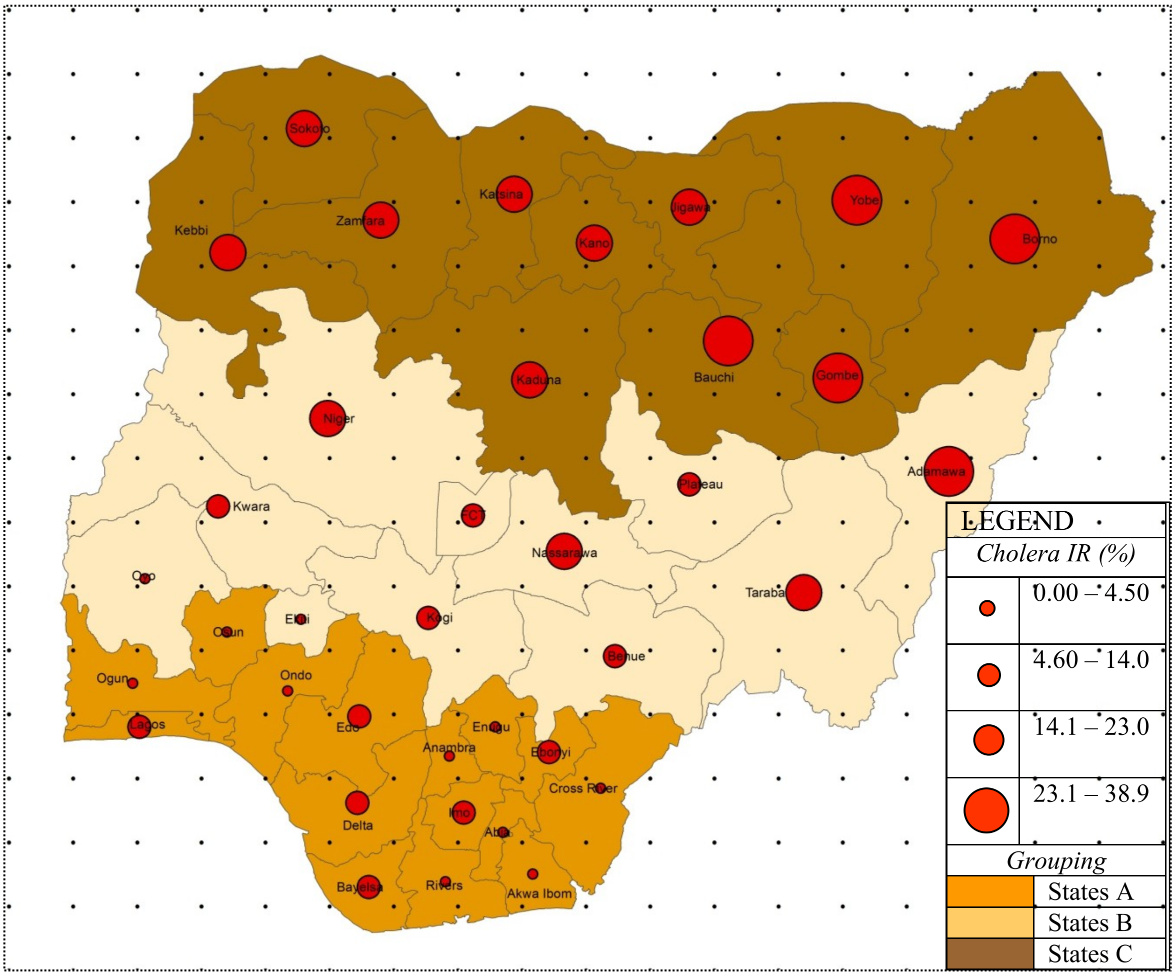

Figure 7.1: Map of Nigeria showing: **(a)** ERA interim grid cells covering the country **(b)** grouping of states based on annual rainfall totals into region A, B, and C, and **(c)** annual mean of cholera incidence rate (IR) for individual states between 2000 and 2011

7.2.3 Socioeconomic and demographic data

Annual state level socioeconomic data between 2000 and 2011 were obtained from the Nigerian National Bureau of Statistics (NBS). Data obtained includes percentages of population having access to pipe borne water, adult literacy, and absolute poverty. State's population census (2006) was obtained from the Nigerian Population Commission (NPC), Abuja, Nigeria. Annual population estimate for each state was calculated forward and backward in time using Nigerian population growth rate index provided by World Bank (2012). Population density for each of the 36 states and FCT were computed by dividing each state's population with its aerial cover (more information can be found in section 5.2).

7.2.4 Model overview

Two modelling approaches were adopted: The Generalised Additive Model (GAM) and Multiple Linear Regressions (MLR). The choices for these approaches were informed by the different spatial and temporal characteristics exhibit in the two sets of the disease data. The hospital data has the advantage of having higher resolution (monthly) and longer time series of cases (1990-2011), but socioeconomic data are not available at this spatial and temporal scale. While on the other hand, the state level data is on annual timescale and span for only 12 years (2000 – 2011), but socioeconomic data are available at states level and for the period of the study. A GAM was used to model the monthly hospital reported cases, while MLR was used to model the state level data.

a. Generalised additive models:

An overview of this technique was discussed in section 6.2.4 of chapter six.

b. Multiple linear regressions:

Stepwise MLR was applied to model (e.g., Stocco et al., 2010; Thomson et al., 2006; Yaka et al., 2006) the meteorological and socioeconomic influences on the spatiotemporal variability of cholera cases and deaths in Nigeria between 2000 and 2011. MLR is a powerful statistical technique that uses the equation of a straight line to predict the outcome of a dependent variable from a linear combination of independent explanatory predictor variables:

$$\boldsymbol{Y_i = b_0 + b_1X_{1i} + b_2X_{2i} \ldots\ldots + b_nX_{ni}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{Equation 7.1}$$

$\boldsymbol{Y_i}$ is the outcome of the dependent variable, b_0 is constant, b_1 is the coefficient associated of variable ($\boldsymbol{X_{i\ldots\ldots}}$).

Since the annual cholera cases and deaths are counts, transformation was carried out in two stages. First, the annual sum cases have natural trend with respect to population, incidence rate (IR) were calculated, defined by the number of case per 100,000 of population, also Case Fatality Rate (CFR) was computed for the death counts, defined as the proportion of fatal cases in relation to the total cases within a specified time (WHO, 2012b). Secondly, considering the skewed nature of both the IR and CFR, their distribution was normalised by a log transformation as LogIR and LogCFR respectively. Finally, to avoid trend effect from influencing the models output, all time series included in the models were de-trended.

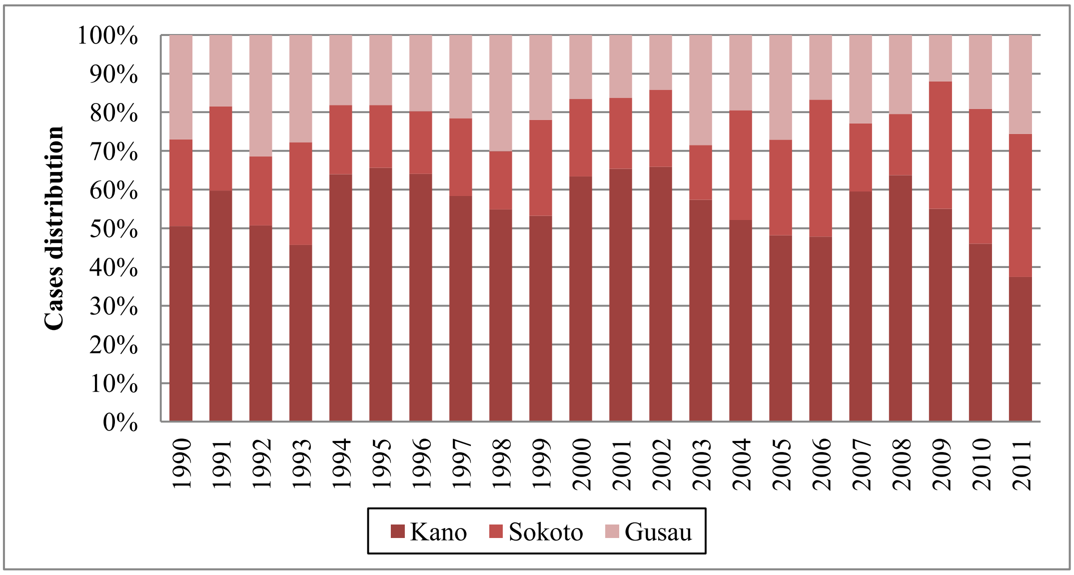

Figure 7.2: Relative distribution of cholera cases from the three selected hospitals (Kano, Sokoto, and Gusau) in northwest Nigeria

7.2.5 Model Fitting

For the GAM model development, monthly cholera counts for the three hospitals in Kano, Sokoto, and Gusau were aggregated, and variables of the corresponding three meteorological stations averaged. Monthly cholera counts were aggregated in order to minimize the effect of bias in reporting to individual hospitals, Figure 7.2 shows the individual contribution of each hospital. Three GAMs were fitted (denoted as models A, B, C), model A was fitted with the combination of non-lagged climatic variables and cases from the previous month; model B, with only the 1-month lagged explanatory climatic variables and cases from the previous month; and model C is the same as GAM A, except previous cases were excluded. All three GAMs were tested for a variety of degrees-of-freedom (DOF) for the fit of $\boldsymbol{s(t)}$, but it was found that those models in which $\boldsymbol{s(t)}$ has 4 DOF have the best fit. In summary, model A is intended to be optimal *explanatory* model of cholera cases, whereas model B by using only lagged variables is intended to be the optimal *predictive* model (with 1-month lead time). Model C, which does not include previous cases, is intended to be used for future climate change studies (since the number of cases in the previous month is unknown in the future). The best models were selected by minimising the Bayesian Information Criteria (BIC) (Dobson, 2010). Variable selections were made separately for each model, although the same variables were retained in all models. The retained variables include mean monthly maximum and minimum temperatures, precipitation totals, average relative humidity, and previous cases.

In the second approach, a stepwise MLR was used to fit the best model for three groups of states (regions A, B, and C) as shown in Figure 7.1. The 36 states and the Federal Capital Territory (FCT) were grouped into three groups based on their annual rainfall totals, grouping was made in order: (a) to investigate the spatiotemporal differences of the influences of both meteorological and socioeconomic factors on cholera incidence and deaths across these three regions, and (b) to have enough data samples (Knofczynski and Mundfrom, 2008) which will allow for more robust statistics during model fit. Three time series were generated by joining the time series of each state for cholera cases and deaths respectively, and their respective meteorological and socioeconomic variables. For each of the regions (A, B, and C), 3 models were fitted: The first and second sets of models consist of only meteorological or socioeconomic predictors respectively, while the third model comprises of the combination of both. The stepwise MLR models were separately developed for IR and CFR with correlated metrological and socioeconomic variables ($r > 0.4$ and p-value < 0.05). Explanatory variables includes seasonal maximum and minimum temperatures, rainfall totals, population density, and percentages of population with access to pipe borne water, absolute poverty, and adult literacy.

7.2.6 Models validation

Details of validation techniques and method used in determining relative influence were discussed in section 6.2.6.

7.4 Results

In recent years Nigeria has experienced increase in cholera cases and deaths, example, in 2010 alone, between the month of January and December, the country reported about 41,784 cases and 1716 deaths (CFR 4.1%) from 222 districts in 18 states (WHO, 2012b) in which most of the cases comes from the northern part of the country as displayed in Figure 7.1. Generally, both the individual and aggregated counts of the monthly hospital-reported cholera cases exhibit a marked annual cycle, with yearly disease maxima occurring between the month of April and August.

7.4.1 Interannual variability of cholera in northwest Nigeria

The estimated effect of other additional confounding factors represented in the GAM as a smooth function of time $\boldsymbol{s(t)}$ is shown in Figure 7.3 for the three models. The shape of the estimated function of both models is similar and follows the seasonality of the disease, with the months of April – August having the highest values of $\boldsymbol{s(t)}$. The model estimates and standard errors for GAMs are presented in Table 7.1. All variables correlated positively with disease cases in both models, mean monthly maximum temperature and monthly rainfall totals appear to be the most important predictors in both the models. Figure 7.4 shows the 22-years models fit for time series of the observed number of cases, and that of the predicted cases for GAMs A, B and C. Model with meteorological variables lagged by one month appears to capture the monthly and interannual variability of the cholera cases more accurately.

Table 7.1: Estimates for GAM A, B and C. Model A is fitted non-lagged climate variables, B is fitted with only 1-month lagged climate covariates, while C has the same composition with A, but previous cases are not included.

Predictors	Model A			Model B			Model C		
	coef.	*std. error*	*p-value*	*coef.*	*std. error*	*p-value*	*coef.*	*std. error*	*p-value*
Monthly mean Tmax (C°)	0.321	0.037	0.001	0.246	0.006	0.001	0.384	0.023	0.000
Monthly mean Tmin (C°)	0.153	0.018	0.101	0.117	0.008	0.007	0.216	0.039	0.018
Rain (mm)	0.206	0.241	0.221	0.305	0.021	0.101	0.281	0.173	0.131
Relative humidity (%)	0.036	0.007	0.001	0.112	0.103	0.001	0.162	0.102	0.041
Previous cases	0.047	0.002	0.201	0.102	0.012	0.104	na	na	na

Abbreviations: coef, coefficient; std error, standard error

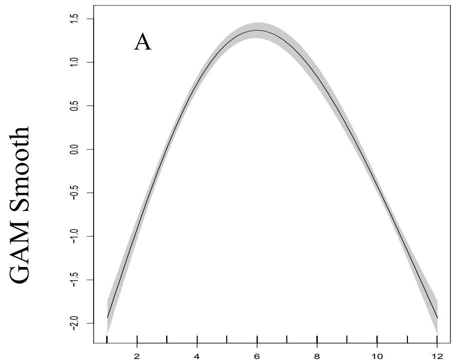

Figure 7.3: Estimated smooth function of time, $\hat{s}(t)$, across 12 months, for models **A**. The shaded area shows the 95% confidence interval about $\hat{s}(t)$.

Cross validation statistics are presented in Table 7.2, all three models show good skill, but as expected from the model fit (Figure 7.4), the lagged model (B) has improved statistic values if compared with non-lagged model A as measured by CVC and skill score (0.71 and 0.67). This demonstrates a good indication for the possibility of potentially predicting cholera cases with a month time lead in this region. Model C which is specifically designed for climate change studies also have a good skill. Predicted cases have a cross-validation correlation of 0.65 with 1990-2011 observed cases, and a skill score of 0.60, meaning the root-mean square error of the predicted cases yielded a 60% improvement over assuming the long term mean of cases is the value in each year (i.e., "persistence").

Table 7.2 Model validation results given CVC and Skill Score

	Kendal Correlation		Skill Score	
Models	**Full**[a]	**CV**[b]	**Full**[a]	**CV**[b]
A	0.703	0.685	0.659	0.641
B	0.734	0.713	0.704	0.672
C	0.681	0.652	0.623	0.592

[a]'Full' and [b]'CV' stands for full and 3-fold cross validated models respectively

In order to evaluate the models further, the estimated coefficient of model A was used to predict cases for Kaduna, and then compare the predicted time series with that observed from Kaduna hospital. This model also appeared to have a fairly good statistic if compared with that of model A (CVC, 0.59 and skill score, 0.45), and the monthly variability of cases is reasonably captured. Another completely new GAM with 4 DOF was fitted specifically for Kaduna city, employing the same variables as for model A, both the estimates and predictive power of this model remains qualitatively similar to model A.

The relative influence for the four months in which cholera cases are generally high is shown in Figure 7.5. In both models; mean monthly maximum temperature and monthly rainfall totals shows a comparatively important influence across the four months with the highest RI of about 35% and 28% across the months. The influence of mean monthly minimum temperature and that of average relative humidity remains almost the same across the months. The function ***s(t)*** which accounts for unobserved explanatory variables, varies in influence from about 8-15%, while previous cases also remains relatively the same, with the highest influence in the month of May.

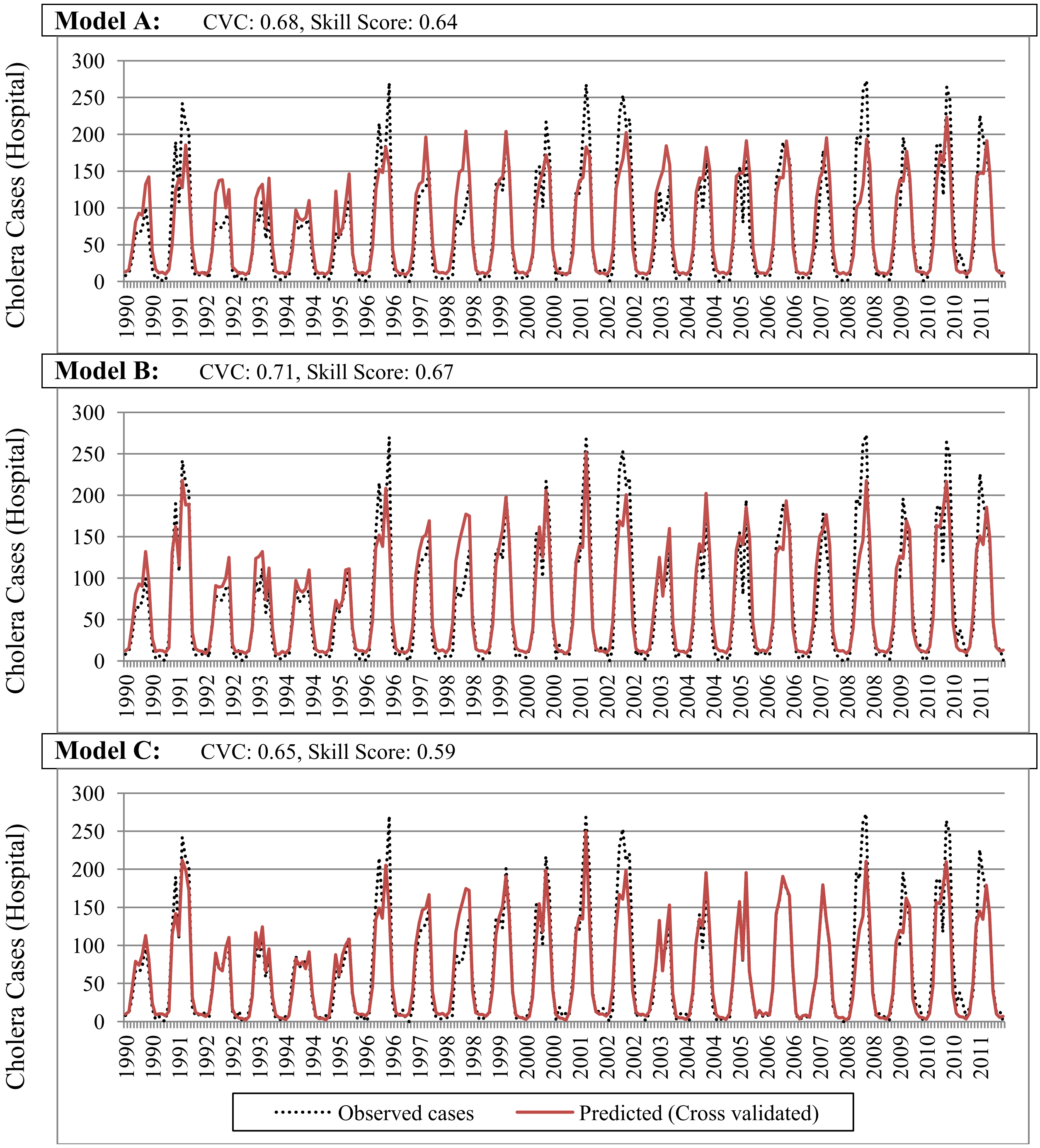

Figure 7.4: The fit for models A, B and C ("observed"; dashed-black "predicted"; red). Model A is fitted non-lagged climate variables, B is fitted with only 1-month lagged climate covariates, while C has the same composition with A, but previous cases are not included.

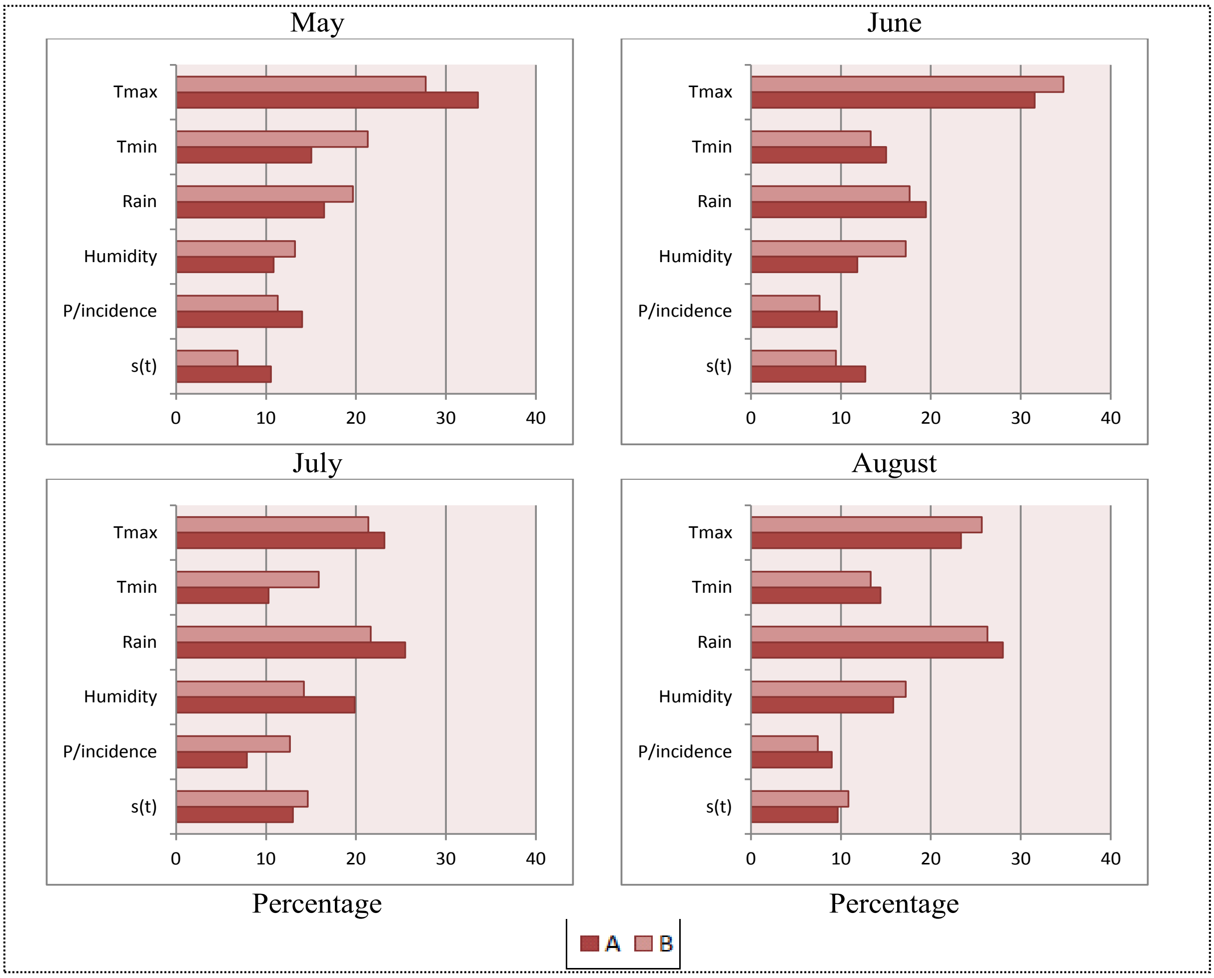

Figure 7.5: The relative influence of explanatory variables on cholera in northwest Nigeria for models **A** and **B** for the months in which the disease burden is typically highest: May, June, July, and August

7.4.2 Spatiotemporal variability of cholera in Nigeria

To gain an estimate about the role of socioeconomic factors in steering cholera IR and CFR, states were grouped into three larger scale regions depending on total annual rainfall. A positive significant relationship between IR and annual seasonal maximum and minimum temperatures, rainfall, absolute poverty, and population density was observed, while a negative but significant relationship with access to pipe borne water and adult literacy (R^2 ranges from 0.20 – 0.60, $p<0.05$) is identified (Table 7.3 present the regression coefficient of both IR and CFR models). Regardless of region and model, individually, maximum temperature, rainfall, and water source appears to be the most important variables in explaining the variability of the disease. Adult literacy is the least important predictor with respect to IR, whilst population density explains the lowest proportion of variability in the CFR. With the exception of access to pipe borne water, socioeconomic variables explain more variability for CFR models than the IR.

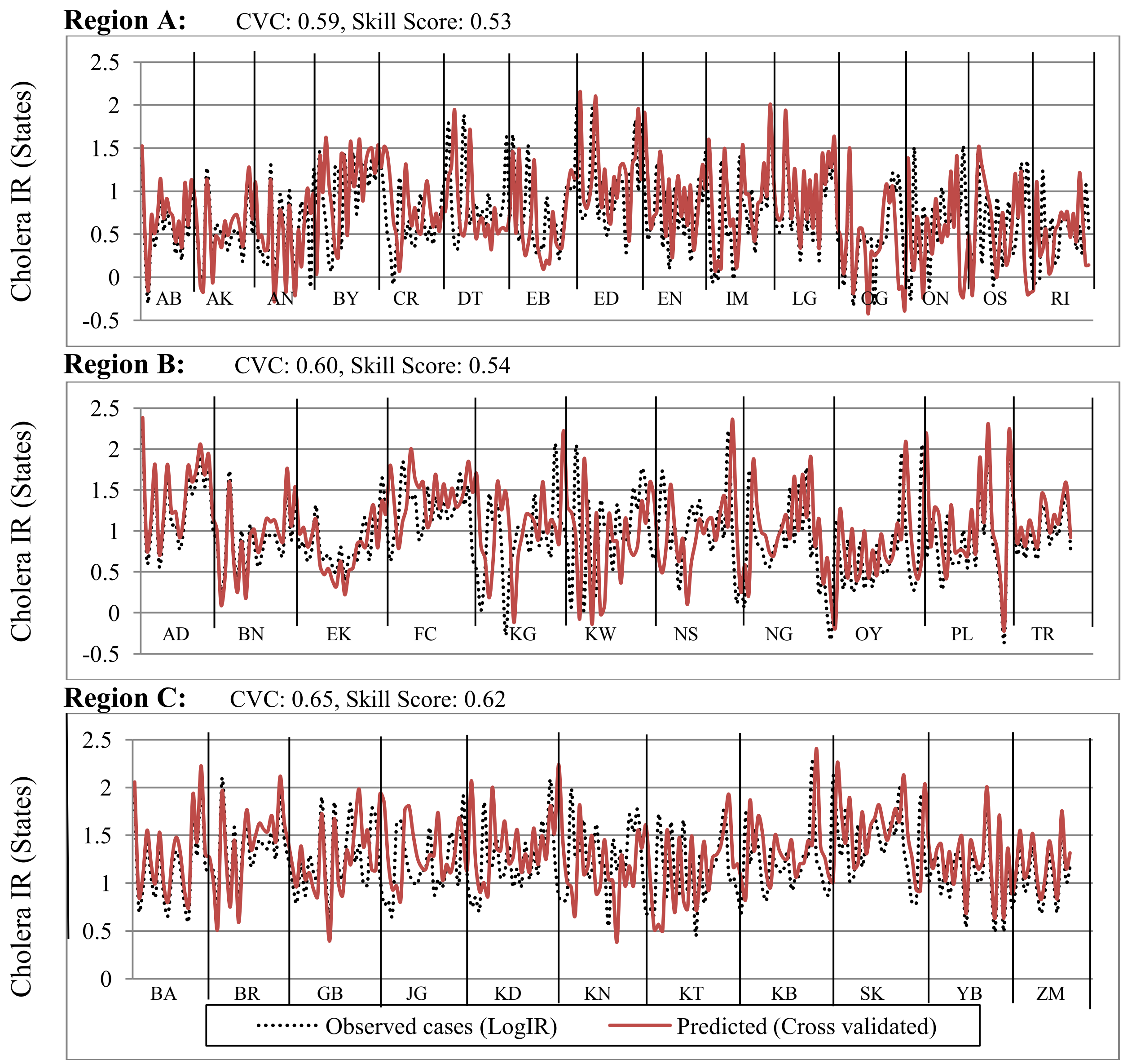

Figure 7.6: Models fit for IR models in the three regions (A, B, and C) ("observed" black "predicted" red) from 2000 to 2011. Models contains the combination of both meteorological and socioeconomic explanatory variables (seasonal maximum and minimum temperatures, annual rainfall totals, percentage of population in absolute poverty, population having access to pipe borne water, adult literacy, and population density per square kilometre).

A higher proportion of variability is consistently explained in both IR and CFR models with the combination of meteorological and socioeconomic explanatory variables. Figure 7.6 shows the models fit for time series of the observed IR, and that of the predicted cases for the best MLR models (with the combination of meteorological and socioeconomic variables).

Table 7.3: Model estimates and validation results, given by Regression Coefficient, CVC, and Skill Score.

	Incidence Rate Models					Mortality Rate Models				
	R^2	CVC		Skill score		R^2	CVC		Skill score	
Region A		Full[a]	CV[b]	Full[a]	CV[b]		Full[a]	CV[b]	Full[a]	CV[b]
Climate-based	0.349	0.591	0.532	0.494	0.451	0.203	0.451	0.448	0.422	0.443
Socioeconomic-based	0.149	0.387	0.362	0.303	0.278	0.123	0.359	0.334	0.252	0.232
Combined	0.365	0.604	0.593	0.594	0.534	0.316	0.562	0.542	0.571	0.567
Region B										
Climate-based	0.194	0.441	0.433	0.395	0.378	0.118	0.343	0.331	0.235	0.259
Socioeconomic-based	0.231	0.481	0.443	0.445	0.423	0.168	0.404	0.396	0.327	0.325
Combined	0.403	0.634	0.601	0.611	0.541	0.261	0.511	0.477	0.481	0.467
Region C										
Climate-based	0.119	0.345	0.324	0.314	0.293	0.124	0.351	0.332	0.288	0.249
Socioeconomic-based	0.350	0.592	0.589	0.541	0.534	0.301	0.544	0.535	0.420	0.414
Combined	0.429	0.655	0.652	0.642	0.623	0.375	0.615	0.601	0.594	0.562

[a]'Full' and [b]'CV' stands for full and 3-fold cross validated models respectively

Cross validation statistics for all models and for all the three regions are presented in Table 7.3, all the models have a relatively good statistics, but as expected, models with the combination of both meteorological and socioeconomic variables has a better statistics values if compared with other models that are either climate-based or socioeconomic-based only. Climate-based models have a better statistics in the southern part of the country (region B) if compared with the north (region C) and vice-versa when looking at the socioeconomic-based ones. Overall the best model in all the regions is the IR model which has the combination of both meteorological and socioeconomic explanatory variables from the northern region (C) as measured by CVC and skill score are (0.65 and 0.62).

The relative influence of the explanatory variables for models of IR and CFR that contains both climate and socioeconomic variables across the study period is shown in Figure 7.7. In both models; seasonal average of maximum temperature and annual rainfall totals shows a comparatively important influence with the highest relative influence of about 27% and 26% respectively. The influence of seasonal average minimum temperature, adult literacy and that of population density remains almost the same across the regions and models. The relative influence of absolute poverty and water source is higher in the northern part of the county (region C).

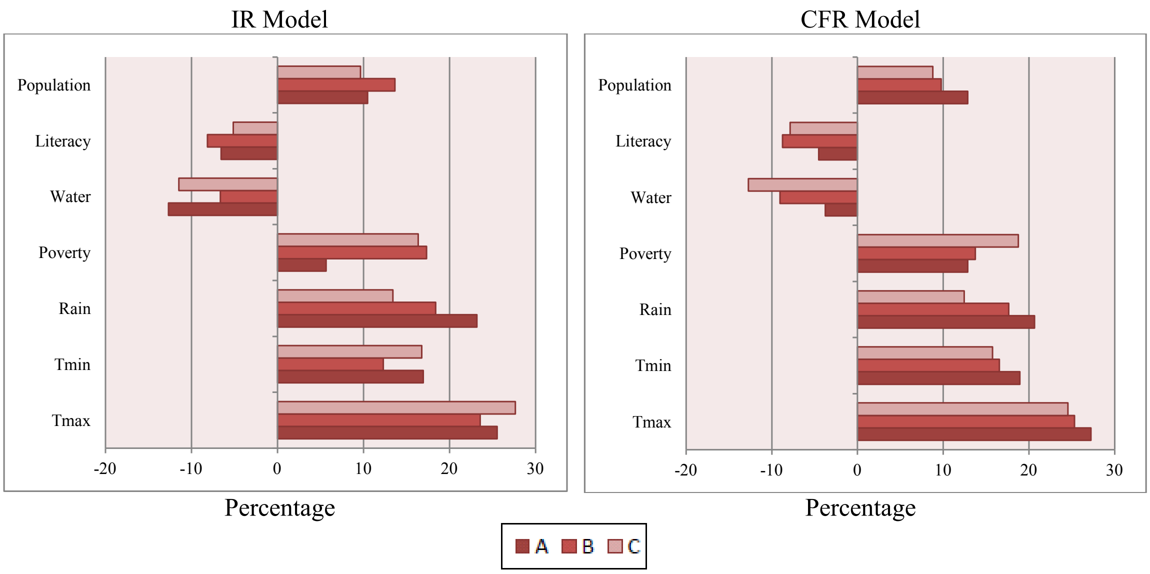

Figure 7.7: The relative influence of explanatory variables (seasonal maximum and minimum temperatures, annual rainfall totals, percentages of population in absolute poverty, having access to pipe borne water, adult literacy, and population density per square kilometre) on cholera incidence rate in Nigeria for models A, B, and C, across the study period.

7.5 Discussion

In this chapter, both GAM and MLR statistical techniques were employed to model the influences of meteorological and socioeconomic conditions on the interannual variability of cholera in Nigeria. GAMs were used to model the monthly aggregate counts of clinically diagnosed hospital-reported cholera cases from 1990 to 2011 in northwest Nigeria, explanatory variables in this models includes mean monthly maximum and minimum temperatures, monthly rainfall totals, monthly average relative humidity, and 1-month previous incidence and ***s(t).*** Stepwise MLR was used to investigate the spatiotemporal variability of the link between cholera incidence, mortality rate and climate under specific consideration of socioeconomic influences using annual state level data between 2000 and 2011. Here, explanatory variables includes seasonal maximum and minimum temperatures, annual rainfall totals, population density, and percentages of population with absolute poverty, adult literacy, and access to pipe borne water. These approaches were adopted because of the differences in the spatial and temporal characteristics of the disease data, and also based on the availability of socioeconomic data. The hospital case data exhibit a marked annual cycle, with yearly disease maxima occurring between the months of April and August, while the state level annual data indicates increase in cases of cholera with most of the cases being reported from the northern part of the country (Figure 7.1).

All models in both the two approaches pointed out to the importance of meteorological variables in explaining the disease dynamics, most especially temperature and rainfall. The positive relationship observed between cholera, temperature and rainfall has been reported by many studies carried out all over the world. Temperature was related to food contamination, which may consequently serve as a vehicle for cholera transmission (Rabbani and Greenough, 1999) depending with the physio-chemical properties of the contaminated food. Similarly, rainfall is well documented to have a positive relationship with cholera (Reyburn et al., 2011; Hashizume et al., 2011). The seasonal cycle observed in the monthly hospital time series corresponds with the rainy season, this is in consistence with what has been found in other regions (e.g. Richard et al., 1999).The link between rainfall and cholera was explained to be a result of flooding which exposes population to the bacterium (Emch et al., 2010; Hashizume et al., 2008), this explanation might also be applicable to Nigeria. Because in the northern part of Nigeria, the beginning of rain season is usually associated with heavy downpours which consequently bring about flooding (NIMET, 2012), thereby increasing the risk of contaminating sources of drinking water through sewage collapse. In slums areas, where most of the resident are using a local toilet system (pit latrines), during heavy downpours, sewage water can overflow or seep though the ground into local sources of drinking water like wells, or by pressure into roasted pipes that leak due to aging or lack of maintenance. On the other hand during the peak of the dry and hot season people tend to use drinking and cooking water from sources with higher risk of contamination, which includes stagnant waters and wells with lower depths (Oger and Sudre, 2013). A typical example is the cholera outbreak in March 1999 in Kano city where many lives were lost, this outbreak was directly associated with the interruption of domestic water supply (WHO, 2012b), which necessitate resident to source water from contaminated sources. Another problem that might facilitate cholera outbreak during the rainy season is the poor drainage system which is a peculiar characteristic of major cities in Nigeria, after heavy rainfall houses are usually flooded in some cases sub-merged with dirty water from open gutters.

The positive relationship observed in the MLR models between cholera and socio economic variables, such as absolute poverty and population density is in agreement with previous findings for other regions (e.g., Matsuda et al., 2008; Snowden, 2008). Poverty is associated with environmental sanitation which can cause the disease to propagate (Rajendran et al., 2011; Reiner et al., 2012), while population densities allow the disease to spread quickly possibly via faecal contamination (Penrose et al., 2010; Rajendran et al, 2011). In a related study, Ali et al. (2002a) using a risk spatial model reported that areas associated with the risk of cholera morbidity and mortality are associated with population density, low educational status and proximity to surface waters.

In Nigeria, population living in urban and peri-urban slums are more at risk and vulnerable of contracting the disease, because these areas are mostly densely populated by low income earners and basic infrastructures are not readily available, which results to many people defecating in the open. In all the major cities of Nigeria you hardly find public conveniences, according to United Nation Children's Fund (UNICEF, 2012) report over 34 million Nigeria are defecating outside. In areas like this, after a heavy downpour, surface outwash, collapsed sewages, and open drainage may lead to contamination of sources of drinking water like wells and rivers. Since cholera can spread via contaminated food and water, transmission of the disease will be made easy and rapid. The results also reveals negative relationships between IR and CFR with adult literacy, this shows that as more adults become literate, cases and deaths from cholera decreases, this finding is in line with the studies conducted in Latin America, Bangladesh, and Tanzania (Ackers et al., 1998; Ali et al., 2002b; Traerup, 2010) respectively. Those with a higher level of education are expected to make more rational decisions by taking measures to avoid contracting the disease, and if infected they seek an immediate medical treatment for the disease before fatality occurs (Ali et al., 2002b). Water sources was also one of the important predictors in explaining the interannual variability in both IR and CFR, and was negatively associated, suggesting that as more people have access to safe drinking water there will be less contraction of the disease by individuals (e.g., Reiner et al., 2012; Rajendran et al., 2011).

Table 7.4: Summary of the variability of some climatic variables based on the three regions (A,B, and C) given by annual mean and standard deviation

Regions	Rainfall (mm)	Max. Temp (°C)	Min. Temp (°C)
A			
Mean	1936	31.0	23.0
STD	166.1	0.42	0.31
B			
Mean	1504	32.6	22.5
STD	195.2	0.46	0.34
C			
Mean	767.3	34.1	20.5
STD	122.3	0.52	0.51

MLR models shows that socioeconomic variables contribute more in explaining the variability of both cholera IR and CFR in the northern part of the country (Table 7.3). Generally, socioeconomic data shows that this part of the country has lower level of adult literacy and higher level of poverty. Documented evidence has established this kind of spatial differences within countries whereby high cholera rates was attributed to poor socioeconomic status (e.g., Ali et al., 2002b; Penrose et al., 2010). Lower socioeconomic status in the northern part of the country may be the reason why IR and CFR are higher in this area and as a result why socioeconomic variables were able to explain a greater proportion of interannual variability in this region. On the other hand climate shows more importance in determining the interannual variability of the disease towards the southern part of the country (Table 7.3). For example, climate explains 35% of cholera variability in region A (south) and only 12% in region C (north). This variation in influences between climate and socioeconomic factors may be connected to the lesser socioeconomic challenges in the southern part of the country (compared to the north) which allows for the climate to show more prominence. Also the latitudinal variation in rainfall amount and variability (Table 7.4) might be responsible for the higher importance of climate in the southern region.

7.6 Conclusion

Influences of meteorological and socioeconomic explanatory variables on cholera interannual variability in Nigeria were investigated. Result from both modelling approaches highlighted the importance of both meteorological and socioeconomic variables in explaining and predicting the disease in Nigeria. It has been shown that increases in temperature, rainfall, poverty, and population density may increase both cholera cases and deaths, while improvement of drinking water and adult literacy might reduce the risk of contracting the disease.

The results emphasises the importance of including socioeconomic factors in studies of this nature, this is because socioeconomic variables help in explaining a higher proportion of interannual variability in both the IR and CFR than using climate information alone. Models with only meteorological or socioeconomic variables do not accurately capture the interannual variability like that of the combination of both.

The new data provided by this study will serve as a basis for the potential prediction of cholera in Nigeria which could help authorities in controlling or even avoiding outbreaks. Also, with the growing concern of the potential impact of climate change on the dynamic of infectious diseases in the future, this study has provided a background for assessing the future impact, which is the next step of this study.

This chapter addresses the second part of objective four by developing and validating suites of regional empirical statistical models capable of: (1) explaining the influences of climate and socioeconomic conditions on the interannual variability of cholera (2) predicting cholera with a one month time lead, and (3) estimating future risk of climate change on the disease. The GAM (model C) developed in this chapter will be applied for assessing the potential of climate change on the disease in the subsequent chapter.

Chapter Eight:

Projecting the Impact of Climate Change on Meningitis and Cholera in Northwest Nigeria

Chapter Eight

Projecting the Impact of Climate Change on Meningitis and Cholera in Northwest Nigeria

8.1 Introduction

Assessing the potential impact of climate change on meteorologically-sensitive infectious diseases is essential (Grasso et al., 2012), specifically for regions where changes to disease distribution and seasonality may have adverse health impacts (Murray et al., 2013; WHO, 2013a), especially in developing countries with low coping capacity (Shuman, 2011). The Sahel, including northwest Nigeria, are areas identified as "hotspots" of climate change (Diffenbaugh and Giorgi, 2012), and are projected to be disproportionately affected due to the vulnerability of the populations (Suk and Sumenza, 2011).

Projecting the future risk of infectious disease involves a number of uncertainties (as discussed in section 2.9), as many factors that influence these diseases, both climatic and non-climatic, may change in the future. For example, the recent introduction of the conjugate vaccine that is expected to provide a long-term protection against the primary serogroup of meningitis that occurs in the region, serogroup A (Greenwood and Stuart, 2012), may greatly reduce the disease burden in the future. While improved sanitary condition, education, and poverty reduction may reduce the risk of cholera in the future. Nevertheless, these potential future developments are uncertain. Despite these uncertainties, the present study is useful because it indicates the potential impact of climate change on future diseases risk in the absence of interventions such as widespread vaccination campaigns, improved healthcare delivery or, in the case that meningitis serogroups that are not vaccinated against become more common. In turn, estimates of the potential future of infectious diseases burden inform authorities as they develop mitigation and adaption strategies, particularly to protect the vulnerable populations expected to be disproportionately impacted (Mendelsohn et al., 2006).

In this chapter, empirical statistical models that were developed and validated in chapter six and seven are applied to assess the potential impact of future climate change on meningitis and cholera incidence in northwest Nigeria. Statistically downscaled variables from AOGCM projections that participated in CMIP5 were used as explanatory variables. A part of results from this chapter has been published in the Journal of Weather, Climate, and Society with contribution from seven co-authors (see Appendix B attached). AJM and DFS assist in statistical downscaling.

Table 8.1: List of climate models used in this study[1,2].

Model	Modeling centre	Institution
BCC-CSM1.1	BCC	Beijing Climate Center, China Meteorological Administration
CESM1-CAM5	NSF-DOE-NCAR	National Center for Atmospheric Research
CSIROMk3.6.0	CSIRO-QCCCE	Commonwealth Scientific and Industrial Research Organization in collaboration with the Queensland Climate Change Centre of Excellence.
GFDL-ESM2G	NOAA GFDL	Geophysical Fluid Dynamics Laboratory
GFDL-ESM2M	NOAA GFDL	Geophysical Fluid Dynamics Laboratory
GISS-E2-R	NASA GISS	NASA Goddard Institute for Space Studies
HadGEM2-ES	MOHC	Met Office Hadley Centre
IPSL-CM5ALR	IPSL	Institute Pierre-Simon Laplace
MIROC5	MIROC	Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology
MIROC-ESM	MIROC	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies
MIROC-ESMCHEM	MIROC	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies
MRI-CGCM3	MRI	Meteorological Research Institute
NorESM1-M	NCC	Norwegian Climate Centre

[1]-CESM1-CAM5 and GFDL-ESM2M were not available for the RCP2.6 scenario when analysis was done.
[2]-GFDL-ESM2G and HadGEM2-ES were not available for the RCP8.5 scenario when analysis was done.

8.2 Materials and methods

8.2.1 Disease models

Empirical models for meningitis and cholera were used for projecting the future potential cases of the diseases in northwest Nigeria. These statistical models were developed and validated in chapter six and seven using GAM approach which can better account for the seasonally-varying influence of additional climatic and non-climatic influences that may influence the diseases. GAM has been used for projection studies (e.g., Astrom et al., 2013). These models were developed based on monthly aggregate of clinically-diagnosed cases of meningitis and cholera from three selected hospitals in the region, and monthly weather variables from nearby meteorological stations. Validation results suggests the ability of the models to predict independent observations not used in model fitting (see details for model developments and validation in section 6.21. and 7.2.1).

In this chapter, models specifically designed for climate change studies in which previous cases were not included during model fitting are used (and in which cases were adjusted to filter the bias of vaccination campaigns carried out in the case of meningitis) were applied. Predicted cases have a cross-validation correlation 0.75(0.65) and a skill score of 0.52(0.59) with 1990-2011 observed cases for meningitis and (cholera) respectively, meaning the root-mean square error of the predicted cases yielded a 52 and 59% improvement over assuming the long term mean of cases is the value in each year (i.e., "persistence") for both models. These models were used to project potential cases risk for two 21st century time slices, 2020-2035 and 2060-2075, by forcing them with an ensemble of downscaled future climate simulations.

8.2.2 Climate experiments

In this study, a wide range of climate models output were employed, monthly output from thirteen coupled AOGCM that participated in the CMIP5 are employed (Table 1). These new sets of models have undergone a few changes and improvement, if compared with the former CMIP3. This is in addition to the new climate change scenarios introduced – the family of "Representative Concentration Pathways" (RCP) (van Vurren et al., 2011) that reflected the important of potential GHG emission mitigation (Taylor et al., 2012).

Model fields were obtained from the Earth System Grid - Program for Climate Model Diagnosis and Intercomparison (ESG-PCMDI) gateway at Lawrence Livermore National Laboratory, http://pcmdi3.llnl.gov/esgcet/home.htm. Model scenarios used in this study include the historical simulation and three future projections. The historical simulation was forced by observed natural and anthropogenic atmospheric composition changes spanning 1861-2005 in all of the models; it is used to provide a baseline against which to assess climate change in the three future projections. The future projections are distinguished by the values of their RCPs. In this study the RCP2.6, RCP6.0 and RCP8.5 scenarios for 2006-2100 are used, with the numbers representing the globally-averaged top-of-the-atmosphere radiative imbalance (in W m^{-2}) in 2100 (Moss et al., 2010). Compared to the Special Report on Emissions scenarios (SRES) that informed the climate projections for the previous CMIP experiment (CMIP3), The CO_2 concentration in RCP2.6 is below B1, in RCP6.0 is slightly above A1B, and in RCP8.5 exceeds A2. Therefore, a broad range of potential GHG trajectories for the 21st century are represented by the three chosen scenarios. Generally, multiple ensemble members are available for each CMIP5 scenario for the given model. Assuming to have sufficient models in the ensemble to get reliable estimates of a potential climate change signal, only one ensemble member (the first) from each CMIP5 model and scenario is used here. The variables used include near surface maximum and minimum temperature, precipitation, relative humidity, wind speed, and cloud fraction (to estimate changes in sunshine hours), while dust was assumed to remain constant in the future (because an analogous AOGCM variable for dust does not exist). Nevertheless, a sensitivity test in which dust was increased by +/-15% was performed for meningitis projections because of the potentially important role of this variable on meningitis incidence as reported by (Abdussalam et al., 2014a; Dukic and Hayden et al., 2012; Agier et al., 2013; Martiny and Chiapello, 2013). Only the first four variables mentioned above that were used in cholera models development are used for the disease projection. A comparison of the annual cycle of the historical AOGCM simulations versus observations for some climatic variables relevant to the present study was also evaluated.

The AOGCM outputs are statistically downscaled to each of the three cities (Kano, Sokoto and Gusau). A variety of statistical downscaling techniques of varying complexity are available (e.g., Gutiérrez et al., 2012; Wilby and Dawson, 2012). Many of the more complex downscaling techniques were developed for daily timescales. In this study, since the hospital disease cases used in developing the models are on monthly resolution, only monthly average climate data are required and therefore resolving the high-frequency variability (the intent of more complex approaches) is not necessary. Two relatively simple but robust downscaling techniques were employed, and both essentially involve three steps: (1) bilinearly interpolating the AOGCM output to the coordinates of each city; (2) computing the AOGCM climate change signal for a given variable for a specified future RCP period (e.g., 2020-2035) relative to the AOGCM historical period that overlaps with the observational record (1990-2005); and (3) adding this change signal (which includes changes in the mean and the variance) to the 1990-2005 observational record to compute the downscaled future climate in

2020-2035 or 2060-2075 for a given variable and city. The reason of using the two techniques (as described below) is to compare the sensitivity of the simulated climate changes to the techniques. Basically both the two methods were produced with bias correction.

The first technique is a simple perturbation method, expressed as follows:

$$X_{f_{m,y}}=\left[\bar{X}_{p,obs_m}\right]+\left[\bar{X}_{f,gcm_m}-\bar{X}_{p,gcm_m}\right]+\left[X_{p,obs_{m,y}}-\bar{X}_{p,obs_m}\right]\times\left[1+\frac{\bar{\sigma}_{f,gcm_m}-\bar{\sigma}_{p,gcm_m}}{\bar{\sigma}_{p,gcm_m}}\right] \quad .8.1$$

Where $X_{f_{m,y}}$ is the downscaled future value of variable X for a given month, m, and year, y. Downscaled variables include maximum temperature, minimum temperature, rainfall, relative humidity, wind speed and sunshine hours. Dust was not downscaled because there is no analogous variable in the AOGCMs (however, a sensitivity test to changes in dust of +/-15% was done, described later). $\bar{X}_{p,obs_m}$ is the mean present-day observed climate for a given month averaged across all years of the historical period (1990-2005), as calculated from the airport weather station in each city. $\bar{X}_{f,gcm_m}$ and $\bar{X}_{p,gcm_m}$ are the mean future (e.g., 2020-2035 or 2060-2075) and present-day (1990-2005) averages, respectively, for a given month in the AOGCM. $X_{p,obs_{m,y}}$ is the observed climate for a given year and month. $\bar{\sigma}_{f,gcm_m}$ and $\bar{\sigma}_{p,gcm_m}$ are the mean future and present-day standard deviations from the monthly mean over the period, respectively, for a given month in the AOGCM. Therefore, the above equation is in essence a Reynolds averaging approach: the monthly mean AOGCM change signal (bracketed term 2) is added to the present-day observed monthly mean (bracketed term 1), then the observed perturbation for each year and month is added back to the mean change signal (bracketed term 3). First, however, the perturbation term is multiplied by the fractional change in the standard deviation (bracketed term 4) prior to adding it back to the mean, in order to account for changes in the variability of a given variable in the future. This is done so on a fractional basis to account for the fact that variability in a AOGCM may be dampened or enhanced compared to the observed variability due to the coarse spatial resolution and physical assumptions of the AOGCM. Adjusting the observed perturbation on a fractional (rather than absolute) basis accounts for such differences. Likewise, the change in the mean of variable X, expressed in bracketed term 2, is modified slightly when downscaling rainfall, wind speed and sunshine hours to be expressed as a fractional change. This is done because (1) AOGCMs often underestimate the magnitude of rainfall and wind speed and (2) future changes in sunshine hours must be estimated by changes in the AOGCM cloud fraction fields because "sunshine hours" are not an output field in the AOGCMs.

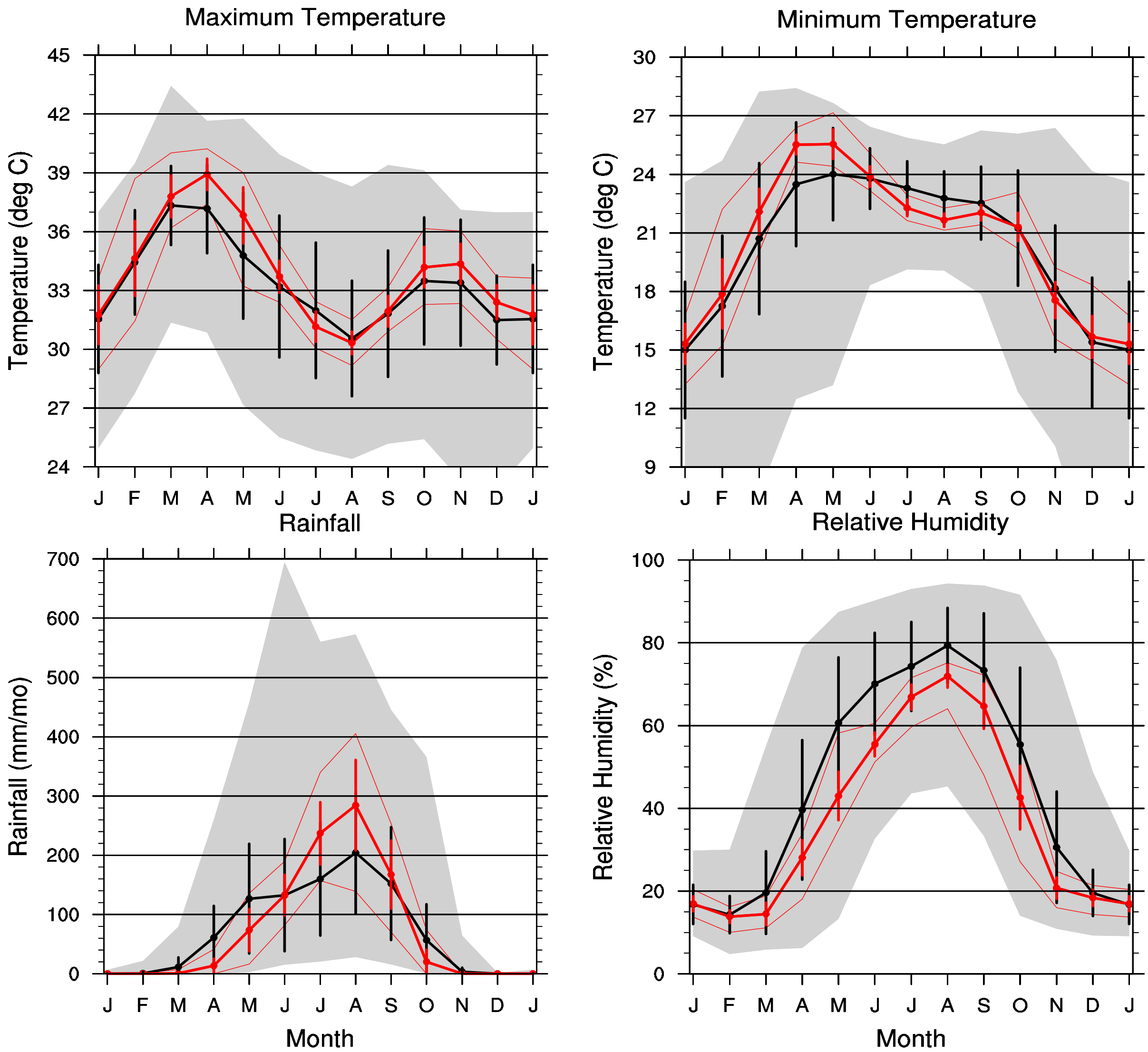

Figure 8.1: Annual cycle of the observed present day (1990-2005) maximum temperature (^{o}C), minimum temperature (^{o}C), monthly total rainfall (mm) and relative humidity (%) averaged for the three cities, in comparison with the ensemble of historical AOGCM simulations for the same 16-year period. The thick and thin red lines represent the mean and range of observed monthly values, respectively. The thick black line and gray shaded areas represent the mean and range of the AOGCM simulations, respectively. The vertical lines represent +/- 1 standard deviation from the means for the observations and AOGCM projections, respectively.

In the second approach, gamma method similar to that of Ines and Hansen (2006), Deque (2007), Michelangeli et al. (2009), and Hopson and Webster (2010) was used, which is sometimes referred to as cumulative distribution function-transform (CDF-t) (this approach is described by Abdussalam et al. (2014b)). The resulting model projections of future diseases incidence using the gamma versus the perturbation method were nearly indistinguishable, and therefore only the results from the perturbation method are presented here.

Student's t-tests are used to test for significance between the observed present-day climatic variables, meningitis and cholera cases versus their respective future projections. The tests account for the uncertainty due to the interannual variability within each period, and the uncertainty due to the climate model projections. For example, there are 13 climate models for the RCP6.0 scenario, and each is used to simulate cholera cases for a 16-year present-day and a 16-year future period, representing a total of 208 members for each period. This test compares the mean and variance of each period to determine if the meningitis incidence is statistically different between the periods. Where meningitis changes are expressed as percentages in the text, the uncertainty is given as the 95% confidence interval bounding the projected mean change

8.3 Results

8.3.1 Climate projection and evaluation

The annual cycle of the historical AOGCM simulations versus observations for some climatic variables relevant to the present study were evaluated. Although the range of historical simulations about the observed annual cycle is large, the ensemble mean captures the observed seasonal cycle and magnitude of maximum and minimum temperature, rainfall, and humidity with remarkable accuracy. This lends confidence that the statistically downscaled climate projections are based on models that, on average, reasonably simulate the climate of northwest Nigeria on this time scale.

Figure 8.1 shows that the models capture the seasonal cycle of maximum and minimum temperature, rainfall, and relative humidity, as measured by the ensemble mean values (the black line compared to the red line). For maximum temperature during the hottest months (February – April), the ensemble mean of the models is nearly perfect, and there is a 1.5-2 degree cold bias during April and May. The models exhibit a larger standard deviation and range than the observations because there are more data points used for the statistics: for the observations there are 16 data points for each month (because there are 16 years of data for 1990-2005). For the models there are 13 times as many data points, since there are 13 models. In summary, these plots indicate that, collectively, the models are able to capture the seasonal cycle and magnitude of the key meteorological variables that impact both meningitis and cholera, albeit with some small biases. This indicates the models are resolving key atmospheric processes, which in turn suggests that the models' climate change projections for 2020-2035 and 2060-2075 may have reasonable fidelity. Also, testing the diseases models with the ensemble simulations reveals the same annual cycle for the recent control period of both meningitis and cholera (1990-2005).

Figure 8.2 shows the annual cycle of the observed present day maximum temperature, rainfall and relative humidity for the aggregate of the three cities, in comparison with the RCP6.0 simulations for 2020-2035 and 2060-2075. Even in the near future (2020-2035) maximum temperature increases of about 0.5-1^{o}C are statistically significant ($p<0.01$) compared to 1990-2005 in 7-out-of-12 months, including those months from February-April in which disease cases are greatest. In the far future (2060-2075) statistically significant ($p<0.01$) maximum temperature increases of 1-3^{o}C occur in 9-of-12 months, and increases are also significant ($p<0.1$ or 0.05) in the other three months. Humidity does not change significantly in the near or distant future except for a small but significant increase in December of about 1% ($p<0.10$; 2020-2035) to 2% ($p<0.05$; 2060-2075). While rainfall, for example, exhibits statistically significant changes during December and January in both future periods but rainfall amounts is nearly zero during these months already, so the changes are almost imperceptible. Likewise, July-August rainfall is projected to increase in the future, a result consistent with Vizy et al. (2013).

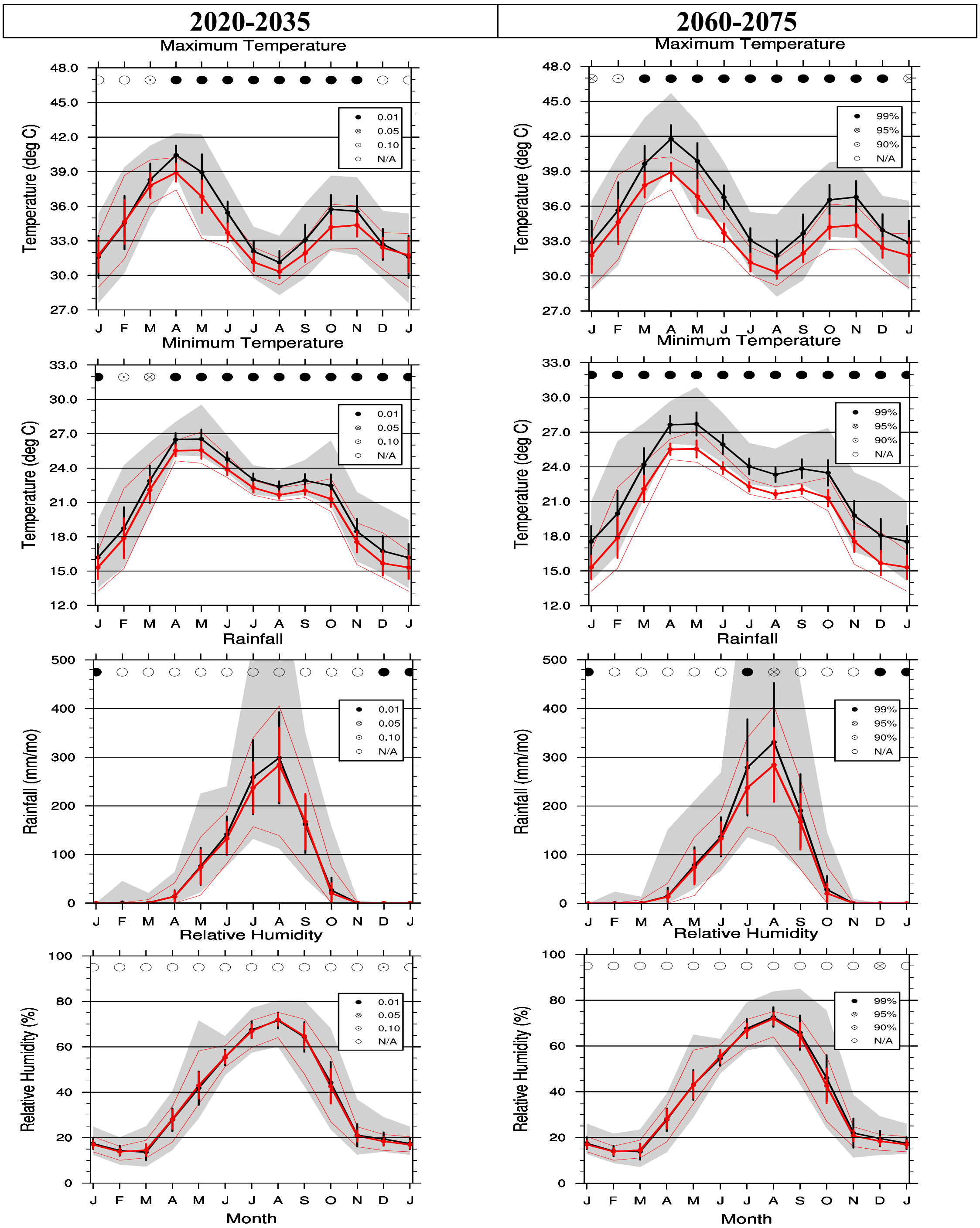

Figure 8.2: Annual cycle of the observed present day (1990-2005) maximum temperature (^{o}C), minimum temperature (^{o}C), monthly total rainfall (mm) and relative humidity (%) averaged for the three cities, in comparison with the ensemble of downscaled RCP6.0 AOGCM projections in 2020-2035 (left) and 2060-2075 (right). The red and black lines and gray shading are as described in the Figure 8.1 caption. The dots on top represent the significance level ($p<0.01$, $p<0.05$, $p<0.10$, or N/A for no significance) of the future changes versus the observations, as indicated in the legend.

8.3.2 Meningitis Projections

Projection results indicate statistically significant increases in meningitis cases during most months of the meningitis season (approximately November through May) in the future (Figure 8.3). The results suggest future temperature increases due to climate change have the potential to significantly increase meningitis cases in both the early (2020-2035) and late (2060-2075) 21st century, and for the seasonal onset of meningitis to begin about a month earlier on average by late century, in October rather than November. Annual incidence may increase by 47+/-8 %, 64+/-9 %, and 99+/-12 % for the RCP 2.6, 6.0 and 8.5 scenarios respectively in 2060-2075 with respect to 1990-2005. Changes are largest and have the strongest statistical significance ($p<0.01$) in the hot, dry peak months of the meningitis season, with increases over the present day case rate (23 cases per 100,000 of population for the month of March) to rates ranging from 29 to 30 and 31 to 42 in the near (2020-2025) and far future (2060-2075) respectively, depending on the RCP. The months with the largest increases coincide with the months in which maximum temperature increases are largest (Figure 8.2). There is little difference among projected meningitis case rates among the three scenarios for 2020-2035, for example in March increases range from 26-30%, but larger differences among the scenarios occur for 2060-2075 after the RCP emissions scenarios diverge (Moss et al., 2010), with March increases of about 35%, 52%, and 83% for RCP 2.6, 6.0, and 8.5 respectively.

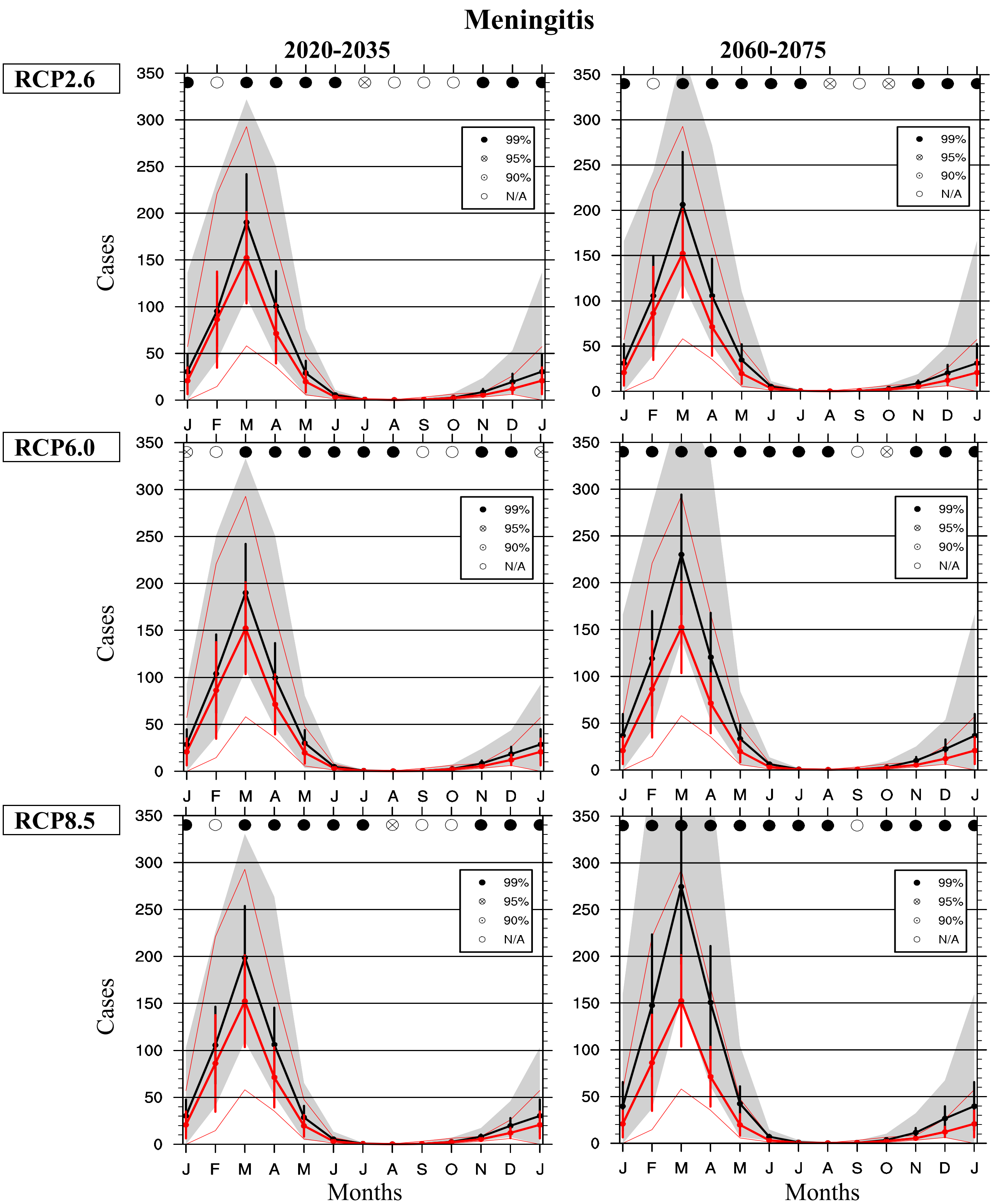

Figure 8.3: The annual cycle of present-day (1990-2005) meningitis cases compared with projections from the ensemble of downscaled AOGCM in 2020-2035 (left) and 2060-2075 (right) for the three different future scenarios: RCP2.6 (top), RCP6.0 (middle), and RCP8.5 (bottom). The red and black lines are as described in Figure 8.1, but for meningitis cases.

Because there are no AOGCM projections of changes in the number of dusty days, a sensitivity experiment was performed in which future dusty days each month were increased or decreased by 15% for the RCP6.0 scenario (Figure 8.4). The results clearly exhibit sensitivity to the number of dusty days (compare Figure 8.4 to middle panels of Figure 8.3). For example, March cases in 2020-2035 are projected to be 32 per 100,000 (25 per 100,000) for the +15% dust (-15% dust) case compared to projections of 29 cases per 100,000 for our assumption of no change in dust, with the +/-15% dust case results being significantly different from each other and from the no change case ($p<0.01$). Changes of a similar magnitude occur for the 2060-2075 period. How dust may change is uncertain, although humidity, rainfall, and wind are not projected to change significantly during the peak of the season, suggesting dustiness may change little, all else equal (e.g., Shao et al., 2011). On the other hand, land use may change dramatically in the future, for example widespread irrigated agriculture may become established in the region, which may reduce the number of dusty days (e.g., Cowie et al., 2013), conversely, overgrazing could lead to dustier conditions.

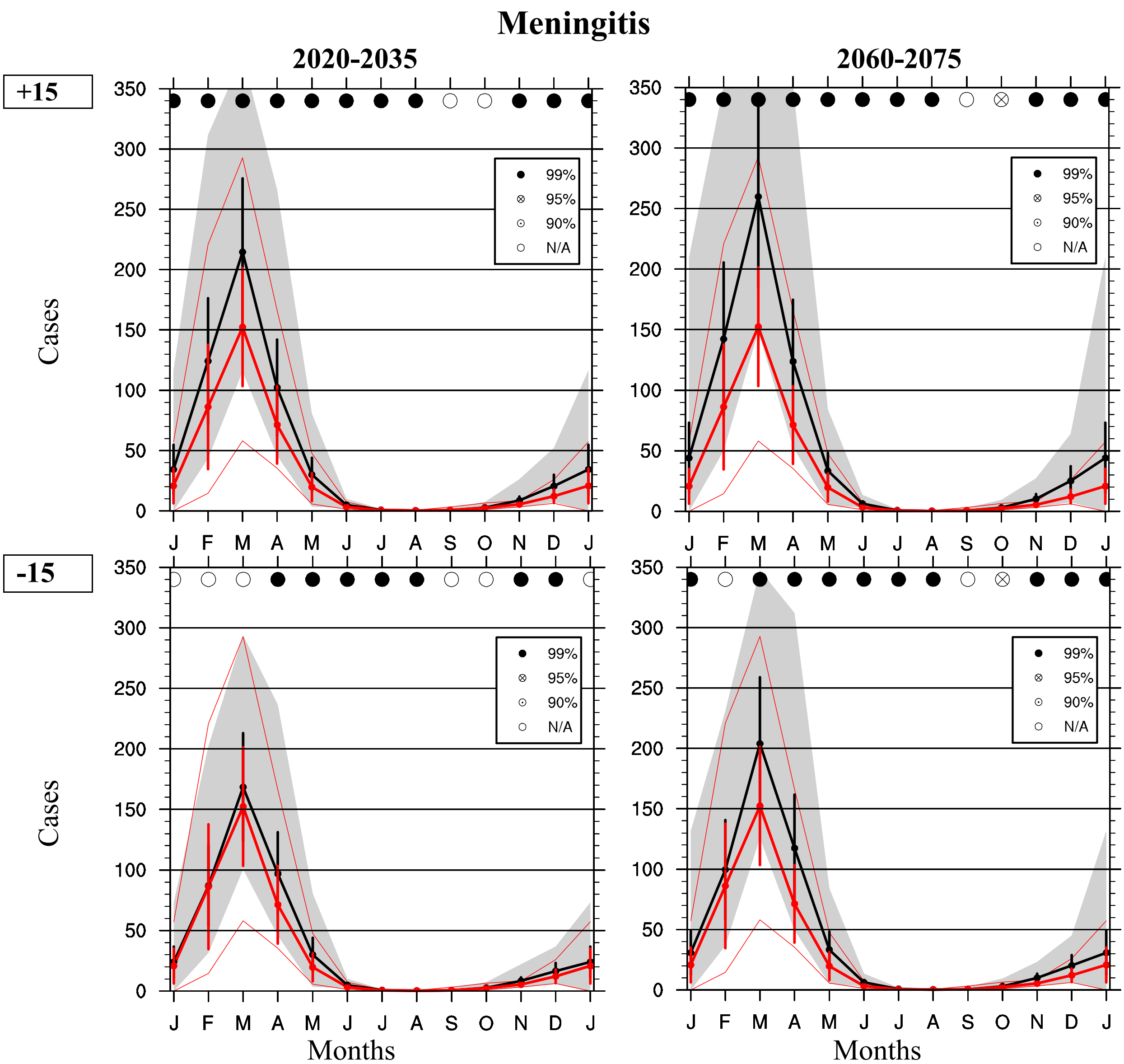

Figure 8.4: Similar to the middle panels of Figure 8.3 for the RCP6.0 projections of meningitis cases, but with the number of dusty days increased (top) and decreased (bottom) by 15%.

8.3.3 Cholera projections

Result from cholera projections indicate statistically significant increases in cases during most months (approximately April through September), most especially in the far future, for RCPs 6.0 and 8.5 (Figure 8.5). Changes are largest and have the strongest statistical significance ($p<0.05$) towards the end of the dry season and the beginning of the rainy season, with increases over the present day case rate (25 cases per 100,000 of population in the month of June) to rates ranging from 27 to 29 and 30 to 35 in the near (2020-2025) and far future (2060-2075) respectively, depending on the RCP. The months with the largest increases coincide with the months (May and June) in which maximum temperature increases are also large. Cases only showed potential increases in the wettest months of July and August in the far future projections for RCPs 6.5 (8.3 and 7.9%) and 8.0 (17 and 21%) respectively. This finding corroborate that of a related study of diarrheal diseases in Botswana by Alexander et al. (2013) where diarrheal disease incidences was suggested to increase with hot conditions and decline likely in the wet season. There is little difference among projected cholera case rates among the three scenarios for 2020-2035, for example in May and June increases ranges from 13-16% and 10- 16% respectively, but larger differences among the scenarios occur for 2060-2075 after the RCP emissions scenarios diverge (Moss et al., 2010), with May increases of about 20%, 27%, and 40% for RCP 2.6, 6.0, and 8.5 respectively.

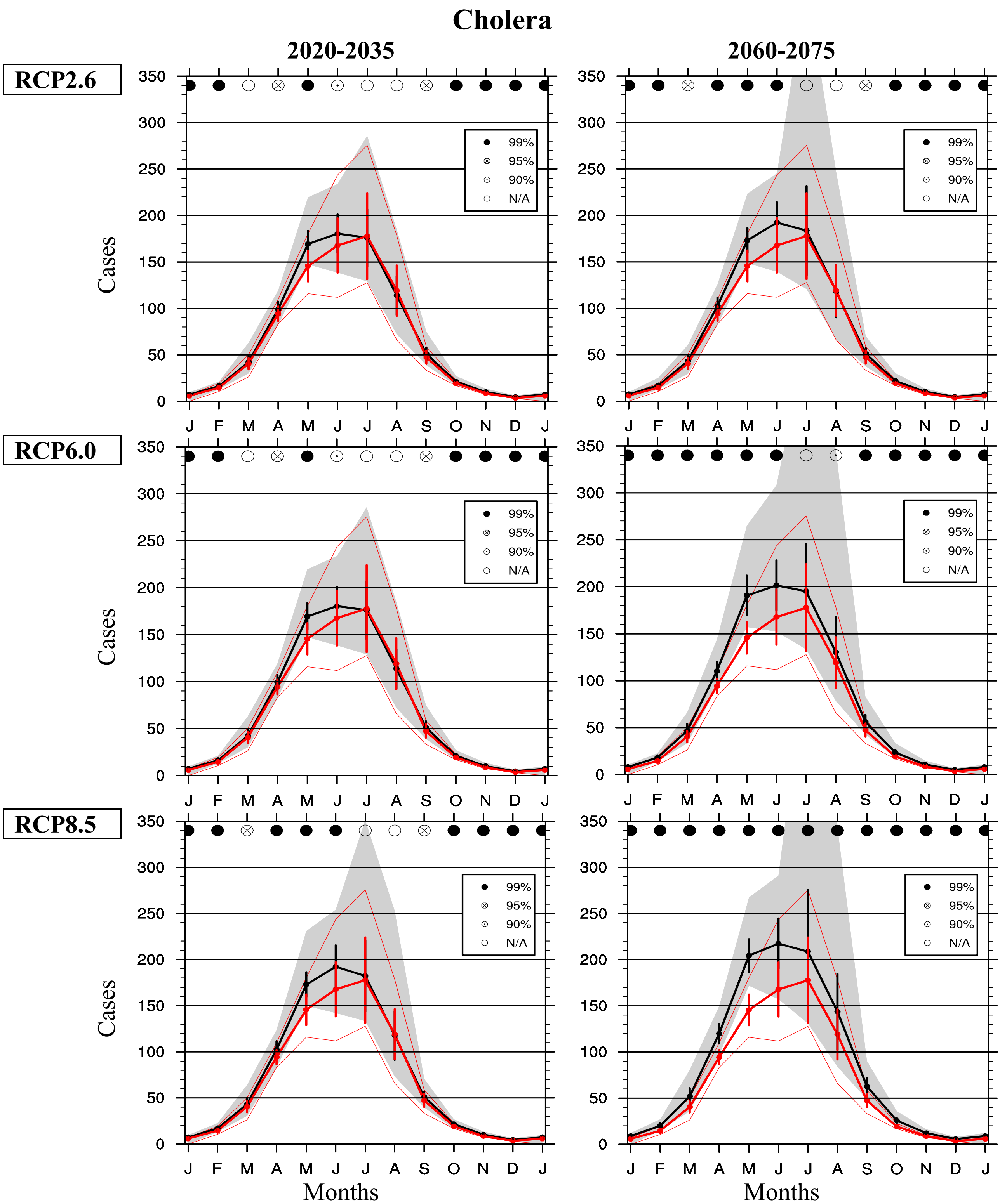

Figure 8.5: The annual cycle of present-day (1990-2005) cholera cases compared with projections for the ensemble of thirteen downscaled AOGCM in 2020-2035 (left) and 2060-2075 (right) for the three different future scenarios: RCP2.6 (top), RCP6.0 (middle), and RCP8.5 (bottom). The red and black lines are as described in Figure 8.1.

8.4 Discussion

There is increasing need to assess the potential impact of climate change on infectious diseases, especially in vulnerable regions that are projected to be disproportionately affected. Even though many promising developments may reduce the future risk for infectious diseases transmission despite enhanced risk due to climate change, there may also be increased challenges for preventing and controlling disease outbreaks (Ebi et al., 2013). Meningitis and cholera are diseases that remain a health burden in the region under investigation, and their sensitivity to climate is raising concern about their future dynamics. In this study the potential impact of future climate change on the risk of both diseases were assessed by forcing validated empirical models of meningitis and cholera developed specifically for the region. In order to assess uncertainties in the projections, multi model ensemble from thirteen monthly AOGCMs simulations from CMIP5 were used (e.g., Giorgi, 2005).

The results indicate statistically significant increases in meningitis and cholera cases in the future, across all time periods, and RCPs used in the projections. Results suggest that both diseases' cases in northwest Nigeria may increase in the future, primarily as a result of warmer temperatures. During the peak of meningitis season cases could potentially increase due to climate change by 26-30% for 2020-2035, and by 35-83% for 2060-2075. While in the case of cholera cases might increase by 13-16% for 2020-2035, and by 20-40% for 2060-2075 during the beginning of the rainy season (month of May). Surprisingly, in the nearest future, cholera cases have not shown a potential increases in the wettest months, this finding corroborate that of Alexander et al. (2013) in Botswana. However, in the far future, cases have shown potential increases in the wettest months of July and August for RCPs 6.0 and 8.5 by about 8(9)% and 18(21)% respectively. Although increases are less if compared with those in the hot months of May and June.

Given that projected climate changes in northwest Nigeria are similar for other regions of the Sahel (Chou et al., 2013), as are the climate-driven dynamics of meningitis and cholera transmission (e.g., Alexander et al., 2013; Dukic et al., 2012), these results may be broadly applicable throughout Sahelian Africa. It is noteworthy that the WAM which brings about precipitation in the Sahel is not well simulated in climate models (Bock et al., 2011; Marsham et al., 2013); however the AOGCMs have vigorously improved if compared with the previous GCMs; they now include the representation of the ocean, atmospheric chemistry, vegetation, carbon cycle, land surface, aerosols, and sea ice at a finer spatial resolution (McMichael et al., 2006). This reduces uncertainties that may affect the results of this study.

However, it should be noted that the potential future risk of these diseases is not only depending on climatic factors, but rather upon population vulnerability, vaccination and other social and health risk factors that were already associated with the diseases. With regards to this, the results presented here are not projection of the reality in the future, but rather they demonstrate trajectories of possible changes in the risk of these diseases primarily due to climate if current prevention and treatment strategies, land use patterns, and lifestyles remain similar in the future. This is because with planning and development of mitigation and adaptation capacity, increases in these diseases incidences associated to climate change might be largely prevented. Clearly, some or all of these factors will change, and therefore these results may encourage governments and public health workers to enhance efforts to control meningitis and cholera incidence, for example, by intensifying the administration and evaluation of the current conjugate vaccine that protects against serogroup A, and to focus on less common serogroups that could potentially cause epidemics in the case of meningitis, and improvement in the quality of life, sanitation, vaccination, drinking water, education and health care delivery in the case of cholera.

Without an insight of what is likely to happen in the future, it's difficult to develop assumption about future adaptation to changes in the risk of these diseases associated to climate change (Martens et al., 1999). For this reason, public health workers and decision makers in national and regional governments needs to be furnished with information regarding the potential risk on these diseases attributed to climate change, and possibly how these risks could be avoided

8.5 Conclusion

Projecting the potential impact of climate change on meteorologically-sensitive infectious diseases is essential, especially for regions such as northwest Nigeria, where the projected climate change impacts, and infectious disease risk, are both large. Findings from this study showed a significant potential future increases in meningitis and cholera cases, primarily due to warming climate. Results indicates that changes are largest and most statistically significant during the hottest months for meningitis and (March and April) and also during hot months of May and June (beginning of rain season) in the case of cholera. Significant changes in the onset and cessation of meningitis are projected in the 2060-2075 results, suggesting the disease season may lengthen. Cholera cases were projected to be less or equal in the wettest month for nearest future, and less increases in the far future for RCPs 6.0 and 8.5. The study only provides estimation based on the future modelled climate simulation, which may not be exactly reflecting reality. In that case, the estimation was done assuming all other non-climatic factors that may affect the future dynamics of these diseases remains constant.

Finally, changes in climate extremes may have more adverse impact on the dynamics of these diseases than that of the mean climate (which was investigated here). For example, increase in the intensity and occurrences of heat events may increase the risk of transmission and contraction of both diseases. Likewise, occurrence of extreme rainfall may increase the risk of flooding which in turn might facilitate the risk of cholera. As such in pertinent to further investigate the potential future impact of these events, this will help to further identify the climatic effects that otherwise may be obscured by the mean values.

The chapter addresses the fifth objective of this thesis by applying developed and validated empirical statistical models specifically design for climate change studies in previous chapters to assess the potential impact of future climate change on meningitis and cholera incidence in northwest Nigeria. Ensemble of statistically downscaled variables from AOGCM projections that participated in the CMIP5 were used as explanatory variables.

Chapter Nine:
Synthesis and Further Research

Chapter Nine

Synthesis and Further Research

9.1 Introduction

The general methodology applied for this study was discussed in the introductory chapter and illustrated in figure 1.4. This concluding chapter will outline how this research contributed to the research gaps identified in chapter two and point out the new contribution to existing knowledge. The chapter will also summarise some of the key findings and discussions of this research. Limitations and recommendations for areas that require further research will be outlined. Also, the potential application of this research will be highlighted.

9.2 General summary

The motivation for this study came from the IPCC AR4, which clearly highlighted the gap in information regarding climate and diseases relationships from developing countries. The report also emphasises the need to carryout assessment studies on the potential future impact of climate change on diseases. The current study has successfully filled this gap in information from one on these countries in Africa – Nigeria. This was achieved by statistically modelling the relationship between the selected diseases and climate, while taking into account the additional effects of other non-climatic factors. Developed models were then applied to assess the potential risk of these diseases in the near and far future. Prior to the modelling and projections, spatial and time characteristics of both the meteorological and diseases conditions of the targeted region were investigated.

Research gaps identified and addressed

The literature review (chapter two) addresses the first objective of this thesis and has provided a substantial and systematic review, by bringing existing information together with regard to the relationship between climate and infectious diseases. The review has demonstrated the multidisciplinary nature of this study by reviewing literature from different disciplines, such as meteorology, epidemiology, statistics, and medical and social sciences. The review has also identified a number of gaps, some of which were addressed in this study. The major gaps identified and addressed are:

a. There is little research on the relationships between climate and infectious diseases in developing countries, especially in Africa, and none from the most populous country on the continent – Nigeria. Apart from Greenwood in 1984 who briefly reported on meningitis, this study is the first of its kind that provided information on the relationship between climate and infectious diseases. The study also provides a background for the possibility of predicting the selected diseases based on climate information with a lead of one month.
b. The study adopted a systematic approach by reducing the level of uncertainties in both climate-disease models development and projection studies (as highlighted in section 2.9 of the literature review). The uncertainties were reduced by: (a) using longer and more reliable disease time series that were directly collected from the archive of the selected hospitals in the region that fulfilled a set of criteria; (b) evaluating disease data using data from different sources; (c) accounting for the additional effects of other non-climatic factors in the models, though not directly in the GAMs; (d) validating and evaluating developed models using independent disease time series that were not included in models fitting; (e) adopting a multi-model approach to disease projection

by using the ensemble of thirteen simulations from the most recent and improved AOGCMs that participated in the CMIP5 project; and (f) statistically downscaling the simulations to the selected cities using two different approaches.

c. Very few studies of climate-disease relationships considered socioeconomic factors. In this study, socioeconomic factors were considered in two ways: by collectively accounting for the unobserved seasonally-varying climatic and non-climatic risk factors via functions such as ***s(t)*** in the GAMs, and in the MLR models, socioeconomic factors were directly included.

d. Projecting the potential impact of climate change on infectious diseases is essential, especially for regions where the projected climate change impacts, and infectious disease risk, are both large. This study is the first to assess the potential impact of climate change on meningitis and cholera using the most state-of-the-art AOGCM simulations from the CMIP5 project.

The candidate diseases

Meningitis and cholera are the two infectious diseases identified for the purpose of this research. The choice of these diseases is based on their associated burden; sensitivity to climate; and the availability of good quality, long time records. Both diseases have a historical record of high morbidity and mortality in northwest Nigeria, based on statistics available on the WHO archives. The diseases are also among the most important infectious diseases classified using the global burden of DALYs (WHO, 2011c), and are also reported to be sensitive to climate (WHO, 2005a).

The targeted region and cities

Northwest Nigeria was chosen as the target for this research because of its vulnerability to climate change due to its physical and socioeconomic characteristics, such as widespread poverty, desertification, ecological disruption, high population growth rate and extreme meteorological events. In particular, the region suffers from several critical issues of human and infrastructural development that require urgent attention. The selection of cities was based on hospitals meeting the following criteria: (a) proximity to meteorological stations with long-term measurement records; (b) similar climatic patterns; and (c) consistently reported records of infectious disease cases. In Nigeria, the FMoH classifies four categories of hospital based on ownership status: federal, state and local public hospitals, and private hospitals. Personal communication with FMoH staff prior to the data collection indicated that the state-owned hospitals best suited the above criteria because most of the infectious disease cases are treated at these hospitals.

Spatiotemporal characteristics of meteorological conditions and selected diseases in the targeted region

Chapters four and five provided information on the spatial and time characteristics of meteorological and disease conditions in the region under investigation. The results that were significant (in statistical terms) indicated that temperature trends in the region and West Africa have been on the increase since the 1990s. All computed temperature indices for the northwest region reflected global trends, indicating increases in warming and heat events at statistically significant levels ($p<0.05$). Rainfall indices also showed positive trends in the regional time series, and in all stations except Kaduna. Chapter five identified the hotspots of meningitis and cholera in Nigeria, and revealed the important role of social risk factors as regards these infectious diseases. Geographical location, poverty, overcrowding and literacy status all appear to be important social factors in determining the incidence of these diseases in Nigeria.

Model development and validation

The development and validation of empirical statistical models of the relationships between climate and the targeted diseases in northwest Nigeria is one of the most important aspects of this thesis. This objective was achieved in chapter six and seven. In summary, suites of regional models were developed, which are capable of: (a) explaining the influences of climatic conditions on the interannual variability of meningitis and cholera, taking into consideration the additional effect of other non-climatic factors; (b) predicting diseases with a one month time lead; and (c) estimating the future impact of climate change on the diseases. The models were designed specifically for climate change studies, and were used to assess climate change's potential future impact on diseases in the region.

Population offset term was not accounted for in this study, for the main reason that diseases cases were obtained from individual hospitals. While there will obviously be some fluctuation in the population within a hospital's "catchment" area, there is also an upper bound on the number of patients, because new hospitals/treatment facilities are eventually built to accommodate population growth. Therefore, it is very difficult to accurately calculate the "population-at-risk" for cases from a specific hospital because the overall population served by the facility, let alone its growth, are difficult to calculate. Therefore population served by the hospitals was assumed to remain approximately constant over time. However population offset term could be accounted for temporal increase by model modification (e.g. Lindsay, 2002). This could be achieved by estimating the population increase using a linear extrapolation of a census data.

Model validation is very important in climate-disease studies; this is because validation will establish their robustness and the confidence in applying them for either climate change studies or operational use. In this study, all models were validated using established validation techniques, and using independent data that were not included in model fitting. The models' development and validation was peer reviewed and published for meningitis (Abdussalam et al., 2014a). Therefore these models are deemed robust and reliable enough to be applied to climate change studies (Abdussalam et al., 2014b) and for predicting diseases with a lead of one month in northwest Nigeria.

Results from these chapters indicate the role of specific meteorological conditions in explaining and predicting monthly meningitis and cholera variability in northwest Nigeria. They also emphasize the importance of additional risk factors that are not well understood but which may be linked to societal and behavioural practices. Higher temperatures, dust concentration, and low humidity are identified as the most important variables in explaining and predicting meningitis. In the case of cholera, the study has provided exploratory information on the influences of meteorological and socioeconomic explanatory variables on cholera's interannual variability in Nigeria. Results from both modelling approaches highlighted the importance of both meteorological and socioeconomic variables in explaining and predicting the disease in Nigeria. It has been shown that increases in temperature, rainfall, poverty, and population density may increase both cholera cases and deaths, while improvement of drinking water and adult literacy might reduce the risk of contracting the disease.

Projecting the impact of climate change

Chapter eight addresses the fifth objective of this thesis by applying the validated empirical statistical models, specifically designed for climate change studies, to assess the potential impact of future climate change on meningitis and cholera incidence in northwest Nigeria. An ensemble of statistically downscaled variables from the AOGCM climate simulation that participated in the CMIP5 was used as explanatory variables. Findings from this study showed significant potential future increases in both meningitis and cholera cases, primarily due to increasing temperature in the future. A sensitivity test for dust concentration reveals that increase or decrease in this variable might have an impact on meningitis in the future. Results indicate that changes are largest and most statistically significant during the hottest months for meningitis (March and April), and during the hot months of May and June (beginning of rain season) in the case of cholera.

9.3 General discussion

The high variability of the West African climate and its direct and indirect impact on population, such as drought, floods and epidemic of diseases has motivated projects like AMMA in order to understand the interaction between epidemics of diseases and variability of climate on different time scales in the region. WAM variability is important in determining the length of dry season which in turns is correlated with the incidence of diseases such as meningitis. For example, several studies have established significant correlation of meningitis incidence with hot, dusty, and windy weather north of the ITD. As meningitis and cholera are known to decrease and increase with the onset of the monsoon respectively, from a seasonal perspective, the variability of meteorological conditions should relate to the variability of incidence in specific regions such as northwest Nigeria.

Investigating the spatial distribution of the selected diseases in Nigeria reveals higher incidence of meningitis and cholera in the northern region. This may have been influenced by both meteorological and socioeconomic conditions. Firstly, meningitis incidence has been well documented to be influenced by hot, dry, and dusty weather conditions which the northern region has favoured very well. Hypothetically, these might be the reasons why fewer cases are reported towards the coastal regions where humidity is always high round the year. However, during the last decade, significant changes in the epidemiology of meningitis have been observed; cases of meningitis are now experienced in the southern part of the country than ever. The occurrence of meningitis in this part of the country might not be unconnected with the southward annual temporary relocation of people from the northern region of the country, or possibly due to the "Saheliazation" as observed recently in Ivory Coast. Also, anecdotal evidence has shown that Harmattan do not usually propagate to the coast, however, recently people residing in this region of the country have been experiencing the encroachment of the dry and dusty wind. In the case of cholera, the reason for the clustering of the disease in the northern region is shown to be related to socioeconomic status of northern states. Another reason could be seen in the vicinity of Lake Chad basin which some of the northern states are neighbouring; the risk of cholera from this basin has been reported to be connected to contamination from the lake, either from the water environment itself or from food contamination.

Statistical models reveal that the most important climatic variables for explaining and predicting meningitis are the monthly means of daily maximum temperature, relative humidity and dustiness with 1-month lag. This result confirmed what has been established in previous studies as discussed in the literature review chapter. Although there is no general agreed-upon physical explanation for the role of meteorological conditions in the incidence of meningitis, results from this study support the hypothesis that hot, dry, dusty conditions may facilitate both the transmission and the development of invasive meningitis in northwest Nigeria. For example, these conditions might be playing important role during the "cold dry" months, aiding in initiating the meningitis season by causing microtrauma to the nasal mucosa. This damage may make it possible for the bacteria to penetrate the nasopharyngeal membrane and subsequently enter the blood stream causing invasive disease. This may explain why reported meningitis cases are highest during the "hot dry" period (February - May) that follows the "cold dry" period.

All models from cholera analysis pointed out to the importance of both meteorological and socioeconomic variables in explaining the disease dynamics. This result also is consistent with what previous studies have found in different part of the globe. The combine roles of these variables could explain the transmission and contraction of the disease in Nigeria. For example, during the peak of the dry and hot season in the northern part of the country, people tend to use drinking and cooking water from sources with higher risk of contamination due to scarcity; this includes stagnant waters and wells with lower depths. Another risk factor that might facilitate cholera outbreak during rainy season is the poor drainage system which is a peculiar characteristic of major cities in Nigeria, after heavy rainfall houses are usually flooded in some cases sub-merged with dirty water from open gutters. Population living in urban and peri-urban slums are more at risk and vulnerable of contracting the disease, because these areas are mostly densely populated by low income earners and basic infrastructures are not readily available, which results in many people defecating in the open. After a heavy downpour, surface outwash, collapsed sewages, and open drainage may lead to contamination of sources of drinking water like wells and rivers. Since cholera can spread via contaminated food and water, transmission of the disease will be made easy and rapid.

Until recently the only strategy for controlling meningitis in Nigeria has been through reactive mass vaccination campaigns after crossing a certain case threshold. While a new vaccine has recently been introduced that is effective and inexpensive enough to be used more broadly and proactively, it is only effective against the strain of bacteria that causes the most common kind of bacterial meningitis (serogroup A). As a result, there will likely be continued epidemics caused by other serogroups as has been recently observed in some countries. In the case of cholera, despite the availability of effective vaccines as recommended by WHO, anecdotal information reveals that this controlling measure has not been in use.

The sensitivity of these infectious diseases to climate is raising concern about their future dynamics; as such there is the need for assessing their potential future risk. Projection results from this study indicate statistically significant increases in meningitis and cholera cases in the future, across all time periods, and RCPs used. Diseases' cases in northwest Nigeria may increase in the future, primarily as a result of warmer temperatures. During the peak of meningitis season cases could potentially increase by 26-30% for 2020-2035, and by 35-83% for 2060-2075. While in the case of cholera cases might increase by 13-16% for 2020-2035, and by 20-40% for 2060-2075 during the beginning of the rainy season (month of May). Given that projected climate changes in northwest Nigeria are similar for other regions of the Sahel (Chou et al., 2013), as are the climate-driven dynamics of meningitis and cholera transmission (e.g., Alexander et al., 2013; Dukic et al., 2012), these results may be broadly applicable throughout Sahelian Africa.

Within the climate range that influence the transmission rate and geographic bounds of infectious disease, many other social, economic, behavioural, and environmental factors also affect disease occurrence. Transmission of infectious diseases is much affected by socioeconomic conditions and by the robustness of public health defence. For example, case surveillance and treatment in fringe areas, management of deforestation and surface water, provision of safe drinking water, accessibility to health care facilities and services, and effective diseases control programmes would tend to offset the increased risk of some infectious diseases due to climate change, such as malaria, cholera and meningitis. For example, cholera could be totally eradicated in developing nation (as achieved in developed ones) if the socioeconomic status of vulnerable and epidemic prone population will be improved. Vaccination is one of the key controlling social factors and could be used to control, or prevent epidemics in the future even if the climate condition is suitable for disease transmission. Future modelling should incorporate these non climate contextual changes that are reasonably foreseeable.

Despite the effort of this study in reducing uncertainties in both statistical model development and projection, yet, a number of limitations still exist. For example, socioeconomic effects could only be directly included in the MLR models for cholera, while in the case of the GAMs these factors are currently limited to only collectively accounted via function such as ***s(t)***. This is because socioeconomic data for the region is not available at the same spatial and temporal resolution with that of disease. As reported in chapter six, the Nigerian authorities have administered four vaccination campaigns for meningitis disease within the study period; however, due to the non-availability of detailed data of these campaigns, this study could not account for this important factor, but rather estimate the potential cases that might have occurred if vaccination had not been administered. Another limitation of this study is that a population offset term was not included; this is because estimating the changes to the population served by a single hospital, the source of disease records, is extremely difficult. For example, as population grows, new hospitals and other treatment facilities are built to accommodate more patients, so the population served by a given hospital does not track regional population growth in a linear fashion.

It should also be noted that the potential future risk of these diseases is not only depending on climatic factors, but rather upon population vulnerability, vaccination and other social and health risk factors that were already associated with the diseases. With regards to this, the results presented in this study are not projection of the reality in the future, but rather they demonstrate trajectories of possible changes in the risk of these diseases primarily due to climate if current prevention and treatment strategies, land use patterns, and lifestyles remain similar in the future. This is because with planning and development of mitigation and adaptation capacity, increases in these diseases incidences associated to climate change might be largely prevented. Clearly, some or all of these factors will change, and therefore these results may encourage governments and public health workers to enhance efforts to control meningitis and cholera incidence, for example, by intensifying the administration and evaluation of the current conjugate vaccine that protects against serogroup A, and to focus on less common serogroups that could potentially cause epidemics in the case of meningitis, and improvement in the quality of life, sanitation, vaccination, drinking water, education and health care delivery in the case of cholera.

9.4 Recommendations for further research

The following recommendations are made for further research:

a. In the current study, only monthly epidemiological data are used in model calibrations. It is recommended that future studies should use a higher temporal resolution data (daily or weekly) if available. This will certainly increase the model's robustness and help to increase understanding based on present day knowledge. Recently, the

Nigerian authorities are keeping good records of epidemiological data on a weekly basis at the district level.

b. Changes in climate extremes may have a more adverse impact on the dynamics of infectious diseases than those of the mean and variability of climate (which was investigated here). This may have more implications for estimating the future impact of climate on diseases. As such, it is highly recommended that future assessment should consider extreme events; because this will help to further identify the climatic effects that otherwise may be obscured by the mean values.

c. In this study, only the potential impact of anthropogenic climate change was taken into account. It is recommended that further studies should consider accounting for possible future changes in other non-climatic factors that may influence these diseases. This is because planning and development of mitigation and adaptation capacity could largely prevent increases in these diseases' incidence associated with climate change. For example, the recently introduced conjugate vaccine for meningitis may reduced the risk of the disease in the future because of its preventative capacity, on the other hand, improved quality of life such as sanitation, education, and poverty eradication may also reduce or help in eradicating the transmission of cholera in the future.

d. This study uses the most recent and improved AOGCMs simulations from CMIP5 project. However, it is recommended that future studies should consider the use of high resolution Regional Climate Models (RCM) data. This may help in reducing uncertainties that might be inherited from climate models, because this model has the advantage of having high resolution outputs, and it also allows for the representation of small scale processes such as soil characteristics and coastal sizes etc.

e. In this study, it has been hypothesised that Lake Chad might be the source of cholera in northwest Nigeria. As such, further study is required in all the Lake’s neighbouring countries to investigate this hypothesis.
f. Monitoring and evaluating the efficacy of the recently introduced conjugate vaccines for meningitis, and the changing epidemiology of the disease, is strongly recommended.

9.5 Research application

The outcomes from this research are not intended only for academic purposes, but rather to form a background for disease forecasting services using climate and socioeconomic information in Nigeria. The developed and validated models, which are peer reviewed and published (Abdussalam et al., 2014a), have the capacity and robustness to predict the selected diseases with a one month lead time.

The author of this thesis plans to communicate the results from the research to the relevant authorities in Nigeria, in order to see the possibility of bringing it into operational use. This will be achieved by improving the existing developed models, provision of forecasts on different time scales, and also by analysing suitable ways of using the forecast product. The forecasts are intended to be on different time scales ranging from inter-seasonal, via interannual to sub-decadal and for the medium (2030) and long term future (end of the century), using seasonal to decadal climate simulations from the most-up-to-date climate models. This will also involve analysing and developing suitable structures that will support best practice in handling this information locally, and coordinate relevant institutions and agencies in the country.

Contact has already been established with a large network of institutions that are interested in disease forecasting, such as the World Health Organisation (WHO), Meningitis Environmental Risk Technologies (MERIT) and the National Centre for Atmospheric Research (NCAR). Contact has also been made with relevant institutions in the country, including the Nigerian Centre for Disease Control (NCDC) of the Federal Ministry of Health (FMoH) and the National Primary Health Development Agency (NPHDA).

References

References

Abdussalam, A. F., Monaghan, A. J., Dukić, V. M., Hayden, M. H., Hopson, T. M., Leckebusch, G. C., & Thornes, J. E. (2014). Climate Influences on Meningitis Incidence in Northwest Nigeria. *Weather, Climate, and Society, 6*(1), 62-76. doi: 10.1175/wcas-d-13-00004.1

Abdussalam, A. F., Monaghan, A. J., Steinhoff, D. F., Dukic, V. M., Hayden, M. H., Hopson, T. M., Leckebusch, G. C. (2014). The impact of climate change on meningitis in northwest Nigeria: an assessment using CMIP5 climate model simulations. *Weather, Climate, and Society*, 6(3), 371-379. doi: 10.1175/wcas-d-13-00068.1

Abeku, T. A., Hay, S. I., Ochola, S., Langi, P., Beard, B., de Vlas, S. J., & Cox, J. (2004). Malaria epidemic early warning and detection in African highlands. *Trends in Parasitology, 20*(9), 400-405. doi: 10.1016/j.pt.2004.07.005

Ackers, M. L., Quick, R. E., Drasbek, C. J., Hutwagner, L., & Tauxe, R. V. (1998). Are there national risk factors for epidemic cholera? The correlation between socioeconomic and demographic indices and cholera incidence in Latin America. *International Journal of Epidemiology, 27*(2), 330-334. doi: 10.1093/ije/27.2.330.

Adedokun, J., Emofurieta, W., & Adedeji, O. (1989). Physical, mineralogical and chemical properties of Harmattan dust at Ile-Ife, Nigeria. *Theoretical and Applied Climatology, 40*(3), 161-169.

Agier, L., Deroubaix, A., Martiny, N., Yaka, P., Djibo, A., & Broutin, H. (2013). Seasonality of meningitis in Africa and climate forcing: aerosols stand out. *Journal of the Royal Society Interface, 10*(79). doi: 10.1098/rsif.2012.0814

Akanda, A. S., Jutla, A. S., & Islam, S. (2009). Dual peak cholera transmission in Bengal Delta: A hydroclimatological explanation. *Geophysical Research Letters, 36*. doi: 10.1029/2009gl039312.

Alexander, K. A., Carzolio, M., Goodin, D., & Vance, E. (2013). Climate Change is Likely to Worsen the Public Health Threat of Diarrheal Disease in Botswana. *International Journal of Environmental Research and Public Health, 10*(4), 1202-1230. doi: 10.3390/ijerph10041202.

Alexander, L. V., Zhang, X., Peterson, T. C., Caesar, J., Gleason, B., Tank, A., . . . Vazquez-Aguirre, J. L. (2006). Global observed changes in daily climate extremes of temperature and precipitation. *Journal of Geophysical Research-Atmospheres, 111*(D5). doi: 10.1029/2005jd006290

Ali, M., Emch, M., Donnay, J. P., Yunus, M., & Sack, R. B. (2002a). Identifying environmental risk factors for endemic cholera: a raster GIS approach. *Health & Place, 8*(3), 201-210.

Ali, M., Emch, M., Donnay, J. P., Yunus, M., & Sack, R. B. (2002b). The spatial epidemiology of cholera in an endemic area of Bangladesh. *Social Science & Medicine, 55*(6), 1015-1024.

Andrews, D. F. (1974). A robust method for multiple linear regression. *Technometrics, 16*(4), 523-531.

Astrom, C., Rocklov, J., Hales, S., Beguin, A., Louis, V., & Sauerborn, R. (2012). Potential Distribution of Dengue Fever Under Scenarios of Climate Change and Economic Development. *Ecohealth, 9*(4), 448-454. doi: 10.1007/s10393-012-0808-0.

Ayuba, H. K., U.M. Maryah., D.M. Gwary. (2007). Climate change impact on plant species composition in sixsemi-arid rangelands of Northern Nigeria. *Nigerian Geographical Journal 5*(1), 35-42.

Bagdonavicius, V., Kruopis, J., Nikulin, M.S. (2011). "Non-parametric tests for complete data", ISTE&WILEY: London & Hoboken ISBN 978-1-84821-269-5

Barua, D., & Cvjetanovic, B. (1970). Cholera during the period 1961-1970. *WHO Public Health Papers, 40*, 15-21.

Basu, R., and J.M. Samet. (2002). Relationship between elevated ambient temperature and Mortality: A review of the epidemiologic evidence. *Epidemiol. Rev, 24*, 190 – 202.

Bengtsson, L., Hodges, K. I., & Hagemann, S. (2004). Sensitivity of the ERA40 reanalysis to the observing system: determination of the global atmospheric circulation from reduced observations. *Tellus Series a-Dynamic Meteorology and Oceanography, 56*(5), 456-471. doi: 10.1111/j.1600-0870.2004.00079.x.

Bertuzzo, E., Mari, L., Righetto, L., Gatto, M., Casagrandi, R., Blokesch, M., Rinaldo, A. (2011). Prediction of the spatial evolution and effects of control measures for the unfolding Haiti cholera outbreak. *Geophysical Research Letters, 38*. doi: 10.1029/2011gl046823.

Besancenot, J. P., Boko, M., & Oke, P. C. (1997). Weather conditions and cerebrospinal meningitis in Benin (Gulf of Guinea, West Africa). *European Journal of Epidemiology, 13*(7), 807-815.

Biasutti, M., & Giannini, A. (2006). Robust Sahel drying in response to late 20th century forcings. *Geophysical Research Letters, 33*(11). doi: 10.1029/2006gl026067.

Biasutti, M., Sobel, A. H., & Camargo, S. J. (2009). The Role of the Sahara Low in Summertime Sahel Rainfall Variability and Change in the CMIP3 Models. *Journal of Climate, 22*(21), 5755-5771. doi: 10.1175/2009jcli2969.1

BNRCC. (2012, April 15). *A report on vulnerability, impacts, and adaptation to climate change in Nigeria*. Retrieved from www.nigeriaclimatechange.org.

Bock, O., Guichard, F., Meynadier, R., Gervois, S., Agusti-Panareda, A., Beljaars, A., Roucou, P. (2011). The large-scale water cycle of the West African monsoon. *Atmospheric Science Letters, 12*(1), 51-57. doi: 10.1002/asl.288.

Borroto, R. J., & Martinez-Piedra, R. (2000). Geographical patterns of cholera in Mexico, 1991-1996. *International Journal of Epidemiology, 29*(4), 764-772. doi: 10.1093/ije/29.4.764.

Bouma, M. J., & Pascual, M. (2001). Seasonal and interannual cycles of endemic cholera in Bengal 1891-1940 in relation to climate and geography. *Hydrobiologia, 460*, 147-156. doi: 10.1023/a:1013165215074.

Bridgman, S. A., Robertson, R. M. P., Syed, Q., Speed, N., Andrews, N., & Hunter, P. R. (1995). Outbreak of cryptosporidiosis associated with a disinfected groundwater supply. *Epidemiology and Infection, 115*(3), 555-566.

Broome, C. V., Rugh, M. A., Yada, A. A., Giat, L. V., Giat, H., Zeltner, J. M., Fraser, D. W. (1983). Epidemic group-C meningococcal meningitis in upper VOLTA, 1979. *Bulletin of the World Health Organization, 61*(2), 325-330.

Brundage, J., & Zollinger, W. (1987). Evolution of meningococcal disease epidemiology in the US Army. *Evolution of meningococcal disease, 1*, 5-25.

Buda, A. & A. Jarynowski. (2010). *Life-time of correlations and its applications vol.1*, Wydawnictwo Niezalezne: 5–21, December 2010 ISBN 978-83-915272-9-0

Burgess, K. R., & Whitelaw, W. A. (1988). EFFECTS of nasal cold receptors on pattern of breathing. *Journal of Applied Physiology, 64*(1), 371-376.

Calvin, K., Edmonds, J., Bond-Lamberty, B., Clarke, L., Kim, S. H., Kyle, P., Wise, M. (2009). 2.6: Limiting, climate change to 450 ppm CO2 equivalent in the 21st century. *Energy Economics, 31*, S107-S120. doi: 10.1016/j.eneco.2009.06.006.

Cameron, A. C., & Trivedi, P. K. (1998). *Regression analysis of count data*: Cambridge University Press.

Campbell-Lendrum, D., Woodruff, R., Prüss-Üstün, A., & Corvalán, C. (2007). Quantifying the health impact at national and local levels.

Carrel, M., Voss, P., Streatfield, P. K., Yunus, M., & Emch, M. (2010). Protection from annual flooding is correlated with increased cholera prevalence in Bangladesh: a zero-inflated regression analysis. *Environmental Health, 9*. doi: 10.1186/1476-069x-9-13.

Cash, B. A., Rodo, X., & Kinter, J. L., III. (2009). Links between Tropical Pacific SST and Cholera Incidence in Bangladesh: Role of the Western Tropical and Central Extratropical Pacific. *Journal of Climate, 22*(7), 1641-1660. doi: 10.1175/2008jcli2177.1.

Ceccato, P., Ghebremeskel, T., Jaiteh, M., Graves, P. M., Levy, M., Ghebreselassie, S., Thomson, M. C. (2007). Malaria stratification, climate, and epidemic early warning in Eritrea. *American Journal of Tropical Medicine and Hygiene, 77*(6), 61-68.

Charles, R. C., & Ryan, E. T. (2011). Cholera in the 21st century. *Current Opinion in Infectious Diseases, 24*(5), 472-477. doi: 10.1097/QCO.0b013e32834a88af.

Chaves, L. F., & Pascual, M. (2007). Comparing Models for Early Warning Systems of Neglected Tropical Diseases. *Plos Neglected Tropical Diseases, 1*(1). doi: 10.1371/journal.pntd.0000033

Cheesbrough, J. S., Morse, A. P., & Green, S. D. R. (1995). Meningococcal meningitis and carriage in western zaire - a hypoendemic zone related to climate. *Epidemiology and Infection, 114*(1), 75-92.

Chevallier, E., Grand, A., & Azais, J. M. (2004). Spatial and temporal distribution of cholera in Ecuador between 1991 and 1996. *European Journal of Public Health, 14*(3), 274-279. doi: 10.1093/eurpub/14.3.274.

Chindo, A., and P.N. Nyelong. (2004). Lake Chad: From Megalake to Minilake. *Arid Wetland Bulletin, 6* 24 – 27.

Chou, C., Chiang, J. C. H., Lan, C.-W., Chung, C.-H., Liao, Y.-C., & Lee, C.-J. (2013). Increase in the range between wet and dry season precipitation. *Nature Geoscience, 6*(4), 263-267. doi: 10.1038/ngeo1744.

Chou, W.-C., Wu, J.-L., Wang, Y.-C., Huang, H., Sung, F.-C., & Chuang, C.-Y. (2010). Modeling the impact of climate variability on diarrhea-associated diseases in Taiwan (1996–2007). *Science of the Total Environment, 409*(1), 43-51. doi: 10.1016/j.scitotenv.2010.09.001.

Christensen, J. H., Carter, T. R., Rummukainen, M., & Amanatidis, G. (2007). Evaluating the performance and utility of regional climate models: the PRUDENCE project. *Climatic Change, 81*, 1-6. doi: 10.1007/s10584-006-9211-6.

Collier, P., Conway, G., & Venables, T. (2008). Climate change and africa. *Oxford Review of Economic Policy, 24*(2), 337-353. doi: 10.1093/oxrep/grn019.

Colwell, R. R. (1996). Global climate and infectious disease: The cholera paradigm. *Science, 274*(5295), 2025-2031. doi: 10.1126/science.274.5295.2025.

Colwell, R. R. (2002). A voyage of discovery: cholera, climate and complexity. *Environmental Microbiology, 4*(2), 67-69. doi: 10.1046/j.1462-2920.2002.00270.x.

Connor, S. J., Ceccato, P., Dinku, T., Omumbo, J., Grover-Kopec, E. K., & Thomson, M. C. (2006). Using climate information for improved health in Africa: relevance, constraints and opportunities. *Geospatial Health, 1*(1), 17-31.

Connor, S. J., & Mantilla, G. C. (2008). *Integration of seasonal forecasts into early warning systems for climate-sensitive diseases such as malaria and dengue* (Vol. 30).

Cook, K. H. (1999). Generation of the African Easterly Jet and Its Role in Determining West African Precipitation. *Journal of Climate, 12*(5), 1165-1184. doi: 10.1175/1520-0442(1999)012<1165:gotaej>2.0.co;2

Cook, R. D. (1977). Detection of influential observation in linear. *Technometrics, 19*(1).

Cookson, S. T., Corrales, J. L., Lotero, J. O., Regueira, M., Binsztein, N., Reeves, M. W., Jarvis, W. R. (1998). Disco fever: Epidemic meningococcal disease in northeastern Argentina associated with disco patronage. *Journal of Infectious Diseases, 178*(1), 266-269.

Cornforth, R. (2012). Overview of the West African Monsoon 2011. *Weather, 67*(3), 59-65. doi: 10.1002/wea.1896.

Costello, A., Abbas, M., Allen, A., Ball, S., Bell, S., Bellamy, R., . . . Patterson, C. (2009). Managing the health effects of climate change. *Lancet, 373*(9676), 1693-1733.

Couvreux, F., Guichard, F., Bock, O., Campistron, B., Lafore, J. P., & Redelsperger, J. L. (2010). Synoptic variability of the monsoon flux over West Africa prior to the onset. *Quarterly Journal of the Royal Meteorological Society, 136*, 159-173. doi: 10.1002/qj.473

Cowie, S. M., Knippertz, P., & Marsham, J. H. (2013). Are vegetation-related roughness changes the cause of the recent decrease in dust emission from the Sahel? *Geophysical Research Letters, 40*(9), 1868-1872. doi: 10.1002/grl.50273.

Cox, J., & Abeku, T. A. (2007). Early warning systems for malaria in Africa: from blueprint to practice. *Trends in Parasitology, 23*(6), 243-246. doi: 10.1016/j.pt.2007.03.008

Craig, M. H., Snow, R. W., & le Sueur, D. (1999). A climate-based distribution model of malaria transmission in sub-Saharan Africa. *Parasitology Today, 15*(3), 105-111. doi: 10.1016/s0169-4758(99)01396-4

CRD. (2012, April 14). Climate Research Division. RClimDex 1.0. Retreaved from http://cccma. seos.uvic.ca /ETCCDMI/software.shtml]

Cunin, P., Fonkoua, M. C., Kollo, B., Bedifeh, B. A., Bayanak, P., & Martin, P. M. V. (2003). Serogroup A Neisseria meningitidis outside meningitis belt in Southwest Cameroon. *Emerging Infectious Diseases, 9*(10), 1351-1353.

Curriero, F. C., Patz, J. A., Rose, J. B., & Lele, S. (2001). The association between extreme precipitation and waterborne disease outbreaks in the United States, 1948-1994. *American Journal of Public Health, 91*(8), 1194-1199. doi: 10.2105/ajph.91.8.1194.

Cvjetano.B, & Barua, D. (1972). Seventh pandemic of cholera. *Nature, 239*(5368), 137-&. doi: 10.1038/239137a0.

Davis, R. E., Knappenberger, P. C., Michaels, P. J., & Novicoff, W. M. (2004). Seasonality of climate-human mortality relationships in US cities and impacts of climate change. *Climate Research, 26*(1), 61-76. doi: 10.3354/cr026061.

Davis, S. J., Caldeira, K., & Matthews, H. D. (2010). Future CO2 Emissions and Climate Change from Existing Energy Infrastructure. *Science, 329*(5997), 1330-1333. doi: 10.1126/science.1188566.

de Magny, G. C., Cazelles, B., & Guegan, J. F. (2006). Cholera threat to humans in Ghana is influenced by both global and regional climatic variability. *Ecohealth, 3*(4), 223-231. doi: 10.1007/s10393-006-0061-5.

de Magny, G. C., Guegan, J. F., Petit, M., & Cazelles, B. (2007). Regional-scale climate-variability synchrony of cholera epidemics in West Africa. *Bmc Infectious Diseases, 7*. doi: 10.1186/1471-2334-7-20.

de Magny, G. C., Murtugudde, R., Sapiano, M. R., Nizam, A., Brown, C. W., Busalacchi, A. J., Lanata, C. F. (2008). Environmental signatures associated with cholera epidemics. *Proceedings of the National Academy of Sciences, 105*(46), 17676-17681.

de Magny, G. C., & Colwell, R. R. (2009). Cholera and climate: a demonstrated relationship. *Transactions of the American Clinical and Climatological Association, 120*, 119-128.

de Magny, G. C., Thiaw, W., Kumar, V., Manga, N. M., Diop, B. M., Gueye, L., Colwell, R. R. (2012). Cholera outbreak in senegal in 2005: was climate a factor? *PLoS One, 7*(8), e44577.

Decker, M., Brunke, M. A., Wang, Z., Sakaguchi, K., Zeng, X., & Bosilovich, M. G. (2012). Evaluation of the Reanalysis Products from GSFC, NCEP, and ECMWF Using Flux Tower Observations. *Journal of Climate, 25*(6), 1916-1944. doi: 10.1175/jcli-d-11-00004.1.

Decosas, J., & Koama, J. B. T. (2002). Chronicle of an outbreak foretold: meningococcal meningitis W135 in Burkina Faso. *Lancet Infectious Diseases, 2*(12), 763-765. doi: 10.1016/s1473-3099(02)00455-3.

Dee, D. P., Uppala, S. M., Simmons, A. J., Berrisford, P., Poli, P., Kobayashi, S., Vitart, F. (2011). The ERA-Interim reanalysis: configuration and performance of the data assimilation system. *Quarterly Journal of the Royal Meteorological Society, 137*(656), 553-597. doi: 10.1002/qj.828.

Deque, M. (2007). Frequency of precipitation and temperature extremes over France in an anthropogenic scenario: Model results and statistical correction according to observed values. *Global and Planetary Change, 57*(1-2), 16-26. doi: 10.1016/j.gloplacha.2006.11.030.

Deroubaix, A., Martiny, N., Chiapello, I., & Marticorena, B. (2013). Suitability of OMI aerosol index to reflect mineral dust surface conditions: Preliminary application for studying the link with meningitis epidemics in the Sahel. *Remote Sensing of Environment, 133*, 116-127. doi: 10.1016/j.rse.2013.02.009

Dezfuli, A. K., & Nicholson, S. E. (2011). A note on long-term variations of the African easterly jet. *International Journal of Climatology, 31*(13), 2049-2054. doi: 10.1002/joc.2209

Diedhiou, A., Janicot, S., Viltard, A., de Felice, P., & Laurent, H. (1998). A fast moving easterly wave of the West Africa troposphere. *Meteorology and Atmospheric Physics, 69*(1-2), 39-47. doi: 10.1007/bf01025182.

Diffenbaugh, N. S., & Giorgi, F. (2012). Climate change hotspots in the CMIP5 global climate model ensemble. *Climatic Change, 114*(3-4), 813-822. doi: 10.1007/s10584-012-0570-x.

Djomou, Z. Y., Monkam, D., & Lenouo, A. (2009). Spatial variability of rainfall regions in West Africa during the 20th century. *Atmospheric Science Letters, 10*(1), 9-13. doi: 10.1002/asl.202

Dobson, A. J. (2010). *An introduction to generalized linear models*: CRC press.

Donaldson, G., Kovats, R., Keatinge, W., & McMicheal, R. (2001). The potential impact of climate change on heat-and cold-related mortality and morbidity.

Druyan, L. M. (2011). Studies of 21st-century precipitation trends over West Africa. *International Journal of Climatology, 31*(10), 1415-1424.

Dukic, V., Hayden, M., Forgor, A. A., Hopson, T., Akweongo, P., Hodgson, A., Pandya, R. (2012). The Role of Weather in Meningitis Outbreaks in Navrongo, Ghana: A Generalized Additive Modeling Approach. *Journal of Agricultural Biological and Environmental Statistics, 17*(3), 442-460. doi: 10.1007/s13253-012-0095-9.

Easterling, D. R., Evans, J. L., Groisman, P. Y., Karl, T. R., Kunkel, K. E., & Ambenje, P. (2000). Observed variability and trends in extreme climate events: A brief review. *Bulletin of the American Meteorological Society, 81*(3), 417-425.

Ebi, K. L., Hartman, J., Chan, N., McConnell, J., Schlesinger, M., & Weyant, J. (2005). Climate suitability for stable malaria transmission in Zimbabwe under different climate change scenarios. *Climatic Change, 73*(3), 375-393. doi: 10.1007/s10584-005-6875-2.

Ebi, K. L., Kovats, R. S., & Menne, B. (2006). An approach for assessing human health vulnerability and public health interventions to adapt to climate change. *Environmental Health Perspectives, 114*(12), 1930-1934. doi: 10.1289/ehp.8430.

Ebi, K. L., Lindgren, E., Suk, J. E., & Semenza, J. C. (2013). Adaptation to the infectious disease impacts of climate change. *Climatic Change, 118*(2), 355-365. doi: 10.1007/s10584-012-0648-5.

ECMWF. (2012, May 30). *Era-Interim Reanalysis data*. Retrieved from the European Centre for Medium-Range Weather Forecasts (ECMWF) at http://data-portal.ecmwf.int/data/d/ interim_full_daily

El-Fadel, M., Ghanimeh, S., Maroun, R., & Alameddine, I. (2012). Climate change and temperature rise: Implications on food- and water-borne diseases. *Science of the Total Environment, 437*, 15-21. doi: 10.1016/j.scitotenv.2012.07.041.

Emch, M., Feldacker, C., Islam, M. S., & Ali, M. (2008). Seasonality of cholera from 1974 to 2005: a review of global patterns. *International Journal of Health Geographics, 7*. doi: 10.1186/1476-072x-7-31.

Emch, M., Yunus, M., Escamilla, V., Feldacker, C., & Ali, M. (2010). Local population and regional environmental drivers of cholera in Bangladesh. *Environmental Health, 9*. doi: 10.1186/1476-069x-9-2.

Ermert, V., Fink, A. H., & Paeth, H. (2013). The potential effects of climate change on malaria transmission in Africa using bias-corrected regionalised climate projections and a simple malaria seasonality model. *Climatic Change, 120*(4), 741-754. doi: 10.1007/s10584-013-0851-z.

Fall, S., Semazzi, F. H. M., Dutta, D., Niyogi, S., Anyah, R. O., & Bowden, J. (2006). The spatiotemporal climate variability over Senegal and its relationship to global climate. *International Journal of Climatology, 26*(14), 2057-2076. doi: 10.1002/joc.1355

Faraway, J. J. (2005). *Extending the linear model with R: generalized linear, mixed effects and nonparametric regression models*: CRC press.

Farmer, P., Almazor, C. P., Bahnsen, E. T., Barry, D., Bazile, J., Bloom, B. R., . . . Weigel, J. L. (2011). Meeting Cholera's Challenge to Haiti and the World: A Joint Statement on Cholera Prevention and Care. *Plos Neglected Tropical Diseases, 5*(5). doi: 10.1371/journal.pntd.0001145

Faruque, S. M., Bin Naser, I., Islam, M. J., Faruque, A. S. G., Ghosh, A. N., Nair, G. B., Mekalanos, J. J. (2005). Seasonal epidemics of cholera inversely correlate with the prevalence of environmental cholera phages. *Proceedings of the National Academy of Sciences of the United States of America, 102*(5), 1702-1707. doi: 10.1073/pnas.0408992102.

Fernandez, M. A. L., Bauernfeind, A., Jimenez, J. D., Gil, C. L., El Omeiri, N., & Guibert, D. H. (2009). Influence of temperature and rainfall on the evolution of cholera epidemics in Lusaka, Zambia, 2003-2006: analysis of a time series. *Transactions of the Royal Society of Tropical Medicine and Hygiene, 103*(2), 137-143. doi: 10.1016/j.trstmh.2008.07.017.

Fewtrell, L., Pruss-Ustun, A., Bos, R., Gore, F., & Bartram, J. (2007). Water, sanitation and hygiene. *World Health Organization, Geneva*, p12-50.

Fink, A., Kotthaus, S., & Pohle, S. (2008). Rainfall Variability in West Africa. *2008 IMPETUS Atlas Benin: Research Results, 2007*, 21-22.

Fischer, M., Hedberg, K., Cardosi, P., Plikaytis, B. D., Hoesly, F. C., Steingart, K. R., Perkins, B. A. (1997). Tobacco smoke as a risk factor for meningococcal disease. *Pediatric Infectious Disease Journal, 16*(10), 979-983. doi: 10.1097/00006454-199710000-00015.

Flamant, C., Knippertz, P., Parker, D. J., Chaboureau, J. P., Lavaysse, C., Agusti-Panareda, A., & Kergoat, L. (2009). The impact of a mesoscale convective system cold pool on the northward propagation of the intertropical discontinuity over West Africa. *Quarterly Journal of the Royal Meteorological Society, 135*(638), 139-159. doi: 10.1002/qj.357.

Foltz, G. R., & McPhaden, M. J. (2008). Trends in Saharan dust and tropical Atlantic climate during 1980–2006. *Geophysical Research Letters, 35*(20).

Fontaine, B., Louvet, S., & Roucou, P. (2008). Definition and predictability of an OLR-based West African monsoon onset. *International Journal of Climatology, 28*(13), 1787-1798. doi: 10.1002/joc.1674.

Forgor, A., M., A. Hodgson, P. Vounosou., et al. (2007). Influence of climatic factors on the incidence of meningococcal and pneumococcal meningitis in northern Ghana. *International Journal of Health Geographics*.

Gadgil, A., & Dhorde, A. (2005). Temperature trends in twentieth century at Pune, India. *Atmospheric Environment, 39*(35), 6550-6556. doi: 10.1016/j.atmosenv.2005.07.032

Gaffga, N. H., Tauxe, R. V., & Mintz, E. D. (2007). Cholera: A new homeland in Africa? *American Journal of Tropical Medicine and Hygiene, 77*(4), 705-713.

Geisser, S. (1993). *Predictive inference: an introduction* (Vol. 55): CRC Press.

Getis, A, & J. K. Ord. (1992). The Analysis of Spatial Association by Use of Distance Statistics. *Geographical Analysis* 24, no. 3.

Giannini, A. (2010). Mechanisms of Climate Change in the Semiarid African Sahel: The Local View. *Journal of Climate, 23*(3), 743-756. doi: 10.1175/2009jcli3123.1.

Giannini, A., Biasutti, M., & Verstraete, M. M. (2008). A climate model-based review of drought in the Sahel: Desertification, the re-greening and climate change. *Global and Planetary Change, 64*(3-4), 119-128. doi: 10.1016/j.gloplacha.2008.05.004.

Gill, C. A. (1923). The prediction of malaria epidemics. *Indian Journal of Medical Research, 10*, 1136-1143.

GinkoMaps Project (2013, January 30). *Topograpic Map of Nigeria*. Retrieved from http://www.ginkgomaps.com/maps_nigeria.html.

Giorgi, F. (2005). Climate change prediction. *Climatic Change, 73*(3), 239-265. doi: 10.1007/s10584-005-6857-4.

Giorgi, F., & Diffenbaugh, N. (2008). Developing regional climate change scenarios for use in assessment of effects on human health and disease. *Climate Research, 36*(2), 141-151. doi: 10.3354/cr00728.

Glass, R. I., & Black, R. E. (1992). The epidemiology of cholera. In D. Barua & W.B Greenough (Eds.), Current Topics in Infectious Disease; Cholera (pp. 129-154).

Goodgame, R. W., & Greenough, W. B. (1975). Cholera in africa - message for west. *Annals of Internal Medicine, 82*(1), 101-106.

Google Earth 7.0. (2013). *West African region* -5° – 25°N, -17° – 35°E. Retrieved from http://www.google.com/earth/index.html

Gosling, S. N., Lowe, J. A., McGregor, G. R., Pelling, M., & Malamud, B. D. (2009). Associations between elevated atmospheric temperature and human mortality: a critical review of the literature. *Climatic Change, 92*(3-4), 299-341. doi: 10.1007/s10584-008-9441-x.

Grasso, M., Manera, M., Chiabai, A., & Markandya, A. (2012). The Health Effects of Climate Change: A Survey of Recent Quantitative Research. *International Journal of Environmental Research and Public Health, 9*(5), 1523-1547. doi: 10.3390/ijerph9051523.

Greenough, G., McGeehin, M., Bernard, S. M., Trtanj, J., Riad, J., & Engelberg, D. (2001). The potential impacts of climate variability and change on health impacts of extreme weather events in the United States. *Environmental Health Perspectives, 109*, 191-198. doi: 10.2307/3435009.

Greenwood, B. (1999). Meningococcal meningitis in Africa. *Transactions of the Royal Society of Tropical Medicine and Hygiene, 93*(4), 341-353.

Greenwood, B. (2006). Editorial: 100 years of epidemic meningitis in West Africa - has anything changed? *Tropical Medicine and International Health, 11*(6), 773-780. doi: 10.1111/j.1365-3156.2006.01639.x.

Greenwood, B., & Stuart, J. M. (2012). A vaccine to prevent epidemic meningitis in Africa. *Lancet Infectious Diseases, 12*(10), 738-739. doi: 10.1016/s1473-3099(12)70182-2.

Greenwood, B. M., Bradley, A. K., Blakebrough, I. S., Wali, S., & Whittle, H. C. (1984). Meningococcal disease and season in sub-saharan africa. *The Lancet, 323*(8390), 1339-1342. doi: Doi: 10.1016/s0140-6736(84)91830-0.

Grenfell, B. T., & Dobson, A. P. (1995). *Ecology of infectious diseases in natural populations* (Vol. 7): Cambridge University Press.

Griffith, K. S., L.S. Lewis., S. Mali., et al. (1976). Treatment of malaria in the United States. *Am J Epidemiol, 103*, 75–80.

Grist, J. P., & Nicholson, S. E. (2001). A study of the dynamic factors influencing the rainfall variability in the West African Sahel. *Journal of Climate, 14*(7), 1337-1359. doi: 10.1175/1520-0442(2001)014<1337:asotdf>2.0.co;2

Gu, G. J., & Adler, R. F. (2004). Seasonal evolution and variability associated with the West African monsoon system. *Journal of Climate, 17*(17), 3364-3377. doi: 10.1175/1520-0442(2004)017<3364:seavaw>2.0.co;2

Guisan, A., & Thuiller, W. (2005). Predicting species distribution: offering more than simple habitat models. *Ecology Letters, 8*(9), 993-1009. doi: 10.1111/j.1461-0248.2005.00792.x.

Gutiérrez, J. M., San-Martín, D., Brands, S., Manzanas, R., & Herrera, S. (2012). Reassessing Statistical Downscaling Techniques for Their Robust Application under Climate Change Conditions. *Journal of Climate, 26*(1), 171-188. doi: 10.1175/jcli-d-11-00687.1.

Hagos, S. M., & Cook, K. H. (2008). Ocean warming and late-twientieth-century Sahel drought and recovery. *Journal of Climate, 21*(15), 3797-3814. doi: 10.1175/2008jcli2055.1

Haines, A., & Patz, J. A. (2004). Health effects of climate change. *Jama-Journal of the American Medical Association, 291*(1), 99-103. doi: 10.1001/jama.291.1.99.

Halperin, S. A., Bettinger, J. A., Greenwood, B., Harrison, L. H., Jelfs, J., Ladhani, S. N., Sáfadi, M. A. P. (2012). The changing and dynamic epidemiology of meningococcal disease. *Vaccine, 30, Supplement 2*(0), B26-B36. doi: http://dx.doi.org/10.1016/j.vaccine.2011.12.032.

Harris, J. B., LaRocque, R. C., Qadri, F., Ryan, E. T., & Calderwood, S. B. (2012). Cholera. *Lancet, 379*(9835), 2466-2476.

Harrison, L. H., Trotter, C. L., & Ramsay, M. E. (2009). Global epidemiology of meningococcal disease. *Vaccine, 27*, B51-B63. doi: 10.1016/j.vaccine.2009.04.063.

Harvell, C. D., Mitchell, C. E., Ward, J. R., Altizer, S., Dobson, A. P., Ostfeld, R. S., & Samuel, M. D. (2002). Ecology - Climate warming and disease risks for terrestrial and marine biota. *Science, 296*(5576), 2158-2162. doi: 10.1126/science.1063699.

Hashizume, M., Armstrong, B., Hajat, S., Wagatsuma, Y., Faruque, A. S., Hayashi, T., & Sack, D. A. (2007). Association between climate variability and hospital visits for non-cholera diarrhoea in Bangladesh: effects and vulnerable groups. *International Journal of Epidemiology, 36*(5), 1030-1037. doi: 10.1093/ije/dym148.

Hashizume, M., Armstrong, B., Hajat, S., Wagatsuma, Y., Faruque, A. S. G., Hayashi, T., & Sack, D. A. (2008). The effect of rainfall on the incidence of cholera in Bangladesh. *Epidemiology, 19*(1), 103-110. doi: 10.1097/EDE.0b013e31815c09ea.

Hashizume, M., Faruque, A. S. G., Terao, T., Yunus, M., Streatfield, K., Yamamoto, T., & Moji, K. (2011). The Indian Ocean Dipole and Cholera Incidence in Bangladesh: A Time-Series Analysis. *Environmental Health Perspectives, 119*(2), 239-244. doi: 10.1289/ehp.1002302.

Hashizume, M., Faruque, A. S. G., Wagatsuma, Y., Hayashi, T., & Armstrong, B. (2010). Cholera in Bangladesh Climatic Components of Seasonal Variation. *Epidemiology, 21*(5), 706-710. doi: 10.1097/EDE.0b013e3181e5b053.

Hastie, T., & Tibshirani, R. (1999). *Generalized Additive Models*: Chapman & Hall Ltd, London.

Hay, S. I., Cox, J., Rogers, D. J., Randolph, S. E., Stern, D. I., Shanks, G. D., Snow, R. W. (2002). Climate change and the resurgence of malaria in the East African highlands. *Nature, 415*(6874), 905-909. doi: 10.1038/415905a.

Hay, S. I., & Lennon, J. J. (1999). Deriving meteorological variables across Africa for the study and control of vector-borne disease: a comparison of remote sensing and spatial interpolation of climate. *Tropical Medicine & International Health, 4*(1), 58-71.

Hayhoe, K., Cayan, D., Field, C. B., Frumhoff, P. C., Maurer, E. P., Miller, N. L., Verville, J. H. (2004). Emissions pathways, climate change, and impacts on California. *Proceedings of the National Academy of Sciences of the United States of America, 101*(34), 12422-12427. doi: 10.1073/pnas.0404500101.

Hegerl, G. C., Karl, T. R., Allen, M., Bindoff, N. L., Gillett, N., Karoly, D., Zwiers, F. (2006). Climate change detection and attribution: Beyond mean temperature signals. *Journal of Climate, 19*(20), 5058-5077.

Held, L., & Paul, M. (2013). Statistical modeling of infectious disease surveillance data *Infectious Disease Surveillance* (pp. 535-544): John Wiley & Sons Ltd.

Hodgson, A., Smith, T., Gagneux, S., Adjuik, M., Pluschke, G., Mensah, N. K., Genton, B. (2001). Risk factors for meningococcal meningitis in northern Ghana. *Transactions of the Royal Society of Tropical Medicine and Hygiene, 95*(5), 477-480.

Hodgson, A., Smith, T., Gagneux, S., Akumah, I., Adjuik, M., Pluschke, G., Genton, B. (2001). Infectious diseases - Survival and sequelae of meningococcal meningitis in Ghana. *International Journal of Epidemiology, 30*(6), 1440-1446.

Hoerling, M., Hurrell, J., Eischeid, J., & Phillips, A. (2006). Detection and attribution of twentieth-century northern and southern African rainfall change. *Journal of Climate, 19*(16), 3989-4008. doi: 10.1175/jcli3842.1

Hopson, T. M., & Webster, P. J. (2010). A 1-10-Day Ensemble Forecasting Scheme for the Major River Basins of Bangladesh: Forecasting Severe Floods of 2003-07. *Journal of Hydrometeorology, 11*(3), 618-641. doi: 10.1175/2009jhm1006.1.

Hoshen, M. B., & Morse, A. P. (2004). A weather-driven model of malaria transmission. *Malaria Journal, 3*. doi: 10.1186/1475-2875-3-32.

Hourdin, F., Musat, I., Guichard, F., Ruti, P. M., Favot, F., Filiberti, M.-A., Gallee, H. (2010). AMMA-MODEL INTERCOMPARISON PROJECT. *Bulletin of the American Meteorological Society, 91*(1), 95-+. doi: 10.1175/2009bams2791.1.

Hoxie, N. J., Davis, J. P., Vergeront, J. M., Nashold, R. D., & Blair, K. A. (1997). Cryptosporidiosis-associated mortality following a massive waterborne outbreak in Milwaukee, Wisconsin. *American Journal of Public Health, 87*(12), 2032-2035. doi: 10.2105/ajph.87.12.2032.

Huei-Ting, T., L, Tzu-Ming. (2005). *Effects of global climate change on disease epidemics and social instability around the world*. Paper presented at the An international workshop, Holmen Fjord, Asker, near Oslo, Holmen Fjord, Asker, near Oslo

Hulme, M., & Tosdevin, N. (1989). THE TROPICAL EASTERLY JET AND SUDAN RAINFALL - A REVIEW. *Theoretical and Applied Climatology, 39*(4), 179-187. doi: 10.1007/bf00867945

IDMC. (2014, February 13). Nigeria: Fragmented response to internal displacement amid Boko Haram attacks and flood season. *Internal Displacement Monitoring Centre*. Retrieved from http://www.internal-displacement.org/countries/nigeria

Ines, A. V. M., & Hansen, J. W. (2006). Bias correction of daily GCM rainfall for crop simulation studies. *Agricultural and Forest Meteorology, 138*(1-4), 44-53. doi: 10.1016/j.agrformet.2006.03.009.

Ingram, W. J. (2006). Detection and attribution of climate change, and understanding solar influence on climate. *Space Science Reviews, 125*(1-4), 199-211. doi: 10.1007/s11214-006-9057-2.

IPCC. (1990). Climate Change 1990: The Physical Science Basis. Contribution of Working Group I to the First Assessment Report of the IPCC. In J.T. Houghton, G.J. Jenkins and J.J. Ephraums (eds.). Cambridge University Press, Cambridge, Great Britain, New York, NY, USA and Melbourne, Australia. 410pp.

IPCC. (1997). Special Report The Regional Impacts of Climate Change: An Assessment of Vulnerability R.T.Watson, M.C.Zinyowera, R.H.Moss (Eds) Cambridge University Press The Edinburgh Building Shaftesbury Road, Cambridge CB2 2RU ENGLAND, UK, pp 517,

IPCC. (1996). Climate Change 1995: Impacts, Adaptation and Vulnerability. Scientific Technical Analysis, Contribution of Working Group II to the Second Assessment Report of the IPCC. In R.T Watson., M.C Zinyowera., R.H Moss., and D.J Dokke, eds. Published by the Press Syndicate of the University of Cambridge The Pitt Building, Trumpington Street, Cambridge CB2 IRP 40 West 20th Street, New York, NY 10011 -4211, USA 10 Stanford Road, Oakleigh, Melbourne 3166, Australia.

IPCC. (2007a). Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the IPCC. In S. Solomon, D. Qin, M. Manning, Z. Chen, M. Marquis, K.B. Averyt, M. Tignor and H.L. Miller, eds. Cambridge, UK: Cambridge University Press, 996 pp.

IPCC. (2007b). Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the IPCC. In M.L. Parry, O.F. Canziani, J.P. Palutikof, P.J. van der Linden and C.E. Hanson, eds. Cambridge University Press, Cambridge, UK, 976 pp.

IPCC. (2007c). Climate Change 2007: Synthesis Report. Contribution of Working Groups I, II and III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Core Writing Team, Pachauri, R.K and Reisinger, A. (eds.) IPCC, Geneva, Switzerland, 104 pp.

IPCC. (2013). Summary for Policymakers. In: Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA

IRI. (2011, February 16). *Map of Africa showing areas vulnerable to climate change*. Retrieved from the Grid-Arendal, Columbia University http://www.grida.no/graphicslib/tag/africa?p=5

IRIN. (2014a, January 26). Health: Cholera sours in Lake Chad basin countries. *Humanitarian news and analysis*; a service of the UN Office for the Coordination of Humanitarian Affairs 2014. Retrieved from http://www.irinnews.org/report/93617/health-cholera-soars-in-lake-chad-basin-countries

IRIN. (2014b, February 16). Floods test Nigeria's preparedness. *Humanitarian news and analysis*; Retrieved from http://www.irinnews.org/report/98644/floods-test-nigeria-s-preparedness

Islam, M. S., Sharker, M. A. Y., Rheman, S., Hossain, S., Mahmud, Z. H., Uddin, A. M. K., Ernst, R. (2009). Effects of local climate variability on transmission dynamics of cholera in Matlab, Bangladesh. *Transactions of the Royal Society of Tropical Medicine and Hygiene, 103*(11), 1165-1170. doi: 10.1016/j.trstmh.2009.04.016.

James, R., & Washington, R. (2013). Changes in African temperature and precipitation associated with degrees of global warming. *Climatic Change, 117*(4), 859-872. doi: 10.1007/s10584-012-0581-7.

Janicot, S., Caniaux, G., Chauvin, F., de Coetlogon, G., Fontaine, B., Hall, N., Taylor, C. M. (2011). Intraseasonal variability of the West African monsoon. *Atmospheric Science Letters, 12*(1), 58-66. doi: 10.1002/asl.280.

Jenks, G. F. (1967). The data model concept in statistical mapping. *International yearbook of cartography, 7*(1), 186-190.

Jetten, T. H., & Focks, D. A. (1997). Potential changes in the distribution of dengue transmission under climate warming. *The American journal of tropical medicine and hygiene, 57*(3), 285-297.

Jones, C., Liddicoat, S., & Lowe, J. (2010). Role of terrestrial ecosystems in determining CO2 stabilization and recovery behaviour. *Tellus Series B-Chemical and Physical Meteorology, 62*(5), 682-699. doi: 10.1111/j.1600-0889.2010.00490.x.

Kalu, A. (1979). The African dust plume: its characteristics and propagation across West Africa in winter. *Saharan dust*, 95-118.

Kanungo, S., & Sur, D. (2012). Cholera and its vaccines. *Pediatric Infectious Disease, 4*(1), 18-24. doi: http://dx.doi.org/10.1016/S2212-8328(12)60006-X.

Karl, T. R., Knight, R. W., & Plummer, N. (1995). Trends in high-frequency climate variability in the 20th-century. *Nature, 377*(6546), 217-220. doi: 10.1038/377217a0.

Kelly-Hope, L., & Thomson, M. C. (2008). Climate and infectious diseases. *Seasonal Forecasts, Climatic Change and Human Health, 30*, 31-70.

Kelly-Hope, L. A., Alonso, W. J., Thiem, V. D., Anh, D. D., Canh, D. G., Lee, H., Miller, M. A. (2007). Geographical distribution and risk factors associated with enteric diseases in Vietnam. *American Journal of Tropical Medicine and Hygiene, 76*(4), 706-712.

Kinlin, L. M., Spain, C. V., Ng, V., Johnson, C. C., White, A. N., & Fisman, D. N. (2009). Environmental exposures and invasive meningococcal disease: an evaluation of effects on varying time scales. *American journal of epidemiology, 169*(5), 588-595.

Knofczynski, G. T., & Mundfrom, D. (2008). Sample sizes when using multiple linear regression for prediction. *Educational and Psychological Measurement, 68*(3), 431-442. doi: 10.1177/0013164407310131.

Koelle, K. (2009). The impact of climate on the disease dynamics of cholera. *Clinical Microbiology and Infection, 15*, 29-31. doi: 10.1111/j.1469-0691.2008.02686.x.

Koelle, K., Pascual, M., & Yunus, M. (2005a). Pathogen adaptation to seasonal forcing and climate change. *Proceedings of the Royal Society B-Biological Sciences, 272*(1566), 971-977. doi: 10.1098/rspb.2004.3043.

Koelle, K., Rodo, X., Pascual, M., Yunus, M., & Mostafa, G. (2005b). Refractory periods and climate forcing in cholera dynamics. *Nature, 436*(7051), 696-700. doi: 10.1038/nature03820.

Kohavi, R. (1995). *A study of cross-validation and bootstrap for accuracy estimation and model selection.* Paper presented at the International joint Conference on artificial intelligence.

Koumare, B., Bougoudogo, F., Cisse, M., Doumbia, T., & Keita, M. M. (1993). Bacteriological aspects of purulent-meningitis in bamako-district upon 1,541 strains collected from 1979 to 1991. *Bulletin De La Societe De Pathologie Exotique, 86*(2), 136-140.

Kovats, R. S., & Butler, C. D. (2012). Global health and environmental change: linking research and policy. *Current Opinion in Environmental Sustainability, 4*(1), 44-50. doi: 10.1016/j.cosust.2012.01.012.

Kovats, R. S., Haines, A., Stanwell-Smith, R., Martens, P., Menne, B., & Bertollini, R. (1999). Climate change and human health in Europe. *British Medical Journal, 318*(7199), 1682-1685.

Kraus, E. B. (1977). SUBTROPICAL DROUGHTS AND CROSS-EQUATORIAL ENERGY TRANSPORTS. *Monthly Weather Review, 105*(8), 1009-1018. doi: 10.1175/1520-0493(1977)105<1009:sdacee>2.0.co;2

Kruger, A. C., & Shongwe, S. (2004). Temperature trends in South Africa: 1960-2003. *International Journal of Climatology, 24*(15), 1929-1945. doi: 10.1002/joc.1096.

Kutz, S. J., Hoberg, E. P., Polley, L., & Jenkins, E. J. (2005). Global warming is changing the dynamics of Arctic host-parasite systems. *Proceedings of the Royal Society B-Biological Sciences, 272*(1581), 2571-2576. doi: 10.1098/rspb.2005.3285

Lafferty, K. D. (2009). The ecology of climate change and infectious diseases. *Ecology, 90*(4), 888-900.

Lafore, J. P., Flamant, C., Giraud, V., Guichard, F., Knippertz, P., Mahfouf, J. F., Williams, E. R. (2010). Introduction to the AMMA Special Issue on 'Advances in understanding atmospheric processes over West Africa through the AMMA field campaign'. *Quarterly Journal of the Royal Meteorological Society, 136*, 2-7. doi: 10.1002/qj.583.

Lafore, J. P., Flamant, C., Guichard, F., Parker, D. J., Bouniol, D., Fink, A. H., Thorncroft, C. (2011). Progress in understanding of weather systems in West Africa. *Atmospheric Science Letters, 12*(1), 7-12. doi: 10.1002/asl.335.

Lapeyssonnie, L. (1963). Cerebrospinal meningitis in africa. [La m'eningite c'er'ebro-spinale en afrique.]. *Bulletin of the World Health Organization, 28 Suppl*, 1-114.

Lavaysse, C., Flamant, C., & Janicot, S. (2010a). Regional-scale convection patterns during strong and weak phases of the Saharan heat low. *Atmospheric Science Letters, 11*(4), 255-264. doi: 10.1002/asl.284

Lavaysse, C., Flamant, C., Janicot, S., & Knippertz, P. (2010b). Links between African easterly waves, midlatitude circulation and intraseasonal pulsations of the West African heat low. *Quarterly Journal of the Royal Meteorological Society, 136*, 141-158. doi: 10.1002/qj.555

Lavaysse, C., Flamant, C., Janicot, S., Parker, D. J., Lafore, J. P., Sultan, B., & Pelon, J. (2009). Seasonal evolution of the West African heat low: a climatological perspective. *Climate Dynamics, 33*(2-3), 313-330. doi: 10.1007/s00382-009-0553-4

Le Barbe, L., Lebel, T., & Tapsoba, D. (2002). Rainfall variability in West Africa during the years 1950-90. *Journal of Climate, 15*(2), 187-202. doi: 10.1175/1520-0442(2002)015<0187:rviwad>2.0.co;2.

Leake, J. A. D., Kone, M. L., Yada, A. A., Barry, L. F., Traore, G., Ware, A., Perkins, B. A. (2002). Early detection and response to meningococcal disease epidemics in sub-Saharan Africa: appraisal of the WHO strategy. *Bulletin of the World Health Organization, 80*(5), 342-349.

Lebel, T., & Ali, A. (2009). Recent trends in the Central and Western Sahel rainfall regime (1990–2007). *Journal of Hydrology, 375*(1), 52-64.

Lindsay, A. P., Hope, V., Marshall, R. J., & Salinger, J. (2002). Meningococcal disease and meteorological conditions in Auckland, New Zealand. *Australian and New Zealand Journal of Public Health, 26*(3), 212-218. doi: 10.1111/j.1467-842X.2002.tb00676.x.

Lingappa, J. R., Al-Rabeah, A. M., Hajjeh, R., Mustafa, T., Fatani, A., & Al-Bassam, T. (2003). Serogroup W-135 meningococcal disease during Hajj, 2000. *Emerging Infectious Diseases, 9*, 665-671.

Lipp, E. K., Huq, A., & Colwell, R. R. (2002). Effects of global climate on infectious disease: the cholera model. *Clinical Microbiology Reviews, 15*(4), 757-+. doi: 10.1128/cmr.15.4.757-770.2002.

Loevinsohn, M. E. (1994). Climatic warming and increased malaria incidence in rwanda. *Lancet, 343*(8899), 714-718. doi: 10.1016/s0140-6736(94)91586-5

Louis, V. R., Russek-Cohen, E., Choopun, N., Rivera, I. N. G., Gangle, B., Jiang, S. C., Colwell, R. R. (2003). Predictability of Vibrio cholerae in Chesapeake Bay. *Applied and Environmental Microbiology, 69*(5), 2773-2785. doi: 10.1128/aem.69.5.2773-2785.2003.

Lowen, A. C., Mubareka, S., Steel, J., & Palese, P. (2007). Influenza virus transmission is dependent on relative humidity and temperature. *Plos Pathogens, 3*(10), 1470-1476. doi: 10.1371/journal.ppat.0030151

Mabaso, M. L. H., Craig, M., Ross, A., & Smith, T. (2007). Environmental predictors of the seasonality of malaria transmission in Africa: The challenge. *American Journal of Tropical Medicine and Hygiene, 76*(1), 33-38.

MacCullagh, P., & Nelder, J. A. (1989). *Generalized linear models* (Vol. 37): CRC press.

Maiden, M. C. J., Ibarz-Pavon, A. B., Urwin, R., Gray, S. J., Andrews, N. J., Clarke, S. C., Stuart, J. M. (2008). Impact of meningococcal serogroup C conjugate vaccines on carriage and herd immunity. *Journal of Infectious Diseases, 197*(5), 737-743. doi: 10.1086/527401.

Mantel, N., & W. Haenszel. (1959). Statistical aspects of the analysis of data from retrospective studies of disease. J. Natl. Cancer Inst. 22: 719-748

Mari, L., Bertuzzo, E., Righetto, L., Casagrandi, R., Gatto, M., Rodriguez-Iturbe, I., & Rinaldo, A. (2012). On the role of human mobility in the spread of cholera epidemics: towards an epidemiological movement ecology. *Ecohydrology, 5*(5), 531-540. doi: 10.1002/eco.262.

Marin, M. A., Thompson, C. C., Freitas, F. S., Fonseca, E. L., Aboderin, A. O., Zailani, S. B.,Vicente, A. C. P. (2013). Cholera Outbreaks in Nigeria Are Associated with Multidrug Resistant Atypical El Tor and Non-O1/Non-O139 Vibrio cholerae. *Plos Neglected Tropical Diseases, 7*(2). doi: 10.1371/journal.pntd.0002049.

Martin, P. H., & Lefebvre, M. G. (1995). Malaria and climate - sensitivity of malaria potential transmission to climate. *Ambio, 24*(4), 200-207.

Marsham, J. H., Dixon, N. S., Garcia-Carreras, L., Lister, G. M. S., Parker, D. J., Knippertz, P., & Birch, C. E. (2013). The role of moist convection in the West African monsoon system: Insights from continental-scale convection-permitting simulations. *Geophysical Research Letters, 40*(9), 1843-1849. doi: 10.1002/grl.50347.

Martens, P., Kovats, R. S., Nijhof, S., de Vries, P., Livermore, M. T. J., Bradley, D. J., McMichael, A. J. (1999). Climate change and future populations at risk of malaria. *Global Environmental Change-Human and Policy Dimensions, 9*, S89-S107. doi: 10.1016/s0959-3780(99)00020-5.

Martiny, N., & Chiapello, I. (2013). Assessments for the impact of mineral dust on the meningitis incidence in West Africa. *Atmospheric Environment, 70*, 245-253. doi: 10.1016/j.atmosenv.2013.01.016

Masui, T., Matsumoto, K., Hijioka, Y., Kinoshita, T., Nozawa, T., Ishiwatari, S., . Kainuma, M. (2011). An emission pathway for stabilization at 6 Wm(-2) radiative forcing. *Climatic Change, 109*(1-2), 59-76. doi: 10.1007/s10584-011-0150-5.

Matsuda, F., Ishimura, S., Wagatsuma, Y., Higashi, T., Hayashi, T., Faruque, A. S. G., . . . Nishibuchi, M. (2008). Prediction of epidemic cholera due to Vibrio cholerae O1 in children younger than 10 years using climate data in Bangladesh. *Epidemiology and Infection, 136*(1), 73-79. doi: 10.1017/s0950268807008175.

Matthews, H. D., & Weaver, A. J. (2010). Committed climate warming. *Nature Geoscience, 3*(3), 142-143. doi: 10.1038/ngeo813.

McGahey, K. e. a. (1905). Epidemic cerebro-spinal meningitis in northern Nigeria. *The British Medical Journal, 4*, 1173-1174.

McMichael, A. J. (2003). Global climate change: will it affect vector-borne infectious diseases? *Internal Medicine Journal, 33*(12), 554-U552. doi: 10.1111/j.1445-5994.2003.00492.x.

McMichael, A. J., & Kovats, R. S. (2000). Global environmental changes and health: Approaches to assessing risks. *Ecosystem Health, 6*(1), 59-66. doi: 10.1046/j.1526-0992.2000.00007.x.

McMichael, A. J., Woodruff, R. E., & Hales, S. (2006). Climate change and human health: present and future risks. *The Lancet, 367*(9513), 859-869.

McMicheal, A., A. Githeko., R. Akhtar., R. Carcavallo., D. Gubler., et al. (2001). *Human health. In: Climate change 2001: Impacts, adaptation, and Vulnerability* (Vol. 451-485). Cambridge: Cambridge University Press, Cambridge, UK, .

McMicheal, A., D. Campbell-Lendrum., S. Kovats., S. Edwards., P. Wilkinson., et al. (2004). Global climate change. In: Ezzati, M., A. Lopez., A. Rodhers., and C. Murray, eds, Comparative quantification of heal risks: global and regional burden of disease due to selected major risks factors. *World Health Organisation, Geneva, Switzerland. , 1543-1649.*

Medina, D. C., Findley, S. E., Guindo, B., & Doumbia, S. (2007). Forecasting Non-Stationary Diarrhea, Acute Respiratory Infection, and Malaria Time-Series in Niono, Mali. *PLoS One, 2*(11). doi: 10.1371/journal.pone.0001181

Meehl, G. A., Arblaster, J. M., & Tebaldi, C. (2005). Understanding future patterns of increased precipitation intensity in climate model simulations. *Geophysical Research Letters, 32*(18). doi: L1871910.1029/2005gl023680.

Meehl, G. A., Covey, C., Taylor, K. E., Delworth, T., Stouffer, R. J., Latif, M., Mitchell, J. F. B. (2007). THE WCRP CMIP3 Multimodel Dataset: A New Era in Climate Change Research. *Bulletin of the American Meteorological Society, 88*(9), 1383-1394. doi: 10.1175/bams-88-9-1383.

Meehl, G. A., Washington, W. M., Collins, W. D., Arblaster, J. M., Hu, A. X., Buja, L. E., Teng, H. Y. (2005). How much more global warming and sea level rise? *Science, 307*(5716), 1769-1772. doi: 10.1126/science.1106663.

Mendelsohn, R., Dinar, A., & Williams, L. (2006). The distributional impact of climate change on rich and poor countries. *Environment and Development Economics, 11*, 159-178. doi: 10.1017/s1355770x05002755.

MERIT. (2012, December, 27). Meningits Environmental Risk Information, 6th International MERIT Techinical Meeting report. Retreived from http://merit.hc-foundation.org/documents/6thMeritWorkshop/6thMERITTechnicalMeetingReport.pdf

Michelangeli, P. A., Vrac, M., & Loukos, H. (2009). Probabilistic downscaling approaches: Application to wind cumulative distribution functions. *Geophysical Research Letters, 36*. doi: 10.1029/2009gl038401.

Miller, A. (2013). UN atlas links climate change to disease spread. *Canadian Medical Association Journal, 185*(1), E38-E38. doi: 10.1503/cmaj.109-4340.

Mitchell, A. (2005). The ESRI Guide to GIS Analysis: Spatial Measurements and Statistics. Vol 2. Redlands: CA: ESRI Press.

Mitra, S., & Washington, S. (2007). On the nature of over-dispersion in motor vehicle crash prediction models. *Accident Analysis and Prevention, 39*(3), 459-468. doi: 10.1016/j.aap.2006.08.002

Mohammed, I., & Nasidi, A. (2000). A severe epidemic of meningococcal meningitis in Nigeria. *Transactions of the Royal Society of Tropical Medicine and Hygiene, 94*(3), 265-270.

Molesworth, A. M., Cuevas, L. E., Connor, S. J., Morse, A. P., & Thomson, M. C. (2003). Environmental risk and meningitis epidemics in Africa. *Emerging Infectious Diseases, 9*(10), 1287-1293.

Molesworth, A. M., Cuevas, L. E., Morse, A. P., Herman, J. R., & Thomson, M. C. (2002). Dust clouds and spread of infection. *Lancet, 359*(9300), 81-82.

Molesworth, A. M., Thomson, M. C., Connor, S. J., Cresswell, M. P., Morse, A. P., Shears, P.,Cuevas, L. E. (2002). Where is the Meningitis Belt? Defining an area at risk of epidemic meningitis in Africa. *Transactions of the Royal Society of Tropical Medicine and Hygiene, 96*(3), 242-249.

Molesworth, A. M., Cuevas, L. E., Morse, A. P., Herman, J. R., & Thomson, M. C. (2002). Dust clouds and spread of infection. *Lancet, 359*(9300), 81-82.

Monerie, P.-A., Fontaine, B., & Roucou, P. (2012). Expected future changes in the African monsoon between 2030 and 2070 using some CMIP3 and CMIP5 models under a medium-low RCP scenario. *Journal of Geophysical Research-Atmospheres, 117*. doi: 10.1029/2012jd017510.

Moore, P. S. (1992). Meningococcal meningitis in sub-saharan africa - a model for the epidemic process. *Clinical Infectious Diseases, 14*(2), 515-525.

Moore, P. S., Hierholzer, J., Dewitt, W., Gouan, K., Djore, D., Lippeveld, T., Broome, C. V. (1990). Respiratory viruses and mycoplasma as cofactors for epidemic group-a meningococcal meningitis. *Jama-Journal of the American Medical Association, 264*(10), 1271-1275. doi: 10.1001/jama.264.10.1271.

Moore, P. S., Plikaytis, B. D., Bolan, G. A., Oxtoby, M. J., Yada, A., Zoubga, A., Broome, C. V. (1992). Detection of meningitis epidemics in africa - a population-based analysis. *International Journal of Epidemiology, 21*(1), 155-162.

Moran, P. A. P. (1950). Notes on Continuous Stochastic Phenomena. doi 17–23. doi:10.2307/2332142

Morens, D. M., Folkers, G. K., & Fauci, A. S. (2004). The challenge of emerging and re-emerging infectious diseases. *Nature, 430*(6996), 242-249. doi: 10.1038/nature02759

Moron, V. (1994). Guinean and sahelian rainfall anomaly indexes at annual and monthly scales (1933-1990). *International Journal of Climatology, 14*(3), 325-341. doi: 10.1002/joc.3370140306

Morris, J. G. (2003). Cholera and other types of vibriosis: A story of human pandemics and oysters on the half shell. *Clinical Infectious Diseases, 37*(2), 272-280. doi: 10.1086/375600.

Moss, R. H., Edmonds, J. A., Hibbard, K. A., Manning, M. R., Rose, S. K., van Vuuren, D. P.,Wilbanks, T. J. (2010). The next generation of scenarios for climate change research and assessment. *Nature, 463*(7282), 747-756. doi: 10.1038/nature08823.

Mshelia, A. D. (2005). Adaptation strategies to climate change. *Journal of Energy and Environment 18*(3), 74-81.

Mueller, J. E., Yaro, S., Madec, Y., Somda, P. K., Idohou, R. S., Njanpop Lafourcade, B.-M., Gessner, B. D. (2008). Association of respiratory tract infection symptoms and air humidity with meningococcal carriage in Burkina Faso. *Tropical Medicine & International Health, 13*(12), 1543-1552. doi: 10.1111/j.1365-3156.2008.02165.x.

Munemoto, M., & Tachibana, Y. (2012). The recent trend of increasing precipitation in Sahel and the associated inter-hemispheric dipole of global SST. *International Journal of Climatology, 32*(9), 1346-1353. doi: 10.1002/joc.2356

Müller, C. (2009). *Climate change impact on Sub-Saharan Africa: an overview and analysis of scenarios and models*: German Development Institute/Deutsches Institut für Entwicklungspolitik (DIE).

Murphy, A. H. (1988). Skill Scores Based on the Mean Square Error and Their Relationships to the Correlation Coefficient. *Monthly Weather Review, 116*(12), 2417-2424. doi: 10.1175/1520-0493(1988)116<2417:ssbotm>2.0.co;2.

Murray, C. J. L., Vos, T., Lozano, R., AlMazroa, M. A., & Memish, Z. A. (2013). Disability-adjusted life years (DALYs) for 291 diseases and injuries in 21 regions, 1990-2010: a systematic analysis for the Global Burden of Disease Study 2010 (vol 380, pg 2197, 2012). *Lancet, 381*(9867), 628-628.

Myers, R. H. (1990). *Classical and modern regression with applications* (Vol. 2): Duxbury Press Belmont, CA.

NBS. (2012). Annual abstract of statisitcs. Federal Republic of Nigeria, Abuja.

NCDC. (2012). Weekly Epidemiology Report (Vol. 2). Abuja: Federal Ministry of Health, Nigeria.

Nelson, E. J., Harris, J. B., Morris, J. G., Jr., Calderwood, S. B., & Camilli, A. (2009). Cholera transmission: the host, pathogen and bacteriophage dynamic. *Nature Reviews Microbiology, 7*(10), 693-702. doi: 10.1038/nrmicro2204.

Nicholson, S. E. (1980). The nature of rainfall fluctuations in sub-tropical west-africa. *Monthly Weather Review, 108*(4), 473-487. doi: 10.1175/1520-0493(1980)108<0473:tnorfi>2.0.co;2

Nicholson, S. E. (2008). The intensity, location and structure of the tropical rainbelt over west Africa as factors in interannual variability. *International Journal of Climatology, 28*(13), 1775-1785. doi: 10.1002/joc.1507

Nicholson, S. E. (2009). A revised picture of the structure of the "monsoon" and land ITCZ over West Africa. *Climate Dynamics, 32*(7-8), 1155-1171. doi: 10.1007/s00382-008-0514-3

Nicholson, S. E. (2013). The West African Sahel: A Review of Recent Studies on the Rainfall Regime and Its Interannual Variability. *ISRN Meteorology, 2013*, 32. doi: 10.1155/2013/453521

Nicholson, S. E., Dezfuli, A. K., & Klotter, D. (2012). A two-century precipitation dataset for the continent of africa. *Bulletin of the American Meteorological Society, 93*(8), 1219-1231. doi: 10.1175/bams-d-11-00212.1

Nicholson, S. E., & Grist, J. P. (2003). The seasonal evolution of the atmospheric circulation over West Africa and equatorial Africa. *Journal of Climate, 16*(7), 1013-1030. doi: 10.1175/1520-0442(2003)016<1013:tseota>2.0.co;2

NIMET. (2011). Daily Meteorological Variables. In N. M. Agency (Ed.). Abuja, Nigeria.

Nolan, D. S., Zhang, C., & Chen, S.-H. (2007). Dynamics of the shallow meridional circulation around intertropical convergence zones. *Journal of the Atmospheric Sciences, 64*(7), 2262-2285. doi: 10.1175/jas3964.1

NPC. (2006). National and State Population and Housing Tables *Priority Tables* (Vol. 1). Abuja, Nigeria.

NPHCDA. (2011). Nigeria CSM Preventive Campaign with MenAfriVac. Abuja: National Primary Health Care Development Agency.

O'Neill, B. C. (2004). Conditional probabilistic population projections: An application to climate change. *International Statistical Review, 72*(2), 167-184.

Obot, N. I., Chendo, M. A. C., Udo, S. O., & Ewona, I. O. (2010). Evaluation of rainfall trends in Nigeria for 30 years (1978-2007). *International Journal of the Physical Sciences, 5*(14), 2217-2222.

Odekunle, T. O. (2010). An Assessment of the Influence of the Inter-Tropical Discontinuity on Inter-Annual Rainfall Characteristics in Nigeria. *Geographical Research, 48*(3), 314-326. doi: 10.1111/j.1745-5871.2009.00635.x.

Odjugo, P. A. O. (2010). Regional evidence of climate change in Nigeria. *Journal of Geography and Regional Planning, 36*(6), 142-150.

Odjugo, P. A. O., and A.I. Ikhuoria. (2003). The impact of climate change and Anthropogenic factors on Desertification in the semi-arid region of Nigeria. *Global Journal of Environmental Science, 2*(2), 118-126.

Oger, P., & Sudre, B. (2013). Water, sanitation and hygiene and cholera epidemiology: An Integrated Evaluation in the Countries of the Lake Chad Basin. Dakar, Senegal: UNICEF WCARO, 2011: 1–107.

Oguntunde, P. G., Abiodun, B. J., & Lischeid, G. (2011). Rainfall trends in Nigeria, 1901-2000. *Journal of Hydrology, 411*(3-4), 207-218. doi: 10.1016/j.jhydrol.2011.09.037

Oguntunde, P. G., Abiodun, B. J., & Lischeid, G. (2012). Spatial and temporal temperature trends in Nigeria, 1901-2000. *Meteorology and Atmospheric Physics, 118*(1-2), 95-105. doi: 10.1007/s00703-012-0199-3.

Oluleye, A., and A. Akinbobola. (2010). Malaria and pneumonia occurrence in Lagos,Nigeria: Role of temperature and rainfall. *African Journal of Environmental Science and Technology, 4*(8), 506-516.

Omotosho, J. B. (2008). Pre-rainy season moisture build-up and storm precipitation delivery in the West African Sahel. *International Journal of Climatology, 28*(7), 937-946. doi: 10.1002/joc.1548

Osei, F. B., & Duker, A. A. (2008). Spatial and demographic patterns of Cholera in Ashanti region - Ghana. *International Journal of Health Geographics, 7*. doi: 10.1186/1476-072x-7-44.

Owusu, K., & Waylen, P. (2009). Trends in spatio-temporal variability in annual rainfall in Ghana (1951-2000). *Weather, 64*(5), 115-120. doi: 10.1002/wea.255

Palmgren, H. (2009). Meningococcal disease and climate. *Global Health Action, 2*(0). doi: 10.3402/gha.v2i0.2061.

Parker, D. J., Burton, R. R., Diongue-Niang, A., Ellis, R. J., Felton, M., Taylor, C. M., Tompkins, A. M. (2005). The diurnal cycle of the West African monsoon circulation. *Quarterly Journal of the Royal Meteorological Society, 131*(611), 2839-2860. doi: 10.1256/qj.04.52

Pascual, M., Bouma, M. J., & Dobson, A. P. (2002). Cholera and climate: revisiting the quantitative evidence. *Microbes and Infection, 4*(2), 237-245.

Pascual, M., & Dobson, A. (2005). Seasonal patterns of infectious diseases. *Plos Medicine, 2*(1), 18-20. doi: 10.1371/journal.pmed.0020005.

Pascual, M., Rodo, X., Ellner, S. P., Colwell, R., & Bouma, M. J. (2000). Cholera dynamics and El Nino-Southern Oscillation. *Science, 289*(5485), 1766-1769.

Patz, J. A. (2000). Climate change and health: New research challenges. *Ecosystem Health, 6*(1), 52-58.

Patz, J. A., Campbell-Lendrum, D., Holloway, T., & Foley, J. A. (2005). Impact of regional climate change on human health. *Nature, 438*(7066), 310-317. doi: 10.1038/nature04188.

Patz, J. A., Epstein, P. R., Burke, T. A., & Balbus, J. M. (1996). Global climate change and emerging infectious diseases. *Jama-Journal of the American Medical Association, 275*(3), 217-223. doi: 10.1001/jama.275.3.217.

Patz, J. A., & Reisen, W. K. (2001). Immunology, climate change and vector-borne diseases. *Trends in Immunology, 22*(4), 171-172. doi: 10.1016/s1471-4906(01)01867-1.

Patz, J. A., Vavrus, S. J., Uejio, C. K., & McLellan, S. L. (2008). Climate Change and Waterborne Disease Risk in the Great Lakes Region of the US. *American Journal of Preventive Medicine, 35*(5), 451-458. doi: 10.1016/j.amepre.2008.08.026.

Paz, S. (2009). Impact of Temperature Variability on Cholera Incidence in Southeastern Africa, 1971–2006. *Ecohealth, 6*(3), 340-345. doi: 10.1007/s10393-009-0264-7.

Patz, J. A., & Lindsay, S. W. (1999). New challenges, new tools: the impact of climate change on infectious diseases - Commentary. *Current Opinion in Microbiology, 2*(4), 445-451. doi: 10.1016/s1369-5274(99)80078-2

Peel, M. C., Finlayson, B. L., & McMahon, T. A. (2007). Updated world map of the Köppen-Geiger climate classification. *Hydrol. Earth Syst. Sci., 11*(5), 1633-1644. doi: 10.5194/hess-11-1633-2007

Peltola, H. (1983). Meningococcal disease - still with us. *Reviews of Infectious Diseases, 5*(1), 71-91.

Penrose, K., de Castro, M. C., Werema, J., & Ryan, E. T. (2010). Informal Urban Settlements and Cholera Risk in Dar es Salaam, Tanzania. *Plos Neglected Tropical Diseases, 4*(3). doi: 10.1371/journal.pntd.0000631.

Petoukhov, V., Claussen, M., Berger, A., Crucifix, M., Eby, M., Eliseev, A. V., Weaver, A. J. (2005). EMIC Intercomparison Project (EMIP-CO2): comparative analysis of EMIC simulations of climate, and of equilibrium and transient responses to atmospheric CO2 doubling. *Climate Dynamics, 25*(4), 363-385. doi: 10.1007/s00382-005-0042-3.

Peyrille, P., Lafore, J.-P., & Redelsperger, J.-L. (2007). An idealized two-dimensional framework to study the West African monsoon. Part I: Validation and key controlling factors. *Journal of the Atmospheric Sciences, 64*(8), 2765-2782. doi: 10.1175/jas3919.1

PHE. (2012, April 14). Public Health England. Factsheet on cholera. Retreaved from http://www.hpa.org.uk/Topics/InfectiousDiseases/InfectionsAZ/Cholera/choleraCholerafactsheet/]

Pinner, R. W., Onyango, F., Perkins, B. A., Mirza, N. B., Ngacha, D. M., Reeves, M., Broome, C. V. (1992). Epidemic meningococcal disease in nairobi, kenya, 1989. *Journal of Infectious Diseases, 166*(2), 359-364.

Portmann, F. T., Doell, P., Eisner, S., & Floerke, M. (2013). Impact of climate change on renewable groundwater resources: assessing the benefits of avoided greenhouse gas emissions using selected CMIP5 climate projections. *Environmental Research Letters, 8*(2). doi: 10.1088/1748-9326/8/2/024023

Pradas-Velasco, R., Antonanzas-Villar, F., & Martinez-Zarate, M. P. (2008). Dynamic modelling of infectious diseases - An application to the economic evaluation of influenza vaccination. *Pharmacoeconomics, 26*(1), 45-56.

Rabbani, G. H., & Greenough, W. B. (1999). Food as a vehicle of transmission of cholera. *Journal of Diarrhoeal Diseases Research, 17*(1), 1-9.

Rajendran, K., Sumi, A., Bhattachariya, M. K., Manna, B., Sur, D., Kobayashi, N., & Ramamurthy, T. (2011). Influence of relative humidity in Vibrio cholerae infection: A time series model. *The Indian journal of medical research, 133*(2), 138-145.

R Core Team. (2013, May 15). R language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0, Retrieved from http://www.R-project.org

Redelsperger, J.-L., Thorncroft, C. D., Diedhiou, A., Lebel, T., Parker, D. J., & Polcher, J. (2006). African monsoon multidisciplinary analysis - An international research project and field campaign. *Bulletin of the American Meteorological Society, 87*(12), 1739-+. doi: 10.1175/bams-87-12-1739.

Reiner, R. C., Jr., King, A. A., Emch, M., Yunus, M., Faruque, A. S. G., & Pascual, M. (2012). Highly localized sensitivity to climate forcing drives endemic cholera in a megacity. *Proceedings of the National Academy of Sciences of the United States of America, 109*(6), 2033-2036. doi: 10.1073/pnas.1108438109.

Reingold A.L., A.W. Hightower, G. A. Bolan, E. E. Jones, H. Tiendrebogo, & C. V. Broome. (1985). Age-specific differences in duration of clinical-protection after vaccination with meningococcal polysaccharide-a vaccine. *The Lancet*., **2**, 114 - 118.

Reyburn, R. (2011). Climate Variability and the Outbreaks of Cholera in Zanzibar, East Africa: A Time Series Analysis (vol 84, pg 862, 2011). *American Journal of Tropical Medicine and Hygiene, 85*(1), 191-191.

Riahi, K., Rao, S., Krey, V., Cho, C., Chirkov, V., Fischer, G., Rafaj, P. (2011). RCP 8.5-A scenario of comparatively high greenhouse gas emissions. *Climatic Change, 109*(1-2), 33-57. doi: 10.1007/s10584-011-0149-y.

Richard, V., Tosi, C., Arzel, B., & Kana, N. (1999). Endemic cholera in Chad: a real public health problem. [L'endemisation du cholera au Tchad: un reel probleme de sante publique.]. *Medecine tropicale : revue du Corps de sante colonial, 59*(2), 169-172.

Righetto, L., Bertuzzo, E., Casagrandi, R., Gatto, M., Rodriguez-Iturbe, I., & Rinaldo, A. (2011). Modelling human movement in cholera spreading along fluvial systems. *Ecohydrology, 4*(1), 49-55. doi: 10.1002/eco.122.

Riou, J. Y., Djibo, S., Sangare, L., Lombart, J. P., Fagot, P., Chippaux, J. P., & Guibourdenche, M. (1996). A predictable comeback: The second pandemic of infections caused by Neisseria meningitidis serogroup A subgroup III in Africa, 1995. *Bulletin of the World Health Organization, 74*(2), 181-187.

Roberts, L. (2008). An ill wind, bringing meningitis. *Science, 320*(5884), 1710-1715. doi: 10.1126/science.320.5884.1710.

Rodo, X., Pascual, M., Fuchs, G., & Faruque, A. S. G. (2002). ENSO and cholera: A nonstationary link related to climate change? *Proceedings of the National Academy of Sciences of the United States of America, 99*(20), 12901-12906. doi: 10.1073/pnas.182203999.

Rogerson, P. (2001). *Statistical methods for geography*: Sage.

Rose, J. B., Daeschner, S., Easterling, D. R., Curriero, F. C., Lele, S., & Patz, J. A. (2000). Climate and waterborne disease outbreaks. *Journal American Water Works Association, 92*(9), 77-87.

Rosenstein, N. E., Perkins, B. A., Stephens, D. S., Popovic, T., & Hughes, J. M. (2001). Meningococcal disease. *New England Journal of Medicine, 344*(18), 1378-1388.

Sasaki, S., Suzuki, H., Igarashi, K., Tambatamba, B., & Mulenga, P. (2008). Spatial analysis of risk factor of cholera outbreak for 2003-2004 in a peri-urban area of Lusaka, Zambia. *American Journal of Tropical Medicine and Hygiene, 79*(3), 414-421.

Savory, E. C., Cuevas, L. E., Yassin, M. A., Hart, C. A., Molesworth, A. M., & Thomson, M. C. (2006). Evaluation of the meningitis epidemics risk model in Africa. *Epidemiology and Infection, 134*(5), 1047-1051. doi: 10.1017/s0950268806005929.

Schellnhuber, H. J. (2009). Regional climate change. *Issues in Science and Technology, 25*(3), 19-20.

Schuchat, A., Robinson, K., Wenger, J. D., Harrison, L. H., Farley, M., Reingold, A. L., Perkins, B. A. (1997). Bacterial meningitis in the United States in 1995. *New England Journal of Medicine, 337*(14), 970-976.

Schumacher, C., & Houze, R. A., Jr. (2006). Stratiform precipitation production over sub-Saharan Africa and the tropical East Atlantic as observed by TRMM. *Quarterly Journal of the Royal Meteorological Society, 132*(620), 2235-2255. doi: 10.1256/qj.05.121

Schwanghart, W., & Schütt, B. (2008). Meteorological causes of Harmattan dust in West Africa. *Geomorphology, 95*(3), 412-428.

Schwartz, J., & Levin, R. (1999). Drinking water turbidity and health. *Epidemiology, 10*(1), 86-90. doi: 10.1097/00001648-199901000-00017.

Segele, Z. T., Lamb, P. J., & Leslie, L. A. (2009). Large-scale atmospheric circulation and global sea surface temperature associations with Horn of Africa June-September rainfall. *International Journal of Climatology, 29*(8), 1075-1100. doi: 10.1002/joc.1751

Semenza, J. C., & Menne, B. (2009). Climate change and infectious diseases in Europe. *Lancet Infectious Diseases, 9*(6), 365-375.

Shao, Y., Wyrwoll, K.-H., Chappell, A., Huang, J., Lin, Z., McTainsh, G. H.,Yoon, S. (2011). Dust cycle: An emerging core theme in Earth system science. *Aeolian Research, 2*(4), 181-204. doi: 10.1016/j.aeolia.2011.02.001.

Shuman, E. K. (2011). Global climate change and infectious diseases. *The international journal of occupational and environmental medicine, 2*(1), 11-19.

Simmons, A., Uppala, S., Dee, D., & Kobayashi, S. (2007). ERA-Interim: New ECMWF reanalysis products from 1989 onwards. *ECMWF newsletter, 110*(110), 25-35.

Snowden, F. M. (2008). Emerging and reemerging diseases: a historical perspective. *Immunological Reviews, 225*, 9-26. doi: 10.1111/j.1600-065X.2008.00677.x

Solomon, S., Alley, R., Gregory, J., Lemke, P., & Manning, M. (2008). A closer look at the IPCC report. *Science, 319*(5862), 409-410.

Soro, B. N., Rey, J. L., Davis, C. E., Coulibaly, A., & Diomande, I. (1988). Epidemiological aspects of meningitis in the north of the Ivory Coast. [Elements d'epidemiologie des meningites dans le nord de la Cote-d'Ivoire.]. *Medecine tropicale : revue du Corps de sante colonial, 48*(2), 145-148.

Speelmon, E. C., Checkley, W., Gilman, R. H., Patz, J., Calderon, M., & Manga, S. (2000). Cholera incidence and El Nino-related higher ambient temperature. *Jama-Journal of the American Medical Association, 283*(23), 3072-3074. doi: 10.1001/jama.283.23.3072-a.

Stanwellsmith, R. E., Stuart, J. M., Hughes, A. O., Robinson, P., Griffin, M. B., & Cartwright, K. (1994). Smoking, the environment and meningococcal disease - a case-control study. *Epidemiology and Infection, 112*(2), 315-328.

Stocco, C., Leite, M. D., Labiak, V. B., das Virgens, J. S., & Nascimento, E. (2010). Influence of Climatic Variables on the Incidence of Meningitis and its Space Distribution in the City of Ponta Grossa-PR, 2001-2005. *Saude E Sociedade, 19*(1), 84-93.

Suk, J. E., & Semenza, J. C. (2011). Future Infectious Disease Threats to Europe. *American Journal of Public Health, 101*(11), 2068-2079. doi: 10.2105/ajph.2011.300181.

Sultan, B. (2005). Influence of climate upon the meningitis onset in West Africa. *M S-Medecine Sciences, 21*(5), 470-471.

Sultan, B., & Janicot, S. (2000). Abrupt shift of the ITCZ over West Africa and intra-seasonal variability. *Geophysical Research Letters, 27*(20), 3353-3356. doi: 10.1029/1999gl011285.

Sultan, B., & Janicot, S. (2003). The West African monsoon dynamics. Part II: The "preonset" and "onset" of the summer monsoon. *Journal of Climate, 16*(21), 3407-3427. doi: 10.1175/1520-0442(2003)016<3407:twamdp>2.0.co;2.

Sultan, B., Janicot, S., & Diedhiou, A. (2003). The West African monsoon dynamics. Part I: Documentation of intraseasonal variability. *Journal of Climate, 16*(21), 3389-3406. doi: 10.1175/1520-0442(2003)016<3389:twamdp>2.0.co;2

Sultan, B., Labadi, K., Guegan, J. F., & Janicot, S. (2005). Climate drives the meningitis epidemics onset in West Africa. *Plos Medicine, 2*(1), 43-49. doi: 10.1371/journal.pmed.0020006.

Sutherst, R. W. (2004). Global change and human vulnerability to vector-borne diseases. *Clinical Microbiology Reviews, 17*(1), 136-+. doi: 10.1128/cmr.17.1.136-173.2004.

Sylla, M., Diallo, I., & Pal, J. (2013). West African Monsoon in State-of-the-Science Regional Climate Models.

Talavera, A., & Perez, E. M. (2009). Is cholera disease associated with poverty? *J Infect Dev Ctries, 3*(6), 408-411.

Tarhule, A., & Woo, M. K. (1998). Changes in rainfall characteristics in northern Nigeria. *International Journal of Climatology, 18*(11), 1261-1271. doi: 10.1002/(sici)1097-0088(199809)18:11<1261::aid-joc302>3.3.co;2-q.

Taylor, K. E., Stouffer, R. J., & Meehl, G. A. (2012). AN OVERVIEW OF CMIP5 AND THE EXPERIMENT DESIGN. *Bulletin of the American Meteorological Society, 93*(4), 485-498. doi: 10.1175/bams-d-11-00094.1.

Thisday. (2014, January 13). NEMA: 16,470 Displaced Nigerians in refugee camps. *Thisday Live*. Retrieved from http://www.thisdaylive.com/articles/nema-16-470-displaced-nigerians-still-live-in-refugee-camps/166659/.

Thomson, A. J. (2010). Climate indices, rainfall onset and retreat, and malaria in Nigeria. *Journal of Vector Borne Diseases, 47*(4), 193-203.

Thomson, A. M., Calvin, K. V., Smith, S. J., Kyle, G. P., Volke, A., Patel, P., Edmonds, J. A. (2011). RCP4.5: a pathway for stabilization of radiative forcing by 2100. *Climatic Change, 109*(1-2), 77-94. doi: 10.1007/s10584-011-0151-4.

Thomson, M. C., Connor, S. J., Ward, N., & Molyneux, D. (2004). Impact of Climate Variability on Infectious Disease in West Africa. *Ecohealth, 1*(2), 138-150. doi: 10.1007/s10393-004-0004-y.

Thomson, M. C., Jeanne, I., & Djingarey, M. (2009). Dust and epidemic meningitis in the Sahel: a public health and operational research perspective. *Wmo/Geo Expert Meeting on an International Sand and Dust Storm Warning System, 7*. doi: 10.1088/1755-1307/7/1/012017.

Thomson, M. C., Molesworth, A. M., Djingarey, M. H., Yameogo, K. R., Belanger, F., & Cuevas, L. E. (2006). Potential of environmental models to predict meningitis epidemics in Africa. *Tropical Medicine & International Health, 11*(6), 781-788. doi: 10.1111/j.1365-3156.2006.01630.x.

Thorncroft, C. D., & Blackburn, M. (1999). Maintenance of the African easterly jet. *Quarterly Journal of the Royal Meteorological Society, 125*(555), 763-786. doi: 10.1256/smsqj.55501

Thorncroft, C. D., Hanh, N., Zhang, C., & Peyrille, P. (2011). Annual cycle of the West African monsoon: regional circulations and associated water vapour transport. *Quarterly Journal of the Royal Meteorological Society, 137*(654), 129-147. doi: 10.1002/qj.728

Tikhomirov, E., Santamaria, M., & Esteves, K. (1997). Meningococcal disease: Public health burden and control. *World Health Statistics Quarterly, 50*(3-4), 170-177.

Tobias, A., Cayla, J. A., Pey, J., Alastuey, A., & Querol, X. (2011). Are Saharan dust intrusions increasing the risk of meningococcal meningitis? *International Journal of Infectious Diseases, 15*(7), E503-E503. doi: 10.1016/j.ijid.2011.03.008

Tomozeiu, R., Pavan, V., Cacciamani, C., & Amici, M. (2006). Observed temperature changes in Emilia-Romagna: mean values and extremes. *Climate Research, 31*(2-3), 217-225. doi: 10.3354/cr031217.

Trærup, S. L. M. (2010). The health impacts of climate change: A study of cholera in Tanzania. In B. c. f. c. c. (BC3) (Ed.), *BC3 Working Paper Series 2010-01*. Bilbao, Spain.

Tu, J. V. 1996. Advantages and disadvantages of using artificial neural networks versus logistic regression for predicting medical outcomes. *Journal of Clinical Epidemiology,* 49**,** 1225-1231.

Tuite, A. R., & Fisman, D. N. (2011). A Transmission Model of the 2010 Cholera Epidemic in Haiti RESPONSE. *Annals of Internal Medicine, 155*(6), 404-404.

UCAR. (2012, June 30). Forecasting to fight Meningtis. *Atmos News*: Retreived from https://www2.ucar.edu/atmosnews/impacts/forecasting-fight-meningitis

UNEP. (2005). Environment for a Secure Future' and 'Protecting Nature's Capital *UNEP 2005 Annual Report* (pp. 80): United Nations Environment Programme.

UNHCR. (2014, March 22). 2014 United Nation Human Commission for Refugees (UNHCR) Regional operation profile – West Africa. Retrieved http://www.unhcr.org/pages/49e484f76.html

UNICEF. (2013, April, 18). *Report on* the*Progress on drinking water and sanitation, report update 2012. UNICEF/WHO, New York.* Retrieved from http://www.unicef.org/media/files/JMPreport2012.pdf

Uppala, S. M., Kallberg, P. W., Simmons, A. J., Andrae, U., Bechtold, V. D., Fiorino, M., Woollen, J. (2005). The ERA-40 re-analysis. *Quarterly Journal of the Royal Meteorological Society, 131*(612), 2961-3012. doi: 10.1256/qj.04.176.

van der Werf, G. R., Randerson, J. T., Giglio, L., Collatz, G. J., Mu, M., Kasibhatla, P. S., van Leeuwen, T. T. (2010). Global fire emissions and the contribution of deforestation, savanna, forest, agricultural, and peat fires (1997-2009). *Atmospheric Chemistry and Physics, 10*(23), 11707-11735. doi: 10.5194/acp-10-11707-2010.

van Oldenborgh, G., Drijfhout, S., Van Ulden, A., Haarsma, R., Sterl, A., Severijns, C., Dijkstra, H. (2009). Western Europe is warming much faster than expected. *Climate of the Past, 5*(1).

van Lieshout, M., Kovats, R. S., Livermore, M. T. J., & Martens, P. (2004). Climate change and malaria: analysis of the SRES climate and socio-economic scenarios. *Global Environmental Change-Human and Policy Dimensions, 14*(1), 87-99. doi: 10.1016/j.gloenvcha.2003.10.009.

van Vuuren, D. P., Den Elzen, M. G. J., Lucas, P. L., Eickhout, B., Strengers, B. J., van Ruijven, B., van Houdt, R. (2007). Stabilizing greenhouse gas concentrations at low levels: an assessment of reduction strategies and costs. *Climatic Change, 81*(2), 119-159. doi: 10.1007/s10584-006-9172-9.

Venables, W. N., & Ripley, B. D. (2002). *Modern applied statistics with S*: Springer.

Vestrheim, D. F., Hoiby, E. A., Aaberge, I. S., & Caugant, D. A. (2010). Impact of a Pneumococcal Conjugate Vaccination Program on Carriage among Children in Norway. *Clinical and Vaccine Immunology, 17*(3), 325-334. doi: 10.1128/cvi.00435-09.

Vizy, E. K., Cook, K. H., Crétat, J., & Neupane, N. (2013). Projections of a Wetter Sahel in the Twenty-First Century from Global and Regional Models. *Journal of Climate, 26*(13), 4664-4687. doi: 10.1175/jcli-d-12-00533.1.

Wallenstein, S., & Wittes, J. (1993). The power of the Mantel-Haenszel test for grouped failure time data. *Biometrics*, 1077-1087.

Wahdan, M. H., Rizk, F., Elakkad, A. M., Elghorou.Aa, Hablas, R., Girgis, N. I., Cvjetano.B. (1973). Controlled field trial of a serogroup a meningococcal polysaccharide vaccine. *Bulletin of the World Health Organization, 48*(6), 667-673.

Washington, R., Harrison, M., Conway, D., Black, E., Challinor, A., Grimes, D., Todd, M. (2006). African climate change - Taking the shorter route. *Bulletin of the American Meteorological Society, 87*(10), 1355-+. doi: 10.1175/bams-87-10-1355.

Watson, J. T., Gayer, M., & Connolly, M. A. (2007). Epidemics after natural disasters. *Emerging Infectious Diseases, 13*(1), 1-5.

Weil, A. A., Khan, A. I., Chowdhury, F., LaRocque, R. C., Faruque, A. S. G., Ryan, E. T., Harris, J. B. (2009). Clinical Outcomes in Household Contacts of Patients with

Cholera in Bangladesh. *Clinical Infectious Diseases, 49*(10), 1473-1479. doi: 10.1086/644779.

Weniger, B. G., Blaser, M. J., Gedrose, J., Lippy, E. C., & Juranek, D. D. (1983). An outbreak of waterborne giardiasis associated with heavy-water runoff due to warm weather and volcanic ashfalL. *American Journal of Public Health, 73*(8), 868-872. doi: 10.2105/ajph.73.8.868.

WHO. (1998). Working Group, 1998: Control of epidemic meningococcal disease: WHO practical guidelines. 2nd ed. WHO/EMC/BAC/98.3, 84pp. Lyon: Foundation Marcel Merieux.

WHO. (2003). McMichael A.J., Campbell-Lendrum D.H., Corvalan C.F., Ebi K.L., Githeko A.K., Scheraga J.D., Woodward A. Climate Change and Human Health. Risks and Responses, *World Health Organisation* Press.

WHO. (2005a). Kuhn, K., Campbell-Lendrum., et al. (2005). Using climate to predict infectious disease epidemics. *Communicable Diseases Surveillance and Pesponse, Protection of the Human, Roll Back Malaria* (Vol. ISBN 92 4 159386 5). Geneva 2005: World Health Organisation. Geneva, Switzerland

WHO. (2005b). *The treatment of diarrohoea, a manual for physicians and other senior health workes. 4th revision*. Retreaved from http://whqlibdoc.who.int/publications/2005/9241593180.pdf

WHO. (2010). managing meningitis epidemic in Africa: A quick reference guide for health authorities and health-care workers. WHO/HSE/GAR/ERI/2010.4, 23pp. Retrieved from http://whqlibdoc.who.int/hq/2010/WHO_HSE_GAR_ERI_2010.4_eng.pdf

WHO. (2011a, July 13). *1997 Conqeuring Suffering Enriching Humanity WHO Health Report. Geneva: World Health Organisation*. Retreived from http://www.who.int/whr/1997/en/

WHO. (2011b, August 2). 2000 World Health Organisation's Report on Global Surveillance of Epidemic-prone Infectious Diseases: Retrieved form http://www.who.int/csr/resources/publications/surveillance/WHO_CDS_CSR_ISR_2000_1/en/

WHO. (2011c, August 6). *Global Burden of Diseases: 2004 update WHO Report. Switzerland, Geneva: World Health Organisation.* Retreaved from http://www.who.int/healthinfo/global_burden_disease/GBD_report_2004update_full.pdf

WHO. (2011d, August 11). *Prevention and control of cholera outbreaks: World Health Organisation policy and reccomendations.* Retreived from http://www.who.int/cholera/technical/prevention/control/en/

WHO. (2011e, August 28). Global Health Observatory (GHO). *Data and statiatics: World Health Organisation*. Retreived from http://www.who.int/research/en/ WHO data and statistics 2011 June, 25

WHO. (2012a, May 19). Meningococcal meningitis. Retreaved from http://www.who.int/mediacentre/factsheets/fs141/en/

WHO. (2012b, June 17). *Cholera fact sheet N107, 2012*. Retreaved from http://www.who.int/mediacentre/factsheets/fs107/en/]

WHO. (2012c, April 21). *Cholera vaccines: WHO position paper, 2010*. Retreaved from http://www.who.int/wer/2010/wer8513.pdf]

WHO. (2013a, April 22): Climate change and health. Retreaved from http://www.who.int/mediacentre/factsheets/fs266/en/].

WHO. (2013b, June 18). *Global task force on cholera control. Cholera country profile*: Nigeria. Last updated January, 2012. Retreaved from http://www.who.int/cholera/countries/NigeriaCountryProfile2011.pdf

Wilby, R., & Dawson, C. (2012). The Statistical DownScaling Model: insights from one decade of application. *International Journal of Climatology*.

Wilby, R. L., & Dawson, C. W. (2013). Statistical DownScaling Model–Decision Centric (SDSM-DC) Version 5.1 Supplementary Note.

WMO. (2012, November 15): *1995 alphanumeric codes. Manual on codes, Vol. I.1, Part A, WMO Publ. 306. 9*. Retrieved from http://www.wmo.int/pages/prog/www/ WMOCodes.html]

Woodruff, R. E., Guest, C. S., Garner, M. G., Becker, N., Lindesay, J., Carvan, T., & Ebi, K. (2002). Predicting Ross River virus epidemics from regional weather data. *Epidemiology, 13*(4), 384-393. doi: 10.1097/01.ede.0000016601.23748.1d.

World Bank. (2012, Februaty 24). *Nigeria: Data*. Retreaved from http://data.worldbank.org/country/nigeria

Xue, Y., De Sales, F., Lau, W. K. M., Boone, A., Feng, J., Dirmeyer, P., Wu, M.-L. C. (2010). Intercomparison and analyses of the climatology of the West African Monsoon in the West African Monsoon Modeling and Evaluation project (WAMME) first model intercomparison experiment. *Climate Dynamics, 35*(1), 3-27. doi: 10.1007/s00382-010-0778-2.

Yaka, P., Sultan, B., Broutin, H., Janicot, S., Philippon, S., & Fourquet, N. (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*. doi: 10.1186/1476-072x-7-34

Zhang, X., & Yang, F. (2004). RClimDex (1.0) user manual. *Climate Research Branch Environment Canada, Downsview*.

Zhang, X. B., Hegerl, G., Zwiers, F. W., & Kenyon, J. (2005). Avoiding inhomogeneity in percentile-based indices of temperature extremes. *Journal of Climate, 18*(11), 1641-1651. doi: 10.1175/jcli3366.1

Zhang, C., Nolan, D. S., Thorncroft, C. D., & Nguyen, H. (2008). Shallow meridional circulations in the tropical atmosphere. *Journal of Climate, 21*(14), 3453-3470. doi: 10.1175/2007jcli1870.1