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COLLEGE OF HEALTH SCIENCES
UNIVERSITY OF GHANA, LEGON

WEATHER VARIABILITY ON ALL-CAUSE AND MALARIA-SPECIFIC MORTALITY IN THREE GEOGRAPHICAL ZONES IN GHANA

BY

ELIZABETH AKOLPOKA AWINI
(10363122)

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DECLARATION

I Elizabeth Akolpoka Awini do hereby declare that, with the exception to the references to the literature and works of researchers, which have been duly acknowledged, this thesis is the result of my original work under the guidance of my supervisors.

Elizabeth A Awini	________________	_______________
(PhD CANDIDATE)	SIGNATURE	DATE
Dr. Patricia Akweongo	__________________	_______________
(PRIMARY SUPERVISOR)	SIGNATURE	DATE
Prof. Philip B. Adongo	__________________	_______________
(SECONDARY SUPERVISOR)	SIGNATURE	DATE
Prof Heiko Becher	__________________	_______________
(SECONDARY SUPERVISOR)	SIGNATURE	DATE

DEDICATION

I wish to dedicate this work of mine to the almighty God for granting me the strength throughout this study and my late parents Mr. Awini Agana and Ms Azoya Akaara through whose efforts I have reached this far.

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LIST OF ABBREVIATIONS

ABBREVIATION	MEANING
ABR	Annual Biting Rate
ACT	Artemisinin-Based Combination Therapy
AEIR	Annual Entomological Inoculation Rate
AIC	Akaike Information Criteria
ANC	Antenatal Care
ARI	Acute Respiratory Infection
AS-AQ	Artesunate Amodiaquine
CHERG	Child Health Epidemiology Reference Group
CHOs	Community Health Officers
CHPS	Community-based Health Planning and Services
CKIs	Community Key Informants
DHIMS	District Health Information Management System
DHDSS	Dodowa Health Surveillance System
DHRC	Dodowa Health research Centre
DOF	Degree of freedom
DSA	Demographic Study Area
GBD	Global Burden Disease
GCV	Generalized Cross Validation

GDHS	Ghana Demographic and Health Survey
GNMCP	Ghana National Malaria Control Programme
GHS	Ghana Health Service
GAMs	Generalized Additive Models
GAMMS	Generalized Additive Mixed Models
GMA	Ghana Metrological Agency
GSS	Ghana Statistical Survey
GWR	Geographical Weighted Regression
HDSS	Health and Demographic Surveillance System
HRS	Household Registration System
HRB	Household Registration Book
ICD	International Classification Diseases
IIDP	Infectious Diseases of Poverty
INDEPTH	International Network for the Demographic Evaluations of Population and their Health in Developing Countries
IPTp	Intermittent Preventive Treatment for Pregnancy
IPTc	Intermittent Preventive Treatment or Children
IRS	Indoor Residual Spray
ITNs	Insecticide Treated Nets
Inter VA	Interpreting Verbal Autopsy
KEMRI	Kenya Medical Research Institute

KHRC	Kintampo Health Research Centre
KHDSS	Kintampo Health Demographic Surveillance System
LISA	Local Indicator of Spatial Association
MA	Moving Averages
MDG	Millennium Development Goals
NMCP	National Malaria Control Programme
NHRC	Navrongo Health Research Centre
NHDSS	Navrongo Health Demographic Surveillance System
OPD	Out Patient Department
PACF	Partial Auto Correlation Function
PCA	Principal Component Analysis
PE	Protective Efficacy
PMI	President Malaria Initiatives
RDT	Rapid Diagnostic Test
RBM	Roll Black Malaria
SP	Sulphadoxine-Pyrimethamine
SSA	Sub-Sahara Africa
TDR	Special programme for Research and Training in Tropical Diseases
UNICEF	United Nation Children's Fund
USAID	United States Agency for International Development
UNDP	United Nations Development Program

VA	Verbal Autopsies
WHO	World Health Organization

ABSTRACT

Background: Climate change with its associated weather variability affects health leading to mortality. It is estimated that climate change contributed 0.2% of the world's annual mortality. Mortality in Ghana is mainly due to malaria, diarrhea, acute respiratory infection, cardiovascular diseases, maternal, neonatal, and road traffic accident, most of which are weather related. Also, relatively high clustering of deaths in the population can hinder efforts to reduce mortality if these clusters are not identified for targeted intervention. This study therefore was to examine the relationship between temperature, rainfall and mortality (all-cause and malaria-specific) and also the clustering of deaths across three geographical zones in Ghana.

Methods: The study utilized longitudinal data (2006-2012) from three Health and Demographic Surveillance Systems (HDSSs) located in three geographical zones (Dodowa-coastal belt, Kintampo-middle belt and Navrongo-northern savannah belt) in Ghana. Data points or variables such as individual identification number, sex of individual, date of birth, date of death or exit, place of death and household assets were extracted from the HDSS sites. Georeferenced data was also collected from the sites. Weather data for the study were obtained from Ghana Meteorological Agency (GMA). Monthly mortality and weather data were generated from the daily data. A Bayesian probability model for interpreting VA, InterVA-4 was used to determine malaria deaths for this analysis. Generalized additive models were fitted with quasi-Poisson link functions to assess the association between monthly mortality and weather variables (temperature, rainfall) allowing for over-dispersion. Trend and seasonal variables were used to adjust for covariates and also model the expected mortality at all-time points. Natural cubic splines were used to adjust for nonlinear time varying covariates. The analysis was stratified by sex, age and socioeconomic status. SaTScan software version 8 was used to determine spatiotemporal distribution of deaths in HDSS sites. This was done for all ages and for children under-five.

Results: Descriptive analysis reveals seasonal patterns of all-cause and malaria-specific mortality. Higher rates of mortality were observed during the rainy season. Association of weather variables (temperature, rainfall) and monthly mortality was evident. The findings indicate that the effect of weather variable on health and mortality varies with location. For children under-five years of age, all-cause mortality was associated with mean temperature in the month of death in Dodowa with relative risk (RR) of 1.315(95% CI, 1.022, 1.692). The RR associated with rainfall below 34.1mm in the previous one month was 1.294 (95% CI, 1.014, 1.651). In Kintampo, the RR associated with rainfall below 22.8mm in the month of death was 0.7666 (0.5961, 0.9858) and that of the previous two months was 0.6940(0.5639, 0.8542). In Navrongo, temperature above 29.3°C was associated with mortality RR=1.549 (95% CI, 1.219, 1.969). For malaria-specific mortality, the RR with higher temperature in the previous three months in Kintampo was 0.6921(0.5174, 0.9260). In Navrongo, the RR with low mean temperature in the previous three months was 1.554 (95% CI, 1.024, 2.359). For under-five malaria-specific mortality, temperature and rainfall in the previous one month significantly associated with mortality in Dodowa. In Kintampo and Navrongo, temperature in the previous three months significantly associated with mortality. The spatiotemporal analysis revealed significant clustering of high mortality in all HDSS areas. Clusters were observed in deprived areas and those close to water bodies.

Conclusion: The findings from this study demonstrate that temperature and rainfall are associated with all-cause and malaria-specific mortality. There is also clustering of mortality in the HDSS sites. This provides information that can assist in interventions for climate change adaptive measures. The results will also assist health managers in the study districts to deliver targeted health services.

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CHAPETR ONE: INTRODUCTION

1.1 Background

The ability to have a healthy long life is an essential part of human development, thus survival can be said to be a measure of a country's development. Survival and life expectancy in developing countries is low and thus mortality remains a public health problem in the developing countries. Though there have been improvements in life expectancy over the years worldwide, that of developing countries is still low (UNICEF, 2012). Sub-Saharan Africa still has the highest child mortality rates with an under-five mortality rate of 92/1,000 live births in 2013 (UNICEF, 2014). This rate is higher than 15 times the average rate for the developed countries.

A worldwide systematic analysis of mortality in men and women aged 15-59 indicated that mortality rates varied among countries and within countries over time (Rajaratnam et al., 2010). It was found that substantial increases in adult mortality occurred in sub-Saharan Africa between 1970 and 2010. For instance, male's mortality rates for Germany declined from 192 per 1,000 in 1970 to 102 per 1,000 in 2010, while male mortality in Algeria declined from and 306 per 1,000 in 1970 to 130 per 1,000 in 2010. However, for the same period, male mortality rates in Cameroon, Nigeria and Ghana increased from 372 per 1, 000 in 1970 to 439 per 1,000 in 2010, 282 per 1,000 in 1970 to 381 per 1,000 in 2010 and 278 per 1,000 in 1970 to 347 per 1,000 in 2010 respectively. Similar variation in mortality was observed for women (Rajaratnam et al., 2010).

The burden of malaria in Sub-Saharan Africa as a contributor to mortality cannot be overemphasized as it is responsible for many deaths worldwide (Ding et al., 2014). Though the 2016 World Malaria report indicated that malaria cases had reduced globally, the burden in Africa remains high (WHO, 2017). About 90% of the world's malaria cases and 91% of malaria deaths were from Africa. Malaria is responsible for many deaths and is the leading cause of deaths and years of life lost due to premature mortality in Africa (Lozano et al., 2013). Though there have been several interventions in the form of case management and control, Ghana is still battling with malaria burden. Evidence from the National Malaria Control Programme indicates that about 10.4 million malaria cases were recorded in 2016 (GNMCP, 2017). Malaria is first among the top ten causes of diseases in Ghana and contributed 38% of all outpatient cases reporting at the health facilities in the country in 2016 (GHS Annual report, 2017). The report also indicated that malaria was first on the list of the top ten causes of inpatient deaths.

Studies have indicated that climate change and weather variability can have implications on health resulting in increase in morbidity and mortality (Åström, Bertil, & Joacim, 2011; Yu, Mengersen, et al., 2011).

Climate change is likely to have various health effects, including changes in the distribution and seasonal transmission of vector-borne diseases. Extreme weather events have been observed during the periods of very elevated temperature, heavy rains and flooding, storms and droughts that cause injury, illness, famine, loss of livelihood and sometimes death. Extreme weather events often stress populations beyond adaptation limits in terms of coping with the negative health effects from these events (McMichael, Woodruff, & Hales, 2006). For example, exposure to extreme weather such as heat waves has been associated with both increased morbidity and mortality (Kovats, Campbell-Lendrum, & Matthies, 2005; Luber & McGeehin, 2008; Yu et al., 2012). These extreme weather conditions have had increasing public health concerns due to its negative impact on human and are projected to further increase according to the Intergovernmental Panel on Climate Change (Field, 2012). However, the impact of these weather events has not been adequately described in Sub-Sahara Africa. The association between extreme weather conditions and mortality is well documented in the developed countries but not so in most developing countries, including Ghana. Few studies in Africa that investigated the association between mortality and season in terms of rainy and dry seasons observed that all-cause mortality peaked in the rainy season (Abdullah et al., 2007; Becher et al., 2008); in terms of time of the year, observed high mortality risk in January and August (Elabbasy & Semary, 2013) or second and third quarters of the year (Mutisya et al., 2010). Understanding the spatial distribution of diseases or death is important for the implementation of appropriate health interventions in areas where these are needed most. Mortality could remain comparatively high because of clustering of deaths in the population, even though overall mortality levels are declining (Omariba, 2004). Studies on clustering of under-five mortality in the then Kassena-Nankana, Kintampo and Dangme West districts in Ghana indicated that there were hot spots or high concentration of all-cause under-five deaths in these areas (Adjuik et al., 2010; Awini et al., 2010; Nettey et al., 2010). This study intends to use Health and Demographic Surveillance System (HDSS) data and weather data from the three HDSS sites in Ghana to determine the relationship between temperature, rainfall and mortality (all-cause and malaria-specific) and also examine the spatial distribution of these deaths.

1.2 Problem Statement

Generally, mortality in Ghana is still high. The rate of decline of mortality in Ghana reported in 2015 was 2.6. With this level of decline, Ghana is likely to miss its sustainable development goals (SDG) target of 25/1,000 live births by 2030. Child mortality rates declined from 127 per 1,000 live births in 1990 to 62 per 1,000 live births in 2015 (UNICEF, 2015). Mortality in Ghana is mainly due to malaria, diarrhea, acute respiratory infection (ARI), cardiovascular diseases, maternal, neonatal and road traffic accident, most of which are weather related. Though the number of malaria cases and deaths have reduced globally, the burden in Ghana is still high. The nation recorded 10.4 million suspected malaria cases at the outpatient department (OPD) in 2016 (GNMCP,2017). Ghana Health Service 2016 annual report also attributed 24.5% of inpatient deaths to malaria (Ghana Health Service, 2017).

Climate change with its associated weather variability affect health leading to mortality (Parry, 2007; Ramin & McMichael, 2009). WHO attributed 0.2% of the world's annual mortality to climate change (WHO, 2009). Notwithstanding this official report, it is likely that the burden might be worst especially in Sub-Sahara Africa since it is predicted to face a heavy burden of climate change and has inadequate adaptive capacity and more vulnerable people (Costello et al., 2009). This could have contributed to the high mortality levels that still exist in Ghana. Also, efforts to reduce mortality could be mired due to comparatively high clustering of deaths in the population (Omariba, 2004). Studies indicate that high clusters of all cause under-five mortality exist in Ghana (Adjuik et al., 2010; Awini et al., 2010; Nettey et al., 2010). However, the effect of climate change on mortality and spatial distribution on all cause and malaria specific mortality for all ages in Ghana remains unknown leading to poor targeting of health interventions to achieve the desired health outcomes. This study sought to determine the association of temperature, rainfall and mortality and the spatial distribution of deaths using large Health and Demographic Surveillance System (HDSS) data in three geographical zones in Ghana.

1.3 Conceptual Framework: Weather Variability and All-cause and Malaria-specific Mortality in Ghana

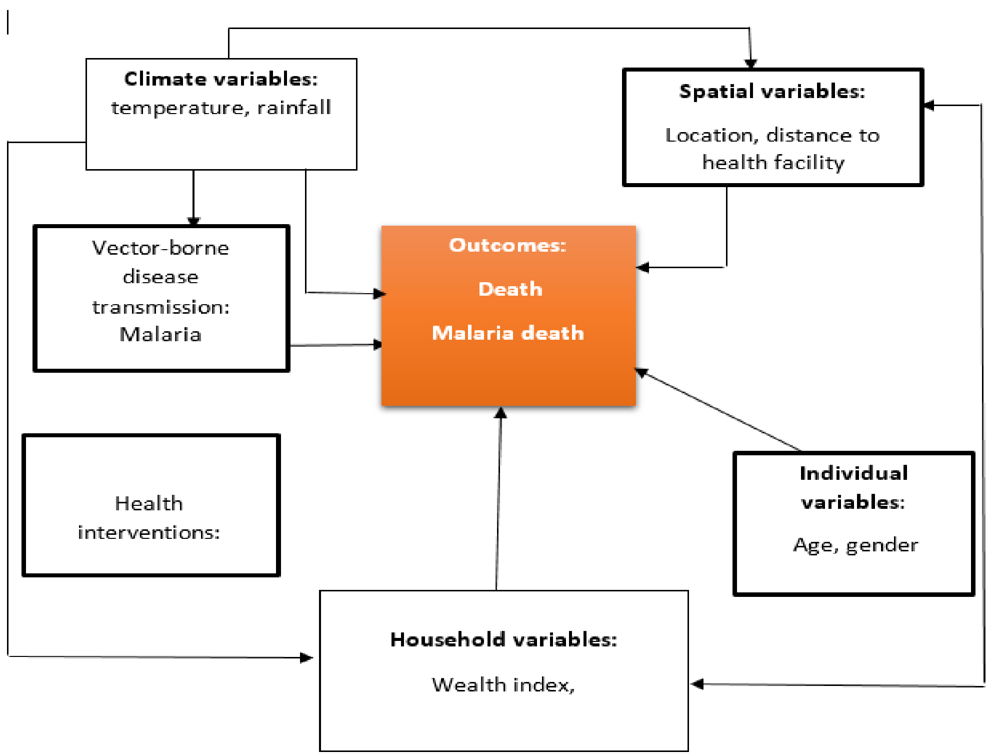

Figure 1: Conceptual framework for modelling weather variability and all-cause and malaria-related mortality [adapted from Mosely & Chen, 2003 and modified]

The conceptual framework adapted for this study is an analytical framework for the study of child survival in developing countries proposed by Mosely & Chen. The principle behind the framework is that all social and economic determinants of child mortality essentially operate through a common set of proximate determinants (biological mechanism) to have effect on mortality. That is, child mortality is due to the influence of social, economic, biological and environmental forces (Mosley & Chen, 2003). The key aspects discussed by the model were proximate determinants which include maternal, environmental and nutritional factors, injury and personal illness control. It discusses how these determinants come to play in the survival of a child.

For the maternal factors, the variables considered in the model include age, parity and birth order; those of the environment include air, insect vectors, water, food and soil. The variables for personal sickness control also include personal preventive measures and medical treatment.

Socioeconomic determinants, which operate through proximate determinants, include individual level variables such as individual productivity, attitudes and norms; household variables such as income and community level variables such as ecological, political, economic and health system among others. This framework is being adapted and modified to model weather variability and all-cause and malaria-specific mortality and how these deaths are spatially distributed.

Weather variability can cause death directly or indirectly. Excess mortality can be experienced from direct impact of varying extreme weather events (floods, heat waves, droughts and hurricanes). Extreme weather events can also affect human health through the transmission of vector-borne, waterborne and food-borne diseases (Burgess, Deschenes, Donaldson, & Greenstone, 2011; Deschênes & Greenstone, 2007; Parry, 2007).

Weather variability can also affect health indirectly through its effect on individual or household income or socioeconomic status. Households can get economic shocks through weather variability as a result of its negative effect on agricultural produce, business and others (Becker, 2007; Deschenes & Greenstone, 2007).

Spatial variables such as location or where an individual lives can have effect on accessibility such as access to health facility, good drinking water, food and others which can lead to mortality

The distribution of disease and deaths outcomes have been found to vary both in space and in time (Musenge, Vounatsou, Collinson, Tollman, & Kahn, 2013; K. Sartorius et al., 2013). This is as a result of remoteness of health facility, location, socioeconomic status, environment, and culture or intervention disparities.

Household indicators of wealth; access to water; access to sanitation; education; occupation and gender of household head can have effect on the care seeking behavior and health outcome of a household member. Household wealth can also determine the type of food they eat, type of work they do and where they live. Studies on determinants of mortality have identified household socioeconomic status as a significant factor (Bello & Joseph, 2014). Access to water and sanitation of a household has effect on the health outcomes of its members. Poor water source and sanitation facilities are linked to negative health outcomes and as such increase in mortality (Bello & Joseph, 2014; El Azar et al., 2009; Kolahi, Rastegarpour, Abadi, & Gachkar, 2010).

1.4 Justification

Analysis of population and individual levels data from three HDSS sites in Ghana will enable the assessment of the effect of weather variability, mortality and the spatial distribution of deaths on all ages and malaria-specific deaths.

Findings from this study will contribute in guiding policy makers on the appropriate and specific interventions that target specific areas and at the right time.

Information on weather variability and mortality will contribute in identifying appropriate adaptive measures and the best strategies to use for the various settings in the country. The vulnerable groups will also be identified for the appropriate intervention.

The results from this study will also contribute in informing the evaluation of the impact of malaria interventions on mortality that is being conducted in the country.

Identification of spatial distributions of mortality will not only help support informed decision making but also help greatly in concentrating limited resources and efforts on areas of high clusters of mortality.

1.5 General Objective

This study investigated the relationship between weather variability (temperature, rainfall) and mortality and the spatiotemporal distribution of all-cause and malaria-specific mortality at the Dodowa, Kintampo and Navrongo Health and Demographic Surveillance Sites (HDSSs) in Ghana (2006-2012).

1.5.1 Specific Objectives

1. To determine the association between monthly temperature, rainfall and all-cause mortality.

2. To determine the association between monthly temperature, rainfall and malaria-specific mortality.

3. To determine spatiotemporal distribution of all-cause mortality

4. To determine spatiotemporal distribution of malaria-specific mortality

CHAPTER TWO: LITERATURE REVIEW

2.0 Introduction

This chapter examined the literature in relation to the study objectives. The literature on mortality was examined, looking at child mortality, adolescent mortality and adult mortality. It was also examined on the global level, continent and country level. Economic burden of malaria was also reviewed in this chapter. Information on malaria transmission, morbidity and mortality was also reviewed. Brief literature on health intervention for malaria such as insecticide treated nets, indoor residual spray and intermittent preventive treatment and management of malaria with artemisinin-based combination therapy (ACTs) has also been presented.

The literature also examined the relationship between temperature, rainfall and mortality. Work done on the relationship between weather variability and mortality was examined including spatial distribution of deaths. The various methods used to investigate the relationship between weather variability and mortality were also examined.

2.1 Method of literature search

Scoping searches was done to inform the search strategy and to assess the volume and the type of literature relating to the study that existed. PubMed, Medline and Google scholar were used for the draft search. The search terms used included: temperature and mortality, temperature and malaria mortality, temperature and malaria-specific mortality, rainfall and mortality, weather and malaria-specific mortality, Season and mortality, daily temperature and malaria-mortality, ambient temperature and malaria specific mortality, effect of daily temperature on malaria-specific mortality, effect of average temperature on mortality, effect of average temperature on malaria-specific mortality, mortality due to rainfall, Malaria specific mortality due to rainfall, daily rainfall and mortality.

The search was done considering the relevance of the information and period. The general search strategy included:

- Searching of electronic bibliographic databases
- Supplementary searching (including references of including studies, citation searching and searching of relevant websites

The databases used include; Medline, EMBASE, PubMed, Dissertation databases, Grey literature databases, reviews, citation and related articles and search engines such as Google Scholar

2.2 Global Mortality Burden

Mortality rates are high in developing countries. Under-five mortality rate worldwide has been estimated as 6.3 per 1000 live births in 2013 with about 50% of these deaths coming from Sub-Sahara Africa (Liu et al., 2014). Most of the countries that failed to achieve MDGs targets for 2015 were from sub-Saharan Africa.

Findings from a systematic analysis of population health data revealed that in 2004, 2.6 million deaths worldwide occurred in adolescents 10-24 years of age (Patton et al., 2009). About 97% (2.56 million) of them were said to be from the developing countries.

A systematic analysis of mortality in men and women aged 15-59 indicated that mortality rates varied among countries (Rajaratnam et al., 2010). It was found that substantial increases in adult mortality occurred in sub-Saharan Africa between 1970 and 2010 which was mainly because of HIV/AIDS. Masquelier and colleagues observed that though child morality declined in SSA over a thirty year period, 1970 to 2000, adult mortality either became stagnant or increased (Masquelier, Reniers, & Pison, 2014). Estimated trends of adult mortality in Africa indicated that the decline in mortality was slower in Western and Eastern Africa compared to the other three regions of Africa (Reniers, Masquelier, & Gerland, 2011).

These high mortality rates in SSA also contribute to low economic development (Lorentzen, McMillan, & Wacziarg, 2008) in that human resource are lost through the death of an individual. Man hours and resources wasted during the funeral also slow development. It is thus not surprising that Stenberg et al., (2014) in their analysis estimated that investing in health yields returns as much as nine times.

It was observed in a systematic analysis of causes of child mortality that 44.8% of under-five deaths in 2008 were attributed to malaria. Some of the other major causes were diarrhea (15.2%), pneumonia (12.8%) and other infectious diseases (10.5%) (Black et al., 2010). About 10% of adult (15+years) deaths in a rural district of southern Ghana between 2006 and 2010 were said to be attributed to malaria (Awini et al., 2014)

2.3.0 Malaria morbidity and mortality

The burden of malaria globally and more especially in Africa is high as it is responsible for many deaths worldwide (Ding et al., 2014). It is the leading cause of morbidity and mortality in most Africa countries (Guinovart, Navia, Tanner, & Alonso, 2006). It is a major contributor of outpatient and inpatients cases at the hospitals (Okiro et al., 2011) with those under-five years being most affected (Kiggundu et al., 2013; Okiro et al., 2013; Roca-Feltrer et al., 2012). It was found that malaria (16.6-25.8%) and pneumonia (16.5-21.1%) were the leading causes of deaths in children under-five in Uganda, Rwanda and

Ghana (Li Liu, Li, Cummings, & Black, 2015). This burden is more pronounced in children and in pregnant women. The children are more vulnerable due to the fact that their clinical immunity to the malaria parasite is low. Though adults have high immunity, this is normally reduced during pregnancy putting pregnant women at more risk of malaria (Adams, Darko, & Accorsi, 2004). Malaria has also been said to contribute to anaemia in both children and adults especially in the vulnerable groups since *Plasmodium vivax* infection is associated with reduction in haemoglobin (Douglas et al., 2012; Phiri et al., 2012) and this can also lead to many years of life with disability (Pasricha, 2014)

2.3.1. Malaria Morbidity

Globally, the population at risk of *P. falciparum* malaria in 2007 was estimated to be 2.37 billion (Guerra et al., 2008) with 451 million clinical cases (Hay et al., 2010). Cibulskis and colleagues, however, estimated 225 million malaria cases in 2009 though they noted that their estimates were lower than other published data for non-African nations (Cibulskis et al., 2011). From the World Malaria report of 2016, incidence rate of malaria had reduced by 18% from 2010-2016. This notwithstanding, about 216 million cases were recorded in 2016.

Available data indicate that most of the population at risk of malaria is from Africa. Out of the 216 million cases of malaria in 2016, about 90% (194.4 million) of them were said to be from Africa (WHO, 2017). The 2013 World Malaria report alluded to the high burden of malaria in Africa though there was a reduction of malaria incidence by 26% from 2010 to 2015 (WHO, 2014). Only 9 countries in the region, were on track of at least 75% decrease in malaria incidence between 2000 and 2013. A decrease of 50-75% by 2015 was estimated for three countries. Only two countries out of the 17 countries in West Africa achieved a reduction of at least 75%. The rest of the countries in Africa were said to have very little information for the determination of trends. About 333 million people in West Africa were estimated to be at risk of malaria with 322 million at higher risk.

Ghana is still battling with the burden of malaria though there have been a lot of malaria interventions. The Ghana National Malaria Control Programme indicated that about 10 million suspected malaria cases were recorded in the country in 2015 (National Malaria Control Programme, 2016). Available data provided by the World malaria report indicates that the number of admissions due to malaria in the country increased from 400 per 100,000 in 2000 to more than 1600 per 100, 000 in 2012 (WHO, 2014). The burden of malaria morbidity is experienced throughout the country. Malaria was said to be responsible for 38.7% of all outpatient cases reporting at the health facilities in 2016 (GHS, 2016) and has been the first among the top ten causes of diseases. About 1.4% of the pregnant women seen at Out-Patient Department (OPD) were diagnosed with malaria. For admissions, 24.8%, and 46.7% among all inpatients, and under-fives were all due to malaria. A study in Accra using health facility and community data from 2001-2006 found that about 50% of health facility visits for under-fives were attributed to fevers diagnosed as malaria while that of those 5 years and above was 37% (Donovan, Siadat & Frimpong, 2012).

2.3.2 Malaria Mortality

Due to malaria morbidity, malaria mortality still remains a public health problem especially in Africa. Malaria is among the leading causes of childhood death in developing countries. It remains the major cause of infectious diseases' mortality in the tropics. The world malaria 2016 annual report estimated that in the year 2016, malaria was exclusively responsible for 445,000 deaths in the world with children under-five years being the most affected (WHO, 2017). About 40% of the deaths in children under-five years was due to malaria and about 91% of malaria deaths occurred in Africa. Lozano et al., (2013), in their systematic analysis for the Burden of Disease Study 2010, observed that malaria was among the leading causes of years of life lost due to premature mortality in 2010. Malaria mortality rates were observed to be higher in poorer countries confirming that malaria is a disease of poverty.

Few studies done in Africa using verbal autopsies indicated that malaria was the main cause of death in most Africa countries (Abdullah et al., 2007; Becher et al., 2008; Hammer et al., 2006). In these studies, differences in levels of malaria mortality by age group and location were observed. The International Network for the Demographic Evaluation of Populations and Their Health in Developing Countries (INDEPTH) Network estimated malaria mortality in Health and Demographic Surveillance System (HDSS) sites and observed that for West Africa sites, the fraction of deaths attributable to malaria was higher than the other regions and varied from 4.90% to 25.53% (Streatfield, Khan, Bhuiya, Hanifi, et al., 2014). Murray et al., (2012) in their work, global malaria mortality between 1980 and 2010, found that the burden of malaria mortality in children and adults is greater than previously estimated. They however observed a rapid decrease in malaria mortality in Africa. According to the 2013 World Malaria report, malaria mortality had reduced by 40% between 2000 and 2010 (WHO, 2014). Notwithstanding, a greater number of deaths in Africa are still attributable to malaria. From the Ghana national malaria control programme report for 2015, the proportion of in-patient malaria deaths for 2010, 2011, 2012, 2013, 2014 and 2015 were 19. 5%, 18.1%, 12.6%, 12.5%, 7.2 and 7.0% respectively (GNMCP, 2015). In 2016, malaria was first on the list of the top ten causes of inpatient deaths in Ghana (GHS, 2017).

2.3.3 The Economic Burden of Malaria

The economic burden of malaria in sub-Sahara Africa nations is enormous. Malaria is normally referred to as a disease of poverty. It causes febrile illness; chronic debilitation, anaemia, complications in pregnancy and delay in cognitive and physical development (Douglas et al., 2012; Keiser, Singer, & Utzinger, 2005). It imposes cost to both individual and governments. The World Health Organization in its Impact Series; "Malaria Funding and Resource Utilization: The first Decade of Roll Back Malaria", indicated that the cost of malaria to Africa was more than U$12 billion annually, which slowed down economic growth (UNICEF, WHO, & PATH, 2010). It is said to be a contributor to national poverty (Chuma, Thiede, & Molyneux, 2006) and thus, suppressing the transmissions increases productivity and gains is more than six times (Jobin, 2014). Households would have to spend the little resources they have in order to treat malaria episode. This includes purchase of drugs, travel expenses and payments at health facilities (Orem, Kirigia, Azairwe, Kasirye & Walker, 2012) with high indirect cost (Man hours lost either from school or work due to the sickness). Onwujekwe and colleagues estimated the economic burden of malaria on households and the health system and observed that the household average cost for treating malaria was $12.57 per outpatient case and $23.20 per inpatient case. For the health system, both recurrent and non-recurrent provider cost per malaria case were $163.49 and $1,905.17 for outpatient and inpatient respectively (Onwujekwe et al., 2013). A study in northern Ghana on economic cost of malaria under the national health insurance scheme observed that the cost borne by patients for treating one episode of malaria in 2009 was $46.20 (Zakaria & Asante, 2013). A study on the economic cost of malaria in Ghana, Kenya and Tanzania showed that the average cost to both the household and health system for treating an episode of malaria ranged from $5.00 for non-complicated malaria to $288.00 for complicated malaria. (Sicuri, Vieta, Lindner, Constenla, & Sauboin, 2013). In case of deaths, the expenses incurred during burial and productivity losses is enormous (Juliet Nabyonga Orem et al., 2012) The total annual cost for treatment and prevention of malaria in under-fives in Ghana in 2009 was estimated to be $37.8 million. However, when productive loses due to premature deaths was considered, the annual cost was up to $66.9 million in 2009 (Sicuri et al., 2013).

2.3.4 Malaria Transmission

Malaria transmission is high in developing countries leading to the high morbidity and mortality observed. Africa has high malaria transmission with the greatest diversity of parasites, mosquito vectors and human victims (Ghansah et al., 2014). There are five malaria parasite species namely *Plasmodium falciparum*, *P. vivax*, *P. Ovale*, *P. Malariae*, and *P. Knowlesi*. The specie that is widely spread is the *P. Vivax* while *Plasmodium falciparum* is a major cause of morbidity and responsible for most deaths (Douglas et al., 2013). Most countries in Africa are malaria endemic; transmission occurs almost year round. It is however, normally associated with rainfall and temperature (Alemu, Abebe, Tsegaye, & Golassa, 2011; Arab, Jackson, & Kongoli, 2014; Chua, 2012; Dery et al., 2010; Kasasa et al., 2013; Mabaso, Craig, Ross, & Smith, 2007; K. Paaijmans et al., 2008; Parham & Michael, 2010; Patz & Olson, 2006). A study in two rural communities in the forest transition zone of Ghana observed strong and persistent transmission over the study period (December 2003 to August 2005) with Annual Biting Rates (ABRs) of 11,643 and

5,329 and Annual Entomological Inoculation Rates (AEIRs) of 866 and 490 (Abonuusum et al., 2011). ABR is the number of mosquito bites per person per year while AEIR is the number of bites by infective mosquitoes per person in a year. In the forest savanna transitional zone, the AEIRs was 269 and 231 respectively for the periods November 2003 to October 2004 and November 2004 to November 2005 (Dery et al., 2010) while in the mountainous forest region from November 2003 to August 2005, the ABRs ranged from 371 to 1890 in four villages and the AEIRs from 40 to 158 (Badu, Brenya, Timmann, Garms, & Kruppa, 2013). A study observed that, AEIRs in the northern or Guinea Savana belt for three years (2001-2004) were 1132, 193 and 157 respectively from first to the third year (Kasasa et al., 2013). Several interventions both curative and preventive such as case management with artemisinin-based combination therapy (ACTs), indoor residual sprayings (IRS), insecticide treated nets (ITNs) and prophylaxis have all been implemented to break the chain of transmission and to reduce morbidity and mortality (Bhattarai et al., 2007; O'Meara, Mangeni, Steketee, & Greenwood, 2010; WHO, 2008b)

2.4 Health Interventions for managing and controlling Malaria

There have been several interventions to reduce malaria transmission and incidence including the introduction and provision of Insecticide Treated Nets (ITNs), Indoor Residual Spray (IRS), Intermittent Preventive Treatment for Pregnancy (IPTp), Intermittent Preventive Treatment for Children (IPTc) and case management of malaria with artemisinin-based combination therapy (ACTs).

2.4.1 Insecticide Treated Nets

Globally, Insecticide Treated Nets (ITNs) have been proven to be beneficial in reducing morbidity and mortality (Binka et al., 1996; D'alessandro et al., 1995; Lengeler, 2004;

Nevill et al., 1996). A study on the effect of ITNs on mortality of Gambia children observed that all-cause mortality and malaria-specific mortality in the intervention villages were 37% and 30% respectively that of the non-intervention villages in children aged 1-4 years in 1991 (Alonso et al., 1991). This results motivated UNDP/World Bank/WHO Special Programme for Research and Training in Tropical Diseases (TDR) to partner about 20 agencies to launch additional four trials to determine the impact of ITNs on all-cause child mortality in Burkina Faso, The Gambia, Ghana and Kenya (Lengeler, 2004). The Burkina Faso study observed a 15% reduction in all-cause mortality in children aged 6 to 59 months over 2 years of intervention (Habluetzel et al., 1997). The study in Ghana showed that ITNs reduced mortality in 6 months to 4 years of age by 17% (Binka et al., 1996). In Gambia, D'alessandro and colleagues observed a 25% reduction in all-cause mortality in children 1-9 years after a year of intervention with ITNs (D'alessandro et al., 1995) while Alonso *et al*, (1993) found about 60% reduction of all-cause mortality in children age 1-4 years who slept under ITNs in malaria transmission season. Kenya's study found a reduction of 33% mortality in children aged 1-59 months (Nevill et al., 1996). Evidence from these studies led to the recommendation by World Health Organization (WHO) and partners that ITNs be used to prevent malaria and as such reduce mortality (WHO, 2003).

The proportion that had access to ITNs has however, been low. A synthesis of 42 household surveys from 1999-2006 found that the proportion of households with ITNs was 6.7% with a range of 0.1%-71.0% (Miller, Korenromp, Nahlen, & Steketee, 2007). Data from national household surveys for 18 countries in Africa revealed that the percentage of households with an ITN was 34% while 23% of children under-five and 27% of pregnant women slept under ITNs (WHO, 2008b). The Ghana health and demographic survey 2014 (GDHS2014) indicated that 68% of households in Ghana owned at least an ITN while 46.6% of children and 43.3 % of pregnant women used ITNs (GSS, 2014).

There are however, some challenges as provision and the use of ITNs are concerned. Funding for ITNs decreased as Global funding for malaria control declined in 2011. The estimated funding of $2.5 billion for malaria programs in 2012 was less than the estimated amount of $5.1 billion required. Thus the projected 3-year number of ITNs delivered in 2012-2014 (400 million) was less than the minimum required for universal coverage (WHO, 2014). Another global challenge identified among others is the mosquito resistance to the pyrethroid insecticides. The challenges at the national level regarding the provision and use of ITNs in Ghana are inadequate funding, negative attitudes towards ITNs use and wrong perception among others (GNMCP, 2010). The individual challenges as regards to ITN ownership and usage are lack of access, inconvenience and negative perception among others (Azabre, Teye, & Yaro, 2014).

These challenges may lead to low coverage and usage of ITNs which will have negative implication on malaria morbidity and mortality and as such all cause-mortality.

2.4.2 Indoor Residual Spray

Indoor Residual Spray (IRS) as with ITNs, has been proven to be very effective for malaria vector control (Yakob, Dunning, & Yan, 2010). A study in Uganda observed that a child living in IRS district had 32% lower risk of anaemia and 46% lower risk of parasitaemia compared to a child in the non-sprayed district (Steinhardt et al., 2013). A review of data on the effect of IRS for preventing malaria revealed that IRS reduced malaria incidence. A random control trial in Tanzania in 1998 observed that IRS reduced re-infection in children with a protective efficacy of 54% while in Mozambique the IRs reduced malaria prevalence over 7 years period from a range of 60-65% to a range of 4-8% (Pluess, Tanser, Lengeler, & Sharp, 2010). Adu., (2013) in her study on the Impact of IRS on malaria parasitaemia in Obuasi metropolis in Ghana observed that there were significant reduction in parasitaemia levels in school aged children by 52% and 60% after 2 times of spraying and eight times of spraying respectively.

Globally, 4% of the population at risk of malaria was protected by IRS in 2012 while for Africa, the population protected by IRS was 8% (WHO, 2014). As at 2010, about 342,867 structures in eight districts in the Northern region had been sprayed; protecting about 849,620 people from malaria, which exceeded the target of protecting 800,000 people in the districts. This number included 20,014 pregnant women and 177,943 children under-five (USAID, 2010).

The decline in global funding for malaria control in 2011 might have affected funding for IRS activities. The emergence of mosquito resistance to the pyrethroid insecticides is another challenge confronted with the malaria vector control activities. Between 2010 and 2013, 49 out of 63 countries (77.8%) reported insecticide resistance to the malaria vector (WHO, 2014).

In Ghana, some of the major challenges faced with the IRS activities included hard-to-reach communities, long travelling time due to dispersed communities, poor road network, inadequate data and political and cultural sensitivity (USIAD, 2010). Funding for IRS activities at the national level is a challenge since the contribution from Government is less than 10% of the total expenditure (WHO, 2014). These challenges, if not addressed will lead to less protection from malaria and as such decline in reduction in morbidity and mortality due to malaria.

2.4.3 Intermittent Preventive Treatment for pregnancy (IPTp)

Intermittent preventive treatment in pregnancy with sulphadoxine-pyrimethamine (SP) has been proven to be effective in reducing placental *P. falciparum* infection, maternal anaemia and low birth weight. A hospital study in Kenya revealed that IPTp with more than one dose of SP was significantly associated with a reduction of 44% placental malaria and 35% low birth weight (Eijk et al., 2004). A randomized control trial in Kilifi, Kenya on the efficacy of intermittent treatment of doses of SP in preventing malaria and severe anaemia observed that the protective efficacy (PE) against peripheral parasitaemia was 85% while that of severe anaemia was 39% (Shulman et al., 1999). A study in southern Ghana on the effect of IPTp in 2006, a year after its implementation indicated substantial reduction in placental malaria (43-57%) and maternal anaemia (33%) from the levels in 2000 with increase in birth weight (Hommerich et al., 2007).

Notwithstanding the fact that IPTp has been shown to be effective and progress made in implementation, the coverage has not been encouraging (Hill & Kazembe, 2006). Household surveys in 13 countries in the Africa region between 2010 and 2012 indicated that the weighted average of all pregnant women who received at least one dose of IPTp was 37%. However, in 2012, 64% of pregnant women attending antennal care (ANC) received at least one dose of IPTp while 38% received at least two doses (WHO, 2014). The national malaria control programme's 2010 annual report indicated that though the percentage of pregnant women who received two doses of IPT increased from 41.88% in 2006 to 63.0% in 2009, it declined to 49.52% in 2010 (GNMCP, 2010). The 2013 annual report of Ghana Health Service also indicated that the proportion of pregnant women who received two doses of SP decreased from 60.91% in 2012 to 55.4% in 2013 (GHS, 2013).

Besides the decline in global funding of malaria control programmes, resistance to SP experienced in many countries is also a major challenge confronting the use of IPTp. A systematic review on the parasitological efficacy of antimalarial for treating and preventing falciparum malaria in pregnancy observed that most of the drugs tried had low cure rate. In 68% (23/34) of the trials involving SP as ITPp, observed placental-positive rate of >10% (McGready, White, & Nosten, 2011). Apart from the emergence of resistance, implementation or operational challenges also exist. In a systematic review on factors that affect the delivery, access and the use of interventions for the prevention of malaria in pregnancy in sub-Saharan Africa, the authors observed that some of the factors were relatively simple while others were health system and sociocultural issues that will need long-term solutions. Some of these factors were unclear policy and guidelines on IPTp, stock outs, user fees, poor quality of care, confusion over timing of each IPTp dose and poor ANC attendance among others (Hill et al., 2013). The challenges or barriers to the implementation and intake of IPTp in Ghana are not quite different. The low intake of IPTp in Ghana may also be partly attributed to prolonged interruption in SP supply due to challenges associated with procurement and drug quality (GNMCP, 2010).

These challenges have led to a high proportion of pregnant women not receiving the IPTp to protect them and their infants from the risk of malaria and its associated complication. The decline in intake of IPTp has implication for malaria control, which will have effect on mortality decline.

2.5 Malaria Case Management

Artemisinin-based combination therapy (ACTs) has been found to be efficacious and effective for managing malaria cases. A comparative efficacy study of antimalarial drugs was carried out in Ghana in 2003 to assist with the review of the antimalarial treatment policy. The children were randomized to receive chloroquine (CHQ), sulphadoxine-pyrimethamine (SP), artesunate + amodiaquine combination (AS-AQ) and artemether+ lumefantrine (Coartem). It was found that the cure rates for the combination therapies AS-AQ and Coartem on day 28 were 100% and 97.5% respectively while that of the mono therapy SP and CHQ were 60% and 25% respectively indicating resistance to the monotherapy (Koram, Abuaku, Duah & Quashie, 2005).

Due to the resistance of malaria parasite to monotherapy, WHO recommended the use of artemisinin-based combination therapy (ACTs) as first-line treatment for uncomplicated malaria in 1998 (WHO, 2012). Countries that implemented and used ACTs effectively as first-line treatment were reported to have declines in malaria cases (RBM, WHO, & UNICEF, 2005)

Ghana adopted the policy to treat uncomplicated malaria with Artesunate Amodiaquine (AS-AQ) as first-line treatment and quinine for severe malaria in 2004 (WHO, 2012). Though countries still managed malaria with monotherapy despite the WHO recommendation for combination therapy (RBM & WHO, 2005), this had improved with time, with countries using mostly ACTs for malaria case management. A household survey in 9 African countries from 2006-2012 indicated that for children who received antimalarial, 68% received ACTs (WHO, 2014). Almost all outpatient department cases diagnosed as malaria (99.2%) in Ghana in 2010 were managed with ACTs (GNMCP, 2010). This proportion of malaria cases in the country managed with ACTs might however, be less since not all the cases get to the health facility for treatment.

For effective case management of malaria, Ghana adopted the policy that requires all suspected cases of malaria to be confirmed before treatment with ACT in 2008 (WHO, 2012) and a Rapid Diagnostic Test (RDT) recommended for use at community level. However, patients are being given antimalarial without being tested (Stoler, al Dashti, Anto, Fobil, & Awandare, 2014).

Globally, the proportion of reported malaria cases that were tested increased between 2005 and 2010. Africa region however, had lower coverage from 26% in 2005 to 45% in 2010 as compared to Eastern Mediterranean and South-East Asia regions with coverage of 60-91% and 58-95% respectively (WHO, 2014). Data from Ghana national malaria control programme indicated that 77.3% of suspected malaria cases in 2016 were tested with about 56.1% of them testing positive (GNMCP, 2016). This means that about 23% of the cases received presumptive treatment and by implication, about half of these cases might be positive for malaria yet they were all treated with antimalarial and most likely ACTs.

Some of the challenges with the implementation and use of ACTs include the cost of ACTs, failure to follow treatment guidelines by some providers and side effects of ACTs among others.

ACTs are more expensive than the chloroquine and SP making it not affordable for patients and as a result, they continue to treat malaria with monotherapies. Prescription with monotherapy for malaria treatment is also as a result of the long and demand procurement process and at times issues of quality. Failure of health workers to adhere to treatment guidelines also leads to prescription with monotherapy and presumptive diagnosis and treatment (Baiden et al., 2014). Some clinicians and other health workers even treat negative test results cases with antimalarial. The consequence of this is improper management of non-malaria febrile illness since they will all be treated with antimalarial. Expensive ACTs will also be used to treat other illness instead of malaria. These lead to improper management of malaria and non-malaria febrile illness which can lead to mortality.

2.6 Climate change/Weather Variability

Generally, the world is said to becoming warmer with increasing temperatures being experienced more over land and at high northern latitudes and less over the Southern Ocean and Northern north Atlantic. Increases in precipitation has been observed in many regions at higher latitudes while most subtropical and land regions experienced decreases (Balbus, et al., 2013). These changes with its varying extreme weather events such as floods, heat waves, droughts and hurricanes, are expected to have a range of health impact (Hess, McDowell, & Luber, 2012), many of which have already been established. It will have effect on diseases such as water and foodborne diseases (diarrheal diseases), injuries from extreme weather events and many more which are climate sensitive (Balbus et al., 2013). In their review of "climate change and human health: the present and future" McMichael et al., (2006) stated that climate change will affect human health in various ways and most of these will be negative. It is projected that by 2100, climate change will increase the global average temperature by 1.1 C to 6.4C with increasing frequencies of extreme weather events (Medina-Ramón & Schwartz, 2007). The impact of this will be greater on the vulnerable people such as children and the elderly (WHO, 2008a). These health impacts will be determined by the level or degree of weather variability and factors such as social, economic, demographic and infrastructures (Parry, 2007).

2.6.1 Weather variability and Morbidity

Weather variability has been observed to affect the distribution and risk of many vector-borne diseases (Frumkin et al., 2008), water-borne diseases and foodborne diseases as well as emerging infectious diseases. Association between extreme temperatures, rainfall and health outcomes such as emergency hospital visits and hospital admissions have been reported (Bush et al., 2014; Hansen et al., 2008; Jagai et al., 2015; Knowlton et al., 2009; Michelozzi et al., 2009; X. Y. Wang, Barnett, Hu, & Tong, 2009). Ye et al., (2012), concluded in their review of temperature and morbidity that, temperature has a significant short-term effect on all-cause and cause-specific morbidity. Some studies found a non-linear relationship between temperature and morbidity with the minimum morbidity occurring at certain threshold values of temperature and increased below or above this value of temperature (Lin et al., 2009; Linares & Diaz, 2008). These threshold temperature values differed by disease and location (Bayentin et al., 2010). Out-patients visits for several diseases outcomes were found to increase with temperature in Thailand with a lag effect of up to two weeks (Pudpong & Hajat, 2011). Emergency room visits in California (Basu et al., 2012) and hospital admissions in Milwaukee (B. Li et al., 2012) were also found to be associated with temperature. Increased temperature was found to increase hospital emergency room admission. The excess risk in admission for ischemic heart disease was 1.7 per 10^{o}F.

Climate or weather variability has been observed to be associated with malaria incidence or morbidity (D. Alonso, Bouma, & Pascual, 2011; Chretien et al., 2014; Krefis et al., 2011; Luo et al., 2012; K. P. Paaijmans et al., 2010; Patz & Olson, 2006; Silal, 2012; Wayant, Maldonado, de Arias, Cousiño, & Goodin, 2010). Malaria incidence risk changes with weather factors such as temperature, rainfall, humidity and land elevation. Temperature and rainfall are also reported to be strongly related to malaria incidence. Temperature affects malaria transmission by its effects on the *anopheles vector* and *Plasmodium parasite* life cycle. Warm air holds more moisture thereby influencing mosquito survival. The temperature and malaria transmission relationship is so sensitive that an increase in 0.5^{o}C can translate to 30%-100% mosquito abundance. In modelling the effect of temperature change on the extrinsic incubation period and reproductive number of *Plasmodium falciparum* in Malaysia, Chua found that a rise in temperature supported the survival of anopheles mosquitoes (Chua., 2012). However, the extent to which a rise or change in temperature affects the incidence of malaria depends on the baseline temperature and land elevation or altitude. For example, the development time of *Plasmodium falciparum* can be doubled with a 6^{o}C drop at a temperature of 26^{o}C (K. Paaijmans et al., 2008). Some studies found that the suitable temperature range for the survival of mosquito larvae is 20-30^{o}C (Amek et al., 2012b; Kirby & Lindsay, 2009). Others estimated the mean temperature favourable for the development of mosquito vector to be between 25-27^{o}C and the development terminating at 10^{o}C and 40^{o}C (Sewe et al., 2015). Patz and Olson in their model, using data on temperature, rainfall, mosquitoes and malaria estimated the suitable temperature for endemic transmission and spread to be around 32-33^{o}C (Patz & Olson, 2006). Paaijmans and colleagues investigated the link between malaria risk and climate and observed that diurnal temperature fluctuations around average temperatures greater than 21^{o}C slow parasite development while fluctuations around average temperatures less than 21^{o}C speed parasite development compared with constant temperatures (Paaijmans, Read & Thomas, 2009). A study in Ethiopia on climate variables and malaria transmission found that monthly minimum temperature and total rainfall were positively associated with malaria but monthly maximum temperature was negatively related (Alemu et al., 2011). In a study to assess the patterns of climate variables and malaria cases in two ecological zones of Ghana (Ejura in the transition and Winneba in the costal savannah), it was observed that there was a two months lag weak correlation between minimum temperature and malaria cases in both areas. However, for mean monthly maximum temperature, there was a strong negative correlation at zero month lag with mean monthly malaria caseload at the transition zone. The coastal savanna zone had a similar relationship though weak. Positive significant correlations between maximum temperature and malaria caseload were however, observed at lag four-month in the transitional zone and lag two-month in the coastal savanna zone (Klutse, Aboagye-Antwi, Owusu, & Ntiamoa-Baidu, 2014). Most studies also found non-linear relationship between temperature and malaria incidence with a threshold at which a rise or drop in temperature increases the incidence of malaria.

Rainfall also has a non-linear relationship with malaria incidence. Rainfall influences the abundance of mosquito vector by providing breeding sites and aiding their development (Imbahale et al., 2011). The abundance of malaria vector in most endemic areas has been found to be greatest in the wetter part of the year (Bhattarai et al., 2007). However, heavy and continuous rains that result in flooding destroys the breeding sites. Intermittent rains with sunshine provide ideal environment for the mosquito vector development. The population of mosquito vector is correlated with lagged of rainfall. Studies have found increased in malaria cases or incidence after periods of rainfall. Rainfall during the previous week was found to be significantly associated with the mosquito vector *gambiae*. A positive association was observed between rainfall seasonal concentration and

Entomologic Inoculation Rate (EIR) in a study to investigate environmental predictors of malaria transmission in Africa (Mabaso et al., 2007). In their study on economic analysis of climate variability impact on malaria prevalence, Akpalu and colleagues, used data on Ghana and showed that malaria prevalence increased with rainfall (Akpalu & Codjoe, 2013). Krefis and colleagues modelled the relationship between rainfall and malaria incidence in children in Ghana and indicated that preceding rainfall had effect on malaria incidence. They observed that weekly malaria incidence lagged a few weeks behind weekly rainfall. Depending on the village cluster, correlation between malaria incidence and rainfall of nine-week lag and one and two-week lag were observed (Krefis et al., 2011). Klutse et al., (2014) also observed a weak positive relationship between mean monthly rainfall at zero-month lag and mean monthly malaria cases in the two study areas (Ejura and Winneba), though weak. The correlation however strengthened at lag up to four months with a strong negative correlation between two-month lag and malaria caseload in the transition zone. Similar findings were observed by Arab and colleagues in their model of effect of weather and climate on malaria distribution where they showed that both annual average temperature and annual total rainfall were negatively associated with malaria incidence (Arab et al., 2014). Studies done in Kintampo health and demographic surveillance system (HDSS) site on malaria transmission and epidemiology indicated that seasonal abundance of malaria vectors was influenced by micro-ecology, rainfall and temperature (Dery et al., 2010) and that EIR peaked during the minor wet season with high vector abundance at the end of the rains (Owusu-Agyei et al., 2009). Similar findings were observed in the Navrongo HDSS site in a study on spatio-temporal malaria transmission patterns (Kasasa et al., 2013). They found that most bites were in the wet seasons and the

EIR was in September, which was the rainy season. This variability in morbidity leads to mortality if not properly managed.

2.6.3 Weather variability and Mortality

Weather variability can cause death directly or indirectly. Excess mortality can be experienced from direct impact of varying extreme weather events (floods, heat waves, droughts and hurricanes). Extreme weather events can also affect human health through the transmission of vector-borne disease, waterborne and food-borne diseases (Burgess et al., 2011; Deschênes & Greenstone, 2007; Parry, 2007). Weather variability can also enhance the progress of an existing chronic disease leading to death (Bi et al., 2011).

There have been several studies that have investigated the association of weather and mortality. Some of these studies investigated association between mortality and season in terms of rainy and dry and demonstrated an association between mortality and season (Abdullah et al., 2007; Becher et al., 2008). Other studies investigated the association between mortality and season in terms of cold and dry season or the time of the year (Elabbasy & Semary, 2013; Mutisya et al., 2010; Ou et al., 2013). Where cause-specific mortality was considered, there were mostly on cardiovascular, cerebrovascular, and respiratory deaths (Gasparrini, Armstrong, Kovats, & Wilkinson, 2012; Goggins, Chan, Yang, & Chong, 2013; Yu, Hu, et al., 2011).

There has also been some evidence on the association between rainfall and mortality. The associations between monthly, weekly or daily rainfall and mortality have been investigated. Most of these studies found significant effect of rainfall on mortality (Alam, Lindeboom, Begum, & Streatfield, 2012; Azongo, Awine, Wak, Binka, & Oduro, 2012).

2.6.3.1 Temperature and Mortality

Temperature can directly or indirectly affect human health. Exposure to extreme (hot or cold) temperatures can cause morbidity and mortality (Luber & McGeehin, 2008). A number of studies have investigated the effect of temperature on mortality and most of these have demonstrated that temperature was associated with mortality (de'Donato & Michelozzi, 2014; Goggins et al., 2013; Kim, Lim, Woodward, & Kim, 2015; Y.-K. Lin, Chang, Wang, & Ho, 2013; Liqun Liu et al., 2011; Son, Gouveia, Bravo, de Freitas, & Bell, 2015; Wichmann, Andersen, Ketzel, Ellermann, & Loft, 2011; Yang, Ou, Ding, Zhou, & Chen, 2012; Yu et al., 2012). Extreme temperature has effect on health. For instance, the 2003 France heat waves claimed 15,000 lives (Fouillet et al., 2006; Le Tertre et al., 2006) with 2056 excess deaths recorded during the 2006 heat waves (Fouillet et al., 2008) and over 70,000 deaths across Europe due to extreme temperature (Conti et al., 2005; Robine et al., 2008). Cold temperatures are also associated with human health. The Czech Republic cold spells in 1987 and Moscow cod spells in 2006 claimed 274 and 370 lives respectively (Kysely, Pokorna, Kyncl, & Kriz, 2009; Revich & Shaposhnikov, 2008). Minimum apparent temperature was associated with mortality in the cold season with 1^{o}C increase in temperature associated with 1.35% increase in mortality (Analitis et al., 2008). Cold spells in China in 2008 caused a short-term increase in all-cause mortality by 13% (95 % CI: 7–19 %) (Ma et al., 2013).

Temperature is found mostly to show a non-linear relationship with mortality. The risk of mortality increases with rise in temperature above and drop in temperature below certain threshold levels. A study in Kenya observed that temperature was associated with under-five malaria/anaemia mortality. They observed a non-linear relationship between temperature and malaria mortality (Sewe et al., 2015). At mean temperature lag 5-8 weeks, the relationship was an inverted U-shape with malaria/anaemia mortality increasing with mean temperature up to 24^{o}C and then decease gradually. However, at lag 9-12 weeks and lag 13-16 weeks, the observed temperature mortality relationship was J-shape with mortality risk increasing linearly with temperature after 24^{o}C.

2.6.3.2 Rainfall and Mortality

Variations in rainfall can have both direct and indirect impact on human health and mortality (Hess et al., 2012). It causes flood, drought, vector-borne, water-borne and foodborne diseases. A number of studies have examined the relationship between rainfall or season and mortality (Abdullah et al., 2007; Allen & Sheridan, 2014; Azongo et al., 2012; Becher et al., 2008; Burkart et al., 2014a; Díaz-Quijano & Waldman, 2012; Egondi et al., 2012; M. Sewe et al., 2015). Abdullah and colleagues examined the patterns of age-specific mortality in children in endemic areas of sub-Sahara Africa and observed that mortality peaked during the rainy season (Abdullah et al., 2007). Similarly, it was observed that under-five mortality was significantly higher in the rainy season in Burkina Faso. However, for adults, the highest mortality was in the dry season. Malaria mortality in children under-five was observed to be higher during rainy season and shortly after the rains (Becher et al., 2008). A systematic review on the effect of season and meteorology suggested that heavy quantities of rainfall and rising temperature cause seasonal excess on mortality due to infectious diseases (Burkart et al., 2014a). High mortality days were also found to be associated with warmer temperature, decreased pressure and a likelihood of precipitation (Allen & Sheridan, 2014). Rainfall was observed to be significantly associated with dengue mortality (Díaz-Quijano & Waldman, 2012). Egondi *et al.*, (2012) observed that rainfall lag of 0–29 days, increased mortality. Azongo *et al.,* (2012) found that mortality risk increased 1.71% for 10mm increase in rainfall while Mrema et al., (2012) observed 1.4% increase in under-five mortality for 10mm increase in rainfall. The association between rainfall and malaria/anaemia mortality was observed from lag of total rainfall week 5. An inverted U-shape relationship was observed at lags 5-8 weeks and 13-16 weeks with mortality risk increasing up to 180mm of rain and decreasing after 180mm of rain. The relationship between rainfall and mortality at rainfall lag 9-12 weeks was however linear and observed to be the strongest (Sewe et al., 2015).

2.7 Spatial Distribution of Deaths

A wealth of literature exists that indicates morbidity and mortality are spatially distributed. This might be due to factors such as location, distance to health facility, quality of service delivery, socioeconomic status, environment and vulnerability inter alia (Asamoah, Moussa, Stafström & Musinguzi, 2011; Atari & Mkandawire, 2014; Bayentin et al., 2010; Chow, Chuang & Gober, 2012; Escaramís et al., 2011; Kazembe, Kleinschmidt, & Sharp, 2006; K. Sartorius et al., 2013; Verpoorten, 2012). It is evident that morbidity and mortality risk in the developed countries are much lower than the developing countries (Li Liu et al., 2012). Even with the developing countries, some countries have lower risk than others. Abdullah et al, noted that there were differences in mortality risk in seven African countries studied (Abdullah et al., 2007). A study in the whole of USA on geographical dimension of temperature related mortality observed that mortality risk varied among the cities and higher risk was associated with land development, minority residents, low income, young and the elderly (Hondula, Davis, Saha, Wegner, & Veazey, 2015). Studies on clustering of under-five all-cause mortality in the three Health and Demographic Surveillance System (HDSS) sites in Ghana, using data up to 2006 all observed hot spots of mortality within the sites (Adjuik et al., 2010; Awini et al., 2010; Nettey et al., 2010). In the Dodowa HDSS sites, two significant clusters were observed and factors such as distance to health facility and insecticide treated nets (ITNs) ownership, could only explain one of the hot spots (Awini et al., 2010). Significant cluster of under-five mortality were observed in the south-eastern part of the Kintampo HDSS site (Nettey et al., 2010) while at the Navrongo HDSS site, persistently higher clustering of mortality were observed mainly in the north-eastern parts of the site (Adjuik et al., 2010). These studies suggested further studies on clustering of mortality within the study areas.

Spatial distribution of heat related morbidity and mortality has also been widely studied in the developed countries (Bassil et al., 2009; Guo, Barnett, & Tong, 2013; Hattis, Ogneva-Himmelberger, & Ratick, 2012; Johnson et al., 2014; Johnson & Wilson, 2009; Vaneckova, Beggs, & Jacobson, 2010). A study to investigate the association between the spatial distribution of vulnerable population, satellite-detected urban heat island and heat-related mortality distribution in Philadelphia observed that spatial distribution of vulnerable population is consistent with heat-related deaths which were concentrated in higher order surface urban heat island intensity levels (Johnson & Wilson, 2009). An analysis of geographical patterns of heat-related mortality among the aged (65 years and above) in Sydney, Australia observed spatial variation in mortality on very hot days and that those living within 5-20km south-west and west of the central business district were affected more (Vaneckova et al., 2010).

2.8 Methods of Measurements

This section discusses the various measurement methods that had been used to estimate causes of deaths, the relationship between temperature, rainfall and mortality and their spatial distribution.

Methods reviewed on estimation of cause of deaths include physician review, where doctors assign the cause of death by evaluating the information from verbal autopsy questionnaires based on clinical experience; data derived algorithm which uses various analytical techniques to derive the cause of death and Bayesian probability model for verbal autopsy interpretation which is based on physicians' experiences and expertise.

For the association between temperature, rainfall and mortality, the methods reviewed include time series model, generalized linear and generalized additive time series models and case cross-over designs. Methods reviewed on spatial distribution of mortality include scan statistics, spatial Empirical Bayesian techniques and panel model with fixed spatial effects.

2.8.1 Estimation of Cause of Death

Various methods have been used to determine cause of death. Some are global while others are location specific. For instance, WHO, UNICEF and other agencies have tried to estimate cause of deaths globally or regionally while other studies have tried to estimate causes of deaths in-country or specific area where they are working. Most of these studies are disease-specific or age-specific. The global studies make use of these specific studies (Lozano et al., 2013; Murray et al., 2012)

For the global estimates, causes of deaths data are obtained from all sources; vital registration, verbal autopsy, mortality surveillance, censuses, surveys, hospitals, police records and mortuaries. For countries where causes of death data from civil registration are available, the data are grouped by International Classification of Diseases (ICD) codes into cause categories and their proportions to total deaths computed (WHO, 2004). For countries that have incomplete data or no cause of death data from civil registration, epidemiological studies and modeling are used to assign deaths to broad category of causes. Child Health Epidemiology Reference Group (CHERG), established by WHO used published or publicly available data for the estimation of cause of deaths in children (Bryce et al., 2005). In the study on Global Burden of Diseases, Injuries and Risk Factors (GBD 2010), data from all sources; vital registration, verbal autopsy, mortality surveillance, censuses, surveys, hospitals, police records and mortuaries were used to estimate annual deaths for the world and for 21 regions between 1980 and 2010 and established 235 causes (Lozano et al., 2013).

Studies that estimate cause of deaths in developing countries where cause of death data is not available from civil registration rely mostly on verbal autopsies (VA). The caregivers of the deceased are interviewed to ascertain information on the events that led to the death of individuals (Adjuik et al., 2006; Becher et al., 2008; Welaga et al., 2013). There are several methods used to assign cause of death from the VA questionnaires. These include physician review; where doctors assign the cause of death by evaluating the information from the questionnaires based on clinical experience; data driven algorithm, which uses various analytical techniques to derive the cause of death and Bayesian probability model for VA interpretation where probability of a given cause in the presence of a particular symptom/sign is given based on physicians' experiences (Abdullah et al., 2007; Peter Byass et al., 2012; Fottrell & Byass, 2010; Welaga et al., 2013).

The physician review method has been widely used to estimate cause of death in various studies especially those at health and demographic surveillance system sites (Abdullah et al., 2007; Adjuik et al., 2006; Becher et al., 2008). However, of late, the Bayesian probability model for interpreting verbal autopsy version 4 (InterVA4) is being used for multi-country or multi-site data cause of death determination. This method has been used to estimate cause of deaths in 22 sites of the INDEPTH Network (Streatfield, Khan, Bhuiya, Alam, et al., 2014).

This dissertation used the InterVA-4 coding and Bayesian method to assign malaria deaths using verbal autopsy data from the three HDSS sites (six districts). This method was chosen in this study for the assignment of malaria deaths over the Physician coding method because this method is cheaper and faster to use. It also overcomes the inconsistencies associated with Physician coding (Fottrell & Byass, 2010) and is more suitable as the data for the analysis came from three different HDSS sites. The InterVA-4 is based on the 2012 WHO VA tool which has 62 ICD-10 cause groups.

2 .8.2 Association of weather variability and Mortality

The methods mostly used to investigate the relationship between weather variables and mortality are the Time series (Azongo et al., 2012; Bai, Woodward, & Liu, 2014; Diboulo et al., 2012; Egondi et al., 2012; Revich & Shaposhnikov, 2008; M. Sewe et al., 2015; C. Wang, Chen, Kuang, Duan, & Kan, 2014; W. Wu et al., 2013) and cross-over designs (Barnett & Dobson, 2010b; Guo, Barnett, Pan, Yu, & Tong, 2011) and are in either a single or multiple locations. Time series models allow for over dispersion and controls for long term trend and seasonality (Kinney, O'Neill, Bell, & Schwartz, 2008; Kovats & Hajat, 2008; Revich & Shaposhnikov, 2008). Cross-over designs also control for seasonal effect and trends. Other models used are spatial methods which quantify effect of temperature on mortality (Kestens et al., 2011; Smargiassi et al., 2009; Vaneckova et al., 2010).

The main statistical methods mostly used to estimate the effect of weather variables and mortality are time series methods because the data are usually time series of daily, weekly or monthly deaths and weather variables. Models commonly used to study the effect of weather variables and mortality are the generalized linear and generalized additive time series models both of which use calendar time and smoothing to control for season and trend. Generalized linear model was first used by (Zeger, Liang & Albert, 1988) to assess the effect of temperature on human health and generalized additive model was developed by (Hastie & Tibshirani, 1990) who combined the generalized linear model and additive model.

2.8.2.1 Time Series designs

Time series designs present numerous advantages so as to deal with delayed effects of extreme weather conditions (Gasparrini, 2011). Anderson and Bell, (2009) used time series approach to examine heat related mortality in 107 US communities allowing for a nonlinear relationship between temperature and mortality. In this analysis, the mortality counts were stratified by cause while the weather variables were community-specific daily mean, minimum and maximum temperatures and mean apparent temperature. Cubic splines were used to model the non-linear effect of temperature on mortality. Azongo *et al*., (2012) applied the time-series Poisson regression approach to assess the relationship between daily mean temperature and mortality and daily precipitation and mortality at the Navrongo HDSS site in Ghana. Natural cubic function splines were used to control for time trends and seasonality with 3 degrees of freedom. They estimated relative risk as change in mortality risk for every one unit drop below temperatures in the 25th percentile and for every one-unit increase in temperatures above the 75th percentile. Mrema *et al.*, (2012) and Ingole *et al.*, (2012) used similar approaches to estimate the association between weather variables and mortality in rural Tanzania and Vadu HDSS site respectively. The only difference is that Mrema *et al.*, (2012) used monthly mortality counts and weather variables while the others used daily mortality counts and weather variables.

Studies on malaria incidence and mortality indicate long-term effect of weather variables (Krefis et al., 2011; Parham & Michael, 2010; Sewe et al., 2015; Silal, 2012). To examine the association between weather variability and under-five malaria deaths, Sewe *et al.*, (2015) used Poisson regression with weekly lagged weather variables to model the expected number of malaria deaths for each week at KEMRI/CDC HDSS site. Time trend was included in the model to control for confounding and smooth cubic splines used to model the time trend and lagged weather variables. The analysis revealed lagged patterns of rainfall and temperature in malaria/anaemia mortality in children in the area. At lags 9-12 weeks and 13-16 weeks of mean temperature, malaria mortality risk increased with increasing temperature from 24^{o}C and at lag 9-12 weeks of rainfall malaria mortality increased linearly with increased rainfall.

Distributed lags models are used to examine short-term and long-term effects or delayed effects of weather variables since mortality risk can depend on both current and previous days' weather events (Analitis et al., 2008; Baccini et al., 2008).

2.8.2.2 Case-Crossover Design

Another method commonly used of recent times to study the effect of weather variables on mortality is the case crossover designs (Basu, 2009; Basu, Feng, & Ostro, 2008; Medina-Ramón & Schwartz, 2007). This is a special matched case-control study where the cases in the study are used as their own control and as such confounders related to individual are controlled for in the design. This design controls for seasonal effect and trend by use of step-function (Barnett & Dobson, 2010a). With time series data on deaths and weather variables, the weather variable such as temperature on the day of the event is compared with temperature on a nearby control day to study the relationship between temperature and the event. This makes it useful for studying the effects of short-term changes in temperature (Guo et al., 2011).

Case-crossover approach was used to study the association between mean daily apparent temperature and non-accidental mortality in nine counties in California (Basu et al., 2008). In this study, each person served as his or her own control with the temperature on the day of death (case period) compared with temperature on days when death did not occur (reference period). The sensitivity of the results was assessed by conducting time series analysis on the same data. Both approaches gave similar results with the same day lag of apparent temperature having the strongest relationship with mortality (2.3% increase in mortality for 10^{o}F increase in mean daily apparent temperature).

Different studies have used different measure of temperature (mean, minimum, maximum) to examine the effect of temperature and mortality. It is however, observed that the temperature measure depends on the setting because no one temperature measure works best for all climates (Barnett, Tong, & Clements, 2010).

In this study, time series approach was used for studying the relationship between temperature, rainfall and mortality. This method was chosen because they have the advantages to deal with delayed effects of extreme weather conditions (Gasparrini, 2011). It is also possible to control for season and time in the models.

2.8.3 Estimation of Spatial Patterns of Mortality

There are various methods for the determination of spatial patterns. Spatial Empirical Bayesian techniques and spatial scan statistics were used to investigate the spatial patterns and to detect local clusters of high risk of stroke and myocardial infarction mortality in selected counties of east Tennessee in the United States of America (Pedigo & Aldrich, 2011) and under-five mortality in Ghana (Adjuik et al., 2010). In Brazil, Barufi *et al.*, (2012) employed the panel model with fixed spatial effects to explore the factors that were associated with infant mortality rates. They discovered that areas with low clusters of infant mortality were those with improved health care infrastructure and social policy measures. Another method that was commonly used in literature to determine spatial pattern of events was the Geographically Weighted Regression (GWR). It is mainly an exploratory technique used to indicate where non-stationarity is taking place on maps (Chen, Wu, Yang, & Su, 2010; Gebreab & Roux, 2012; Hendryx et al., 2012). GWR shows where locally weighted regression coefficient moves away from their regional or global scale values. Combining Bayesian hierarchical regression models with exploratory spatial data analysis techniques, Sparks and Campbell (2012) compared the effects of both racial and poverty segregation on infant mortality risk in US counties (Sparks, Sparks, & Campbell, 2013). James and Porter used Moran's I statistics and local indicator of spatial association (LISA) statistics and spatially weighted path analysis to study the relationship between factors such as economic and social inequality, health infrastructure and deaths (James & Porter, 2012).

2.8.4 Gaps identified in literature

Though there is a lot of literature on weather variability and mortality, there are a few gaps that this study tried to fill. The literature on the relationship between temperature, rainfall and mortality in Ghana has been on all-cause mortality and limited to data from the northern belt of Ghana. No work has been done on weather variability and malaria-specific mortality in Ghana though much has been done on weather variability and malaria morbidity. The study in Ghana on weather variability and mortality did not also consider effect modification of socioeconomic status or wealth index.

This study used data from the three health and demographic surveillance system (HDSS) sites (six districts) in three geographical zones in Ghana to study the relationship between weather variability (temperature, rainfall) and mortality. Analysis of the relationship between temperature, rainfall and mortality was stratified by sex and age. The relationship between weather variability and malaria-specific mortality and the spatial distribution of deaths were also studied. This study used time series Poisson regression models to analyze the association between weather variability and mortality. Generalized additive models (GAMs) were used while controlling for season and time.

CHAPTER THREE: METHODOLOGY

3.1 Study design

This was a descriptive study that utilized longitudinal secondary data from the three Health and Demographic Surveillance System (HDSS) sites in three geographical zones in Ghana. These HDSSs monitor the population in their catchment areas and collect data on each individual. The outcome variable for the study was number of deaths per month while the main exposure variables were monthly temperature and rainfall and then location. Deaths that occurred between 2006 and 2012 were extracted for the analysis. Unique identification number for each individual (individual id) was used to extract the data points needed for the analysis from relational data tables.

For the relationship between temperature, rainfall and mortality, monthly number of deaths were generated from the daily deaths using their dates of death. Individual number of deaths per each month was generated for the number of years or months stayed in the study area. Similarly, monthly rainfall and mean temperature were generated from the daily records and merged with the monthly mortality data using the year and month of death. For the spatiotemporal distribution of deaths, yearly number of deaths and person years per community or village were generated from the death data. Each community centroid was generated using georeferenced data from each of the study areas. Interpreting verbal autopsy version 4.02 (InterVA-4) was used to ascertain malaria deaths for the analysis.

3.2 Study Areas

Navrongo, Kintampo and Dodowa HDSS sites provided data for the analysis. These sites are strategically located in the three geographical zones in Ghana as seen in Figure 1. Located in the northern savanna belt, the Navrongo HDSS is hosted by the Navrongo Health Research Centre (NHRC). The Kintampo HDSS is in the middle belt and is hosted by the Kintampo Health Research Centre (KHRC) while Dodowa HDSS is located in the coastal belt and hosted by Dodowa Health research Centre (DHRC).

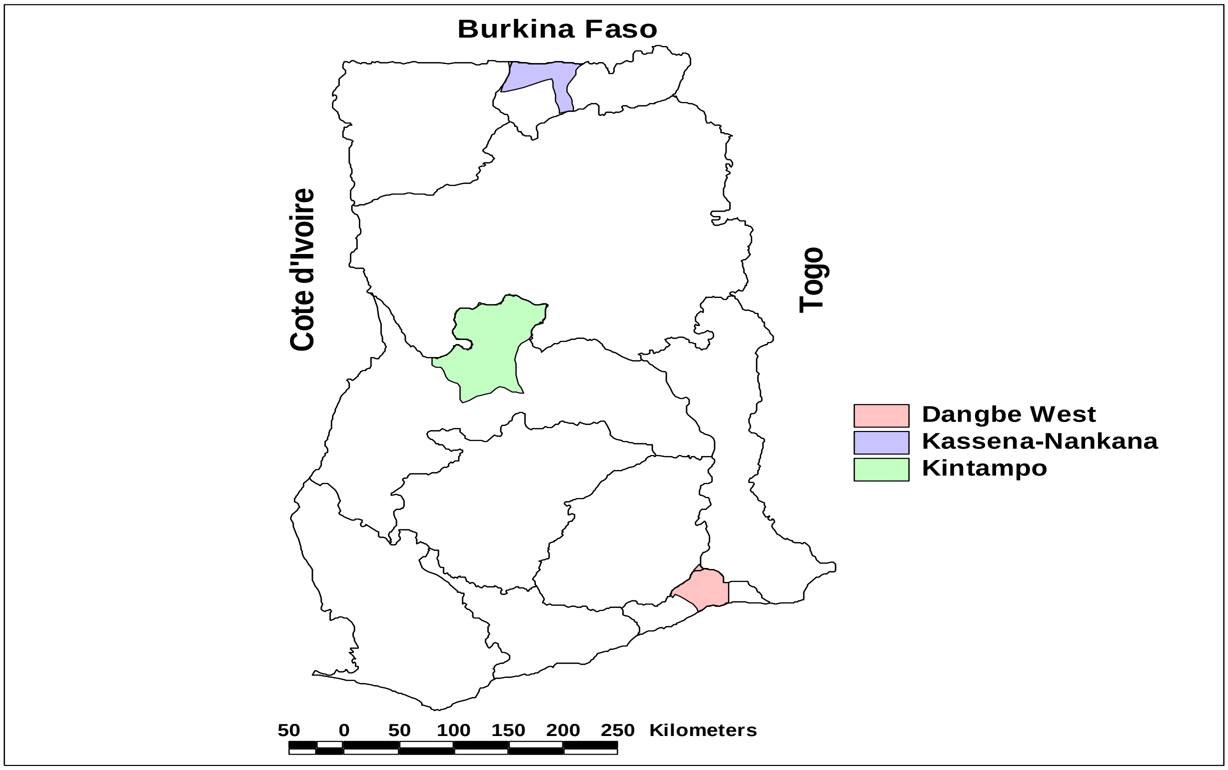

Figure 2: Map showing Health and Demographic Surveillance System Sites in Ghana

3.2.1The Navrongo Health and Demographic Surveillance System (NHDSS) Site

The NHDSS is located in the Upper East region of Ghana which borders Burkina Faso to the north and covers Kassena-Nankana West and East districts, two of the 13 districts in the region. It lies between latitude 10˚ 30' and 11˚ 10' North and longitude 1˚ 10' West. The NHDSS site covers an area of about 1,675 square kilometers with its altitudes stretching to about 400m above sea level. The area is in the Guinea Savana belt with a short rainy season and prolonged dry season from October to March (Oduro et al., 2012). The average annual rainfall is between 850mm and 950 mm. The mean monthly temperature ranges from 18^{o}C to 45^{o}C.

The population of the study area as at June 2014 was 161,429, with females forming about 52.3 percent. About 35.8 percent of the population is less than 15 years, while those 60 years and over constitute 9.5 percent. The area is largely rural, with just about 18 percent of the people living in urban areas (Navrongo and Paga). The population consists of two main ethnic groups from which the area derives its name: the Kassena and the Nankana groups, which form about 49 percent and 46 percent of the population respectively. The main minority ethnic group is the Builsa, who form about three percent of the population. The rest of the population is made up of other ethnic groups from other parts of the country and neighbouring Burkina Faso. About 80% of the households are in the rural area with the residents being mostly subsistence farmers and a few being traders (Kasasa et al., 2013; Oduro et al., 2012). However, there is an irrigation dam and a few dugout wells that supply water for dry season farming,

The main religion in the district had been traditional, with Christianity gradually becoming more prominent. Being largely rural and a traditional society, social behaviour is guided by strong traditional beliefs.

In terms of availability of health facilities, the NHDSS area has two hospitals; one is located in each of the two district capitals. There are also fourteen health centres located in some selected communities. These also include a health centre that is managed by the Catholic mission, as well some others that are owned by private individuals. The area also has 49 functioning Community Health Planning and Service (CHPS) compounds across the entire area. These static health facilities are complemented by community-based health officers

(CHOs) who do periodic visits to houses to deliver door-to-door services in most parts of the study area. Residents also use hospitals in Bolgatanga which is 30km away. Malaria continues to be the major cause of morbidity and mortality in the two districts and together with diarrhea, they account for a high proportion of deaths (Adjuik et al., 2006; Azongo et al., 2012).

3.2.2 The Kintampo Health and Demographic Surveillance System (KHDSS) Site

The KHDSS is located in the middle belt in the Brong Ahafo region of Ghana and covers the Kintampo North and South districts, two of the 27 districts in the region. It lies within the forest-savannah transitional ecological belt. The area lies between latitude 7˚ 43ˈ and 8˚ 44ˈ North and longitude 1˚ 25ˈ and 2˚ 1ˈ West and has an elevation ranging between 60 and 150 metres above mean sea level (Dosoo et al., 2012). The KHDSS site covers an area of about 7,162 square kilometers with a population of approximately 150,615 in about 29,073 households in 156 villages.

The area has a mean monthly temperature ranging from 18^{o}C to 38^{o}C and annual average rainfall of 1,250mm with rainy season occurring mainly between April and October. About 70% of the population lives in the rural area and the main economic activity is farming (crops and livestock) (Dery et al., 2010; Kikuchi et al., 2015; Nettey et al., 2010; Owusu-Agyei et al., 2009; Owusu-Agyei et al., 2012).

In terms of health facilities, the KHDSS has two hospitals, eight health centres, four private clinics, two maternity homes and 64 functional community health planning services (CHPS) compounds (KNMHD, 2014; KSDHD, 2014) as well as a tertiary health educational institution. There are also a number of traditional health facilities within the study area. Apart from these, the nearby districts' hospitals are easily accessible geographically by some of the people of the sub-Districts in the study area.

3.2.3 The Dodowa Health and Demographic Surveillance System (DHDSS) Site

The Dodowa HDSS operates within the boundaries of the Shai-Osudoku and Ningo-Prampram districts which are part of the 16 districts of Greater Accra Region. The region is located in the south-eastern part of Ghana and lies between latitude 5˚ 45ˈ South and 6˚ 05ˈ North and longitude 0˚ 05ˈ East and 0˚ 20ˈ West. The districts or HDSS site covers an area of about 1,528.92 square kilometers, which is about 41.5% of the total land size of the Region. It is about 40.8 kilometers away from the national capital, Accra.

The land is flat and at sea level with isolated hills (Gyapong et al., 2013). Its vegetation is a coastal savannah with a small transitional zone along the foothills of the Akwapim Range and has two rainfall seasons; major and minor. Some parts of the district share boundaries with the Volta Lake, which is a source of water for domestic chores for communities along the lake. Temperatures are appreciably high for most parts of the year with the highest temperatures occurring in the months of November to March and lowest at July to August with an absolute maximum temperature of 40^{o}C. The absence of cloud cover for most parts of the year gives way to very high rates of evaporation which leaves most parts of the district dry and with parched soils.

By December 2010, there were 22,767 households with a population of 111,976 under surveillance but grew to 115,000 by end of 2011. As it is with most communities in developing countries, the population is youthful with about 40% of the population below 15 years of age. Children aged below five years form about 15% of the population. The sex ratio of the population is 87 with 39% of the households being female heads (Gyapong et al., 2013; Kikuchi et al., 2015). Migration rate of the area is high because residents migrate in and out of the Demographic Study Area (DSA) due to the closeness of the study area to major towns and cities such as Accra and Tema. The districts are fairly rural and the inhabitants are engaged in mainly farming, fishing, petty trading and artisanal work.

There are a total of 21 static health facilities delivering health services in the districts. Until 2009, there was no district hospital and residents had to use health centres and clinics or go to the nearer hospitals for health care. Many inhabitants live more than five kilometers away from government health facilities. Malaria, diarrhea, ARI, hypertension and skin diseases are the top five most common diseases seen at the outpatient department (OPD) in the district with malaria ranking first.

3.2.4 Summary characteristics of the study area

Table 1 below presents the summary of each of the HDSS areas. Kintampo has the largest land area, minimum temperature and highest rainfall. Navrongo HDSS was the first to start, while Dodowa HDSS was the latest to start.

Table 1: Summary Characteristics of the HDSS Sites

Characteristics	Dodowa	Kintampo	Navrongo
Year HDSS started	2005	1994	1992
First update round	2006	1995	1993
Number of rounds			
2006	2	2	3
2007	2	2	3
2008	2	2	3
2009	2	2	2
2010	2	2	3
2010	2	2	3
2011	2	3	3
2012	2	3	3

3.3 Structure of Health and Demographic Surveillance System Sites

Data for this study was obtained from the three HDSS sites in Ghana (Navrongo HDSS, Kintampo HDSS and Dodowa HDSS). These HDSS sites are members of the INDEPTH Network which maintains dynamic cohorts and monitors the populations at these sites. A dynamic cohort is an open cohort in which the members can leave or come in at any time. The structure of the HDSS is illustrated in Figure 3.

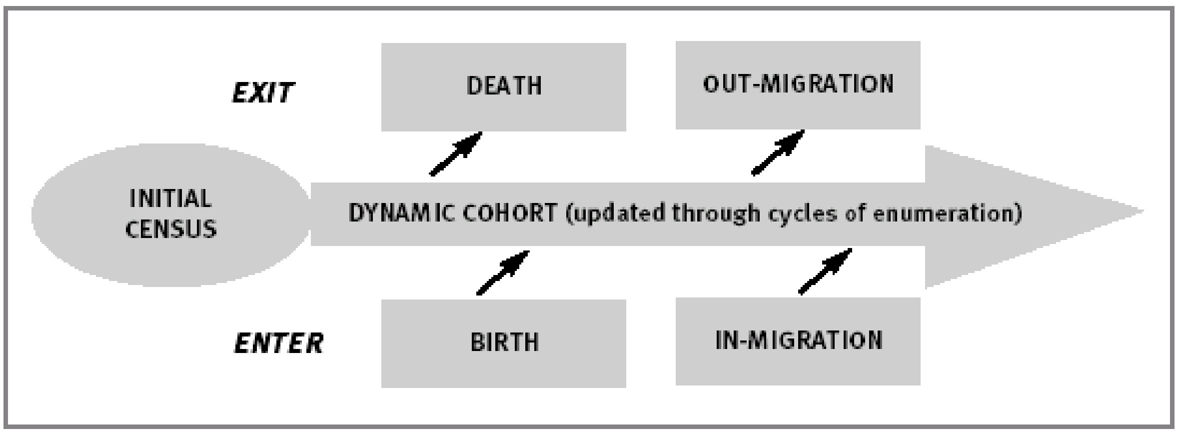

Figure 3: Structure of Health and Demographic Surveillance System

After baseline, (initial census), an individual enters the cohort or become a member of the system by either birth or in-migration. An individual who is in the system exits or leaves the cohort either by outmigration or death.

Activities of HDSSs in Ghana dates back to 1992 when the NHRC started baseline data collection on demographic information of the people. Information collected during baseline includes all individuals in their respective households, their dates of birth, sex, education, occupation, ethnicity and their relationship to each other. Information on household characteristics was also collected.

After the baseline, update commenced in January 1993, where households were visited periodically by trained field workers. During these visits, detail information collected and/or updated included pregnancies, births, marriages, deaths, education, migrations and vaccination status of children. Detail information of all registered events, including dates are also collected on a separate form for each event. For instance, whenever a pregnancy is picked, the estimated date of conception, gestational age, tetanus injection, antennal (ANC) attendance, insecticide treated net (ITN) use and intermittent preventive treatment in pregnancy (IPTp) dose are all recorded. All pregnancies registered are monitored and pregnancy outcome form filled with information on date of delivery, outcome status (live birth or stillbirth) and number of children born to the woman are recorded. If it is a live birth, a separate birth form is filled with details on date of birth, place of birth, antennal (ANC) attendance, IPTp intake and use of ITNs among others.

If a field worker visits a household and a death has occurred, it is registered in a death registration form with information on date and place of death. Trained field supervisors (FSs) then visit family members of the deceased to conduct verbal autopsy (VA) from which cause of death determination is made. The information is obtained by interviewing closed relatives of the deceased or other family members who are familiar with the illness and circumstances leading to the death of the deceased (Becher et al, 2008).

In addition, vaccination status of children is collected/updated during the update rounds and data on household assets, nature of dwelling, IPTp intake and ITN ownership and use are updated annually. Each structure in the HDSS sites is geographically referenced and this data is updated regularly to include new and upcoming housing structures and other relevant features.

Community Key Informants (CKIs) have also been trained to pick events such as pregnancies, births and deaths in their communities to supplement those collected by the field workers. These are volunteers, some of whom are opinion leaders living in the communities of the study area. This is necessary because during periods of two successive visits by field workers, events can be missed which are captured by these CKIs. For all events registered by these CKIs, field supervisors validate them by visiting the households to verify the authenticity or otherwise of those events.

In 1994 and 2005 the KHRC and DHRC respectively established their HDSSs based on the Navrongo model as described above. KHRC started its update in January 1995 while DHRC started its update in January 2006.

3.4 Key Variables

The key variables used for the analysis are shown in Table 1 below

Table 1: Key Variables

Variable	Operation definition	Measurement
Outcome variable		
Death	Death due to any cause	Numeric
Malaria death	Death due to malaria	Numeric
Main exposure variables		
Temperature	Environmental temperature	Numeric values
Rainfall	Cumulative rainfall	Numeric
Location	Geographical location	Coordinates (latitude, longitude)
Other variables		
Wealth index	Wealth index based on assets and possessions of the household	Quintiles (poorest-least poor)
Humidity	Relative humidity	Numeric
Age of individual	Age at death	Numeric
Sex of individual	Sex of individual	Male, female
Date of birth	Date individual was born	Date
Date of death	Date individual died	Date

3.5 Data collection Techniques

Secondary data was used for this study. Data extraction forms were used to extract the data. The forms contained the data points or variables used for the analysis. These included individual identification number, sex of individual, date of birth, date of death or exit, place of death and household assets. The researcher worked with the data managers of the various sites during the extraction of the data or variables. The extraction was done concurrently while merging the various datasets or tables.

The weather data used were also secondary data. The parameters collected included minimum and maximum temperatures, and rainfall. The data was obtained from Ghana Meteorological Agency (GMA), a statutory institution for the provision of meteorological services in Ghana. Satellite stations of the GMA are located closed to the health and demographic surveillance system (HDSS) sites providing the mortality data for analysis in this study.

For the Navrongo HDSS site, weather data were from the satellite station in Navrongo which is a synoptic station that provides data for the entire region. Weather data for Kintampo HDSS site were collected from the satellite stations in Kintampo and Sunyani. Data for the Dodowa HDSS site were from Akuse, located at the eastern boarder of the HDSS.

Average daily temperature for each station was estimated by finding the mean between the minimum and maximum temperatures for that day. These data were then merged with the HDSS death data for the analysis.

3.5.1 Data Management and Extraction (HDSS Data)

The HDSS database is built on a platform of FoxPro (Microsoft Cor., Seattle, USA) database environment and the data are captured and processed using a database called Household Registration System (HRS2) which is a relational model commonly used for HDSS. The database is in FoxPro for windows and is composed of a number of different tables that are related to each other by unique identifiers of individual members in the database. Each table in the relational model has a unique identifier of all households or individual members. The unique identifier in the relational model links information of individual members of household of one table to another. These tables are the "individual table" that contains basic information of the individual such as name, date of birth, sex, educational level, marital status and occupation; the "membership table" contains information on the individual entry type and date, exit type and date, relation to household head and household identification among others. The rest of the tables contain information on each of the events picked. For instance, the Birth table contains information on all births registered such as date, place of birth and mother's identification number among others.

The key variables that were used in this study are individual identification (ID), exit type, deaths, sex, date of birth, date of exit and household assets were extracted from the FoxPro database (DBF) tables and transferred to statistical software, STATA version 13, where the data was cleaned and processed for analysis. Programs or codes were written in STATA to link or merge the variables from the different tables using the unique identifiers. For instance, in order to get the age or date of birth for an individual who is dead, the individual unique identifier was used to merge the "individual table'' and "death table".

3.5.2 Data Cleaning/Processing (HDSS Data)

The data from the three sites were checked for missing values and internal inconsistencies of the responses. Irregularities in the datasets were corrected by using the hard copies of the completed questionnaires and the necessary changes effected. Variables were then recoded where necessary, using STATA version 13. For each of the sites, the individual, membership and the other tables or databases were examined separately before any of them were linked.

3.5.2.1 Dodowa HDSS Data cleaning

From the individual table, three (3) records had problems with their sex. One (1) record had J recorded instead of M or F while for two (2) records, no value was recorded for sex. This was however, checked and the sex corrected and recorded. For the membership table, there were six (6) records with duplicate identification numbers. When these were examined, it was clear that they were true duplicates with all records being the same so one record each was deleted.

Since the study period is between 2006 and 2012, any individual who left the study area before 1st January, 2006 either through death or migration was excluded from the study so, 4,918 records which were in this category were excluded from the analysis. Eighteen thousand five hundred and forty-four (18,544) entered the study area after 31st December, 2012 so these were also excluded from the analysis. About 765 records which had problems with either start date or exit date were checked and rectified. Three hundred and forty-one (341) records were excluded from the analysis because either their start dates were before their birth dates (158) or their end dates were before start dates (183) and the correct dates could not be ascertained.

3.5.2.2 Kintampo HDSS Data cleaning

From the individual table, two (2) records had the same individual identification number but different records for example gender and date of birth so both records were excluded after efforts to rectify them failed. There were, ten (10) records that had a problem with their sex. One (1) record had J, three (3) had N and one (1), S recorded instead of M or F while for five (5) records, no value was recorded for sex. This was however, checked and the sex corrected and recorded. For the membership table, there were ten (10) records with duplicate identification numbers. Eight (8) records had one (1) duplicate each while two (2) records had two (2) duplicates each. When these were examined, it was clear that they were true duplicates with all records being the same so one record each was maintained in the analysis. About 34,949 records were excluded from the analysis because they left the study area before 1st January, 2006 either through death or migrations. Forty-eight thousand, seven hundred and nine (48,709) entered the study area after 31st December, 2012 so were also excluded from the analysis. About 29 records, which had problems with either start date or exit date were checked and rectified. Three hundred and twenty-five (325) records were excluded in the analysis because either their start dates were before their birth dates or their end dates were before start dates and the correct dates could not be ascertained.

3.5.2.3 Navrongo HDSS Data cleaning

From the individual table, three (3) records had the code for sex entered as “N” instead of “M’ (male). This was cross checked and corrected. Five hundred and ninety-nine (599) records were excluded in the analysis because their start dates were before their birth dates.

Eighteen of these records were deaths. For the Navrongo HDSS, data for the period of analysis (2006-2012) were given to me so there were no records that had start dates after 2012 or end date before 2006.

3.5.2.4 Data Cleaning/Processing (Weather Variables)

The daily weather variables for the seven years were checked for missing and implausible values. The satellite station of the GMA in Navrongo provided the needed data for the Navrongo HDSS site. For the Kintampo HDSS site, data from Kintampo and Sunyani satellite stations were used. This was because Kintampo's satellite station did not have enough data for the period. It had only rainfall and humidity data for the analysis period while data for both maximum and minimum temperature covered only two years and one month (January 2006 to January 2008). Initially, data from the Wenchi satellite station was considered since it is a synoptic station and fairly close to Kintampo. However, it was found that Wenchi also did not have temperature data for the whole period of the analysis. Though Wenchi had maximum temperature for all the years, it had only three years minimum temperature (2006, 2007 and 2012). The option was to use Satellite data from the internet, but the correlations were not good enough (Appendix A1). Sunyani satellite station, however, had maximum and minimum temperature data that covered the whole period. The correlation between both minimum and maximum temperature from the Sunyani station and that of Kintampo station for the two years data available was however, relatively higher (Appendix A2). Thus rainfall data from Kintampo and temperature data from Sunyani satellite stations were used for Kintampo HDSS site data analysis.

The Dodowa HDSS site has two proximate satellite stations, Akuse and Afienya. When data from the two stations were examined, it was found that data from the Afienya station had a lot of blanks. Using the Afienya data or trying to get the average between the two stations would have meant dropping some months from the analyses or having to fill in a lot of missing values with assumptions. However, scatter plots of data from the two stations showed a high correlation (Appendix A3). Akuse satellite station however, had blank for only one (1) month September 2012 for the period 2006-2012 and was thus used for the analysis. For the blanks in September 2012, average values of the month of September for the six years was used.

Monthly weather variables were generated from the daily weather data. Monthly average temperature, humidity, wind speed and total rainfall were generated for the analysis. Lag variables for monthly temperature, rainfall humidity were then generated. This was then merged with the monthly mortality data and person year. For the HDSS data, event history analysis was applied, where each individual's person time was calculated for each month for the number of months that the individual stayed at the study site. The number of deaths and person years were then calculated by sex and age group for every month

Trend and season variables were also generated to help adjust for confounding factors and model the expected mortality at all-time points. The lag variables generated were for instance, temperature and rainfall same month (lag0), one month (lag1), two months (lag2) and three months (lag3) before the corresponding mortality count. The purpose of this was to be able to estimate delayed effects of the weather variables on mortality.

3.5.2.5 Distribution of deaths and the choice of monthly analysis over daily or weekly

The deaths from the three sites were recorded as daily events. However, monthly mortality data or deaths, which were created by collapsing the daily mortality counts were used for the analysis. Monthly analysis was chosen to cater for excessive heaping of mortality around the 15th day of every month in the HDSSs as seen in Appendix B1. This may be as result of data collectors' assigning 15th day of the month as the day of the event for a death date that is unknown. About 35.2% of the deaths from the three HDSS were said to have occurred on the 15th day of the month. KHDSS had the highest proportion of deaths recorded as occurring on the 15th day of the month (47.8%) followed by DHDSS recording 40.0% while NHDSS had the lowest proportion (25.1%) of deaths occurring on the 15th day of the month. Consideration was given to weekly analysis but here too, heaping around the third week of the month was observed. Weekly distribution of the deaths for the three HDSS sites are presented in Appendix B2. Performing the analysis on monthly bases allowed for the heaping of deaths on particular days of the month to be removed or reduced (Appendix B3). The day, month and year of death were extracted from the date of death.

3.5.2.6 Re-Distribution of Dodowa HDSS 2006 deaths

For Dodowa HDSS (DHDSS) data however, there was still heaping for June 2006 deaths (Appendix B4). There was however, no known epidemic in the DHDSS during this time. The monthly deaths for 2006 were thus re-distributed. This was done by writing a program in STATA to redistribute the monthly number of deaths in each month in 2006; considering the sex and age group distribution. For instance, the total number of male under-five deaths in 2006 was calculated. The average number of monthly male under-five deaths in 2006 was also calculated. This average was then replaced with the male under-five deaths in June 2006. A new total number of deaths for male under-five deaths in 2006 was then calculated using the new value for June 2006. This was then subtracted from the original total number of deaths in 2006. The difference in deaths was then divided by 12 and added to each month in 2006 including June. This process was repeated for female under-fives and all the four age categories.

Geo-referenced data were checked for blanks and implausible values. The files were converted to shape files for the analysis. Community coordinates were also generated from the compound coordinates for the spatial scan analysis.

3.6. Determination of Malaria Deaths

Interpreting verbal autopsy version 4.02 (InterVA-4) was used to determine malaria deaths for this analysis. This is a Bayesian probability model for interpreting VA where probability of a given cause of death in the presence of a particular symptom/sign is given based on physicians' experiences (Peter Byass et al., 2012).

The VA information used for this analysis were collected using the 2007 WHO VA tool. However, the InterVA-4 was developed based on the 2012 WHO VA tool. A script was thus written to translate the information collected using 2007 WHO VA tool to the 2012 WHO VA tool format. The forms used by the sites to collect the VA information are in three categories for Navrongo and Dodowa HDSS. The forms for neonatal (0-27 days) period, the child (28 days-11 years) and the adults (12 years and above). However, for Kintampo HDSS, four different form categories were used for data collection. These included the infant (0-23 months) form, child (2-11years) form, adult1 (female 12-49 years) and adult (male 12 and above) and female (50 years and above) forms. Each of these form categories was recorded into the 2012 WHO VA tool format. Some of the field/variable names and/or coding differed from site to site so the script was written separately for each site. This then generated the input files that were used in the InterVA-4 model. There is the need to categorise the local condition of malaria and HIV/AIDS into either "low" or "high" when using this model. Since continually, malaria is first on the list of the top ten diseases in Ghana (GHS, 2013), it was categorised as "high" while HIV/AIDS was categorised as "low" in the analysis. The model creates up to three probable causes of death for each individual with their assigned likelihoods. If the sum of the three likelihoods is less than 1, then the residual component is assigned as indeterminate. An individual or a case with limited or inconsistent information is assigned as indeterminate with a likelihood of 1. Registered deaths without VAs were assigned as 'VA not completed'. This group was, however, added to the indeterminate during analysis. Since only malaria deaths were needed in this study, any individual or case with a likelihood of malaria death was considered for malaria death while any individual or case with no likelihood of malaria death was considered as other cause. These likelihoods were then summed up to get malaria deaths for the analysis.

3.7 Estimation of socioeconomic status (Wealth index)

The socioeconomic status is a proxy measure of a household's long-term standard of living; based on social status, assets ownership and availability of utilities, among others. The index measures were combined into a wealth index, using weights derived through principal component analysis (PCA).

PCA is a multivariate statistical technique used to reduce the number of variables in a data set into a smaller number of dimensions. PCA creates uncorrelated components, where each component is a linear weighted combination of the initial variables (Vyas & Kumaranayake, 2006) .

The household assets used were toilet facility, electricity, source drinking water, land, house, motor, bicycle, sewing machine, television, dvd, refrigerator, radio, gas cooker, electric fan, phone, camera, cattle, goat and pigs. All the categorical variables were re-coded into binary variables before applying the PCA. The variables with eigenvalue value greater than one were put together to determine the socioeconomic status of the household of an individual. Normally, a factor is considered significant and worthy of inclusion in the scale if its eigenvalue is greater than the threshold of >1(Bowling, 2014). Asset based wealth measures was chosen for this study because it allows ranking of households and have been shown to be more stable, than other proxy ways of determining socio-economic status (Howe, Hargreaves, & Huttly, 2008).

3.8 Statistical methods

Four Software packages, STATA version 13, R 3.2.2, ArcGIS and Sat Scan, were used for data analysis. All data management processes and some descriptive statistics were done in STATA. STATA and R, were used to fit the time-series models while SaTScan and ArcGIS used to run spatial analysis.

3.8.1 Descriptive Analysis

Summary statistics of monthly mortality data and weather variables were estimated by sex, age and site. Monthly deaths, person years and crude death rates were estimated and presented in Tables (2 &3). Moving averages (MA) of monthly rates were also calculated using the formula; MA (month) =0.25 * rate (month-1) + 0.5 * rate (month) + 0.25 * rate (month+1). With this formula, the first month in 2006 and last month in 2012 had no records. The Box and Whisker plots were used to explore differences in moving average of monthly rates among the 12 different months. Graphs of seasonal patterns of mortality, log of moving averages of monthly rates and weather variables were also plotted and presented using tools from time series analysis.

Monthly crude and sex adjusted rate ratios for all ages and each of the age groups were calculated for each of the sites using the Poisson model. The month of January was used as the baseline where the rate of the other months was compared. This analysis was repeated for malaria deaths from each of the sites. The malaria specific rates and moving averages of the monthly rates were expressed per 1000 person years and plotted.

3.8.2 Modelling the association of weather variables and mortality

Time series methods were used and the Poisson regression models were adapted to estimate the association between weather variables (temperature, rainfall) and mortality at each site. The Generalized additive model (GAM) approach was used to carry out this analysis using the Software package, R version 3.2.2 (2015-08-14). In these models, number of deaths per month was the outcome variable while the exposure variables were the lag strata of temperature and rainfall. The lag periods generated for the analysis were 0 month (lag0), 1 month (lag1), 2 months (lag2) and 3 months (lag3) prior to the event. Season and time trend were also generated and controlled for in the analysis.

3.8.2.1 Generalized additive models (GAM)

Generally, the death rate follows the distribution

$$Y_i = \alpha + \sum_i^n \beta_i \, x_i \qquad (1)$$

which is a Poisson distribution

In generalized additive model (GAM), the second part of equation (1)

$\sum_i^n \beta_i \, x_i$ is replaced with $\sum_{i=1}^n f_i\,(x_i)$ which is a non-parametric function and models the non-linear relationship between the dependent and independent variables. This is done using cubic splines smoothers.

The GAM model used in this analysis is thus given by:

$$Y_t \sim Poisson(\mu_t)$$

$$\log(\mu_t) = \alpha + \sum_{t=1}^{12} s\left(\chi_{it,df}\right) + s\left(time_{t,df}\right)$$

Where Y_t is the observed monthly mortality counts on month t; t is the month of the observation, df denotes degrees of freedom s(.) denotes a smooth cubic spline function, x_i denotes the monthly total rainfall, monthly average temperature at lags 0-3, 'time' represents both seasonal and trend pattern.

The analysis was done using the MGCV package in R which provides functions for generalized additive models (GAM) and generalized additive mixed model (GAMM). Generalized additive models were fitted with quasi-Poisson link functions to assess the association between monthly mortality and weather variables (temperature, rainfall) allowing for over-dispersion. Trend and seasonal variables were used to adjust for confounding factors and also model the expected mortality at all-time points. Natural cubic splines were used to adjust for nonlinear time varying confounders. Seasonal variation in temperature, rainfall and mortality over the duration of the study was displayed. These were examined for each year of measurement as well as in aggregate. However, there was no difference in the years, so aggregate measures were used. The association between weather variables and mortality was also quantified by strata of age, sex and socioeconomic status.

Relative risk of mortality and change in risk ratios of mortality due to lagged changes in temperature and rainfall were examined. Degrees of freedom (df) for the smoothing function were examined in a sensitivity analysis. The df tested were 2, 3, 4, 5, 6, 7and 8. Trend which is the long-term indicator was included in the modeled through a spline curve with two (2) df per year (14 df for 7 years) for each site data. The season was however modeled with different degrees of freedom (df) for each site data (Dodowa 7, Kintampo 5, Navrongo 4). Criteria such as, generalized cross validation (GCV) and test for noise in residuals e.g. Partial Autocorrelation function (PACF) and residual plots were used to select the appropriate df. Model selection was also done using the above criteria. The final models selected for each HDSS site were those with the minimum GCV values.

For all-cause mortality, temperature lag0, lag1 and rainfall lag0, lag1 were included in the final models in Dodowa HDSS. Temperature lag0, lag1 and rainfall lag0, lag1 and lag2 were included in Kintampo and Navrongo HDSS. With malaria-specific mortality, the lag strata included were Dodowa HDSS temperature lag0, lag1 and rainfall lag0, lag1, Kintampo HDSS temperature lag0, lag2, lag3 and rainfall lag0, lag2 and for Navrongo HDSS temperature lag0, lag3 and rainfall lag0, lag1, lag2.

From the smooth curves, both non-linear and approximate linear relationship between temperature and mortality were observed. Similarly, the relationship between rainfall and mortality were observed to be non-linear and approximate linear relationship in all sites except Navrongo HDSS where the relationship with all-cause mortality was linear. Relative risks were calculated as change in risk with mean temperature below the 25th percentile or above the 75th percentile. Linear estimates were also calculated alongside. Relative risk with rainfall lags were also estimated using the percentiles and linear effect except Navrongo HDSS where linear estimates of relative risk were obtained for all-cause mortality. Relative risks of malaria-specific mortality due to lagged changes in temperature and rainfall were also estimated. These analyses were also done stratified by age, sex and socioeconomic status (wealth index). This was done to study the association between temperature, rainfall and mortality in these sub groups since the effect might vary. The relative risks were also estimated with temperature adjusting for rainfall effect and vice versa.

3.8.3 Spatial Analysis

Spatial and temporal clustering of all-cause and malaria-specific mortalities at the HDSS sites were determined using scan statistic as proposed by Kulldorff (Kulldorff, 1997). The SatScan software version 8 developed by Martin Kulldorff was used for the analysis. The software is based on a likelihood-ratio test to identify areas with increased risk and to detect 'hot-spot' clusters. This method was chosen because of the scan statistic in the SaTScan software, Monte Carlo hypothesis testing is used to obtain the p-values. This solves the problem of the assumption of fixed size of cluster and uniform distribution of cases hence testing the null hypothesis that the risk of deaths is the same in all communities in the study areas.

Three different files; the coordinate file, the case file and population files were created for the analysis. The coordinate file is the georeferenced data in the form of longitudes and latitudes (longitude /latitude) of all the communities in the study areas. Number of deaths and person years per each community were calculated and saved as case file and population file respectively. These files were then used to determine the spatial distribution (high clusters) of mortality rates. This was done for all ages and under-fives.

3.9 Quality Control

Quality control was at various levels during data collection, management, and finally during data analysis.

3.9.1 Quality Control during Data Collection

Under the HDSSs field workers and supervisors were given refresher training before each update round starts. Supervisors were trained to check data collection in the field and they paid unannounced visits to the field to make sure field workers really went to the households to conduct the interviews. Also, 5% of households were randomly generated and these households visited by the supervisors and Research Officers for re-interviews. Also, before leaving for the field, 'ghost' households (non-existent houses) were generated to check for fabricated data. Supervisors checked the work of field workers before submitting the forms to a field coordinator through a filing clerk who also checked them. The household registration books and the accompanied forms were then received in the field office for checks before submitting to the Data processing unit for entry.

The researcher visited and worked with the data mangers at all the HDSS sites to correct inconsistencies and errors as much as possible. The data collected from the Meteorological stations were also checked for missing data and possible errors

3.9.2 Quality Control during Data Processing

After the forms were submitted to the data processing unit, the forms were checked by the filing clerk before data entry. The data entry program also has inbuilt checks which checked any inconsistencies such as a male who has been registered as being pregnant or having given birth. The queries were then generated and sent back to the field for correction. All the entries were printed daily and checked for any entry errors by the data manager. For the VAs, each record was entered independently by two data entry clerks for inconsistencies. These records were then compared field by field and any inconsistent entry was checked with the form and corrected.

3.9.3 Quality Control during Data Analysis

The final data check was done during the data management and analysis. Before the main analysis, the data were checked for missing values and internal inconsistencies of the responses. Irregularities in the datasets were corrected by using the hard copies of the completed questionnaires and the necessary changes effected. Records that could not be corrected were excluded from the analysis.

3.10 Ethical Consideration

Ethical clearance: This was obtained from the Ghana Health Service Ethical Review Committee.

(ID NO: GHS-ERC: 10/11/15)

Approval: Approval was obtained from the heads of the three health and demographic surveillance system (HDSS) sites before using their data.

Privacy/confidentiality: This was done by protecting the data. All records were anonymized. No name of any individual was associated with their information and the data was used for what it was intended for only.

Data storage and usage: The data from the HDSS sites are stored securely and used purposely for this study. Based on the University's regulations, the data will be kept by the candidate for a minimum of five years.

CHAPTER FOUR: RESULTS

This chapter presents the overall findings of the study. It gives summary statistics of the mortality, temperature and rainfall over the seven-year period at each of the sites. It also highlights seasonal patterns in mortality, temperature and rainfall. The associations between temperature and mortality and rainfall and mortality are also presented in tables and figures. Also, the spatial distribution of deaths in each of the Health and Demographic Surveillance System (HDSS) sites is presented.

4.1.1 Summary statistics of mortality data

The study considered all deaths and malaria deaths that were recorded between 2006 and 2012 in Navrongo, Kintampo and Dodowa HDSS. In all 23,434 deaths and 2,740,002.4 person years were used for the analysis. The crude rate ratio for the three sites was about 8.6 per 1000 person years.

From the InterVA-4 output, the sum of malaria deaths was 1684.09 for the period 2006-2012 in all three sites. Malaria-specific mortality was 0.6 per 1,000 person years.

The sum of malaria deaths was 442.83 for Navrongo, 744.14 for Kintampo HDSS site, and 497.12 for Dodowa between 2006 and 2012. From the InterVA-4 output, malaria contributed 5%, deaths in Navrongo, 12.1% in Kintampo and 11.5% Dodowa.

A total of 5354 deaths and 768387.56 person years were used for the analysis at the Dodowa HDSS site with a total person years of 768387.56. The crude death rate was about 7 per 1000 person years at this site (Table 2).

On the other hand, for Navrongo HDSS site, a total of 11,201 deaths and 1050193 person years were used in the analysis. The crude death rate at this site was about 10.7 per 1000 person years.

Table 2: All Cause Death Rates by Sex and Age (2006-2012) for all study sites

Site	Age group	Both sexes	Males			Females		
		Death rate/1000	**Number of deaths(n)**	**Person years**	**death rate/1000**	**Number of deaths(n)**	**Person years**	**death rate/1000**
Dodowa	**All**	7.0	2452	356091.1	6.9	2902	412296.5	7.0
	0-4	6.5	344	51393.54	6.7	312	49233.19	6.3
	5-14	1.4	208	140534.6	1.5	197	143571.5	1.3
	15-59	6.1	940	144125.9	6.5	1064	186487	5.7
	60+	43.2	960	20037.07	47.9	1329	33004.74	40.3
Navrongo	**All**	10.7	6242	501477.6	12.5	4959	548715.8	9.0
	0-4	14.7	1011	63908.75	15.8	857	62879.24	13.6
	5-14	1.6	370	198077.9	1.9	253	183974.3	1.4
	15-59	8.2	2283	199171.7	11.5	1342	242566.9	5.5
	60+	51.0	2578	40319.18	63.9	2507	59295.37	42.3
Kintampo	**All**	7.5	3888	453656.9	8.6	2991	467765	6.4
	0-4	12.8	899	65458.18	13.7	753	63678.95	11.8
	5-14	1.8	366	186330.5	2.0	291	174879.1	1.7
	15-59	6.4	1404	175993.3	8.0	1034	203200.6	5.1
	60+	41.1	1219	25874.92	47.1	913	26006.27	35.1

A total of 6,879 deaths with 921,421.8 person years from the Kintampo HDSS site were used. The crude death rate was about 7.5 per 1000 person years in this HDSS (Table 2).

Overall, Navrongo had the highest crude mortality rate compared to Kintampo and Dodowa. However, for all three sites, deaths rates were lowest in the 5 to 14 years age group while those 60 years and above had the highest mortality rate. Children under five years had the second highest death rate (Table 2). Generally, males had higher crude death rate than females. High male death rate was more pronounced in the Navrongo and Kintampo HDSS.

4.2.1 Moving averages of monthly crude death rates at all sites

Moving averages of monthly crude death rates (all deaths) for all the sites have been presented in Figures 4-7. The graphs indicate seasonality of mortality at all three sites (Figure 4). The moving averages of monthly crude death rates for all-cause mortality at the study areas suggested general decline of mortality from 2006 to 2012 in the districts (Figure 4).

It was observed that, the Navrongo HDSS had the highest overall crude death rates from 2006 to 2012 except in the early part of 2006 where the Dodowa HDSS site also had the highest rates. Generally, Kintampo HDSS site had slightly higher rates of death than Dodowa HDSS site especially from 2009 to 2012.

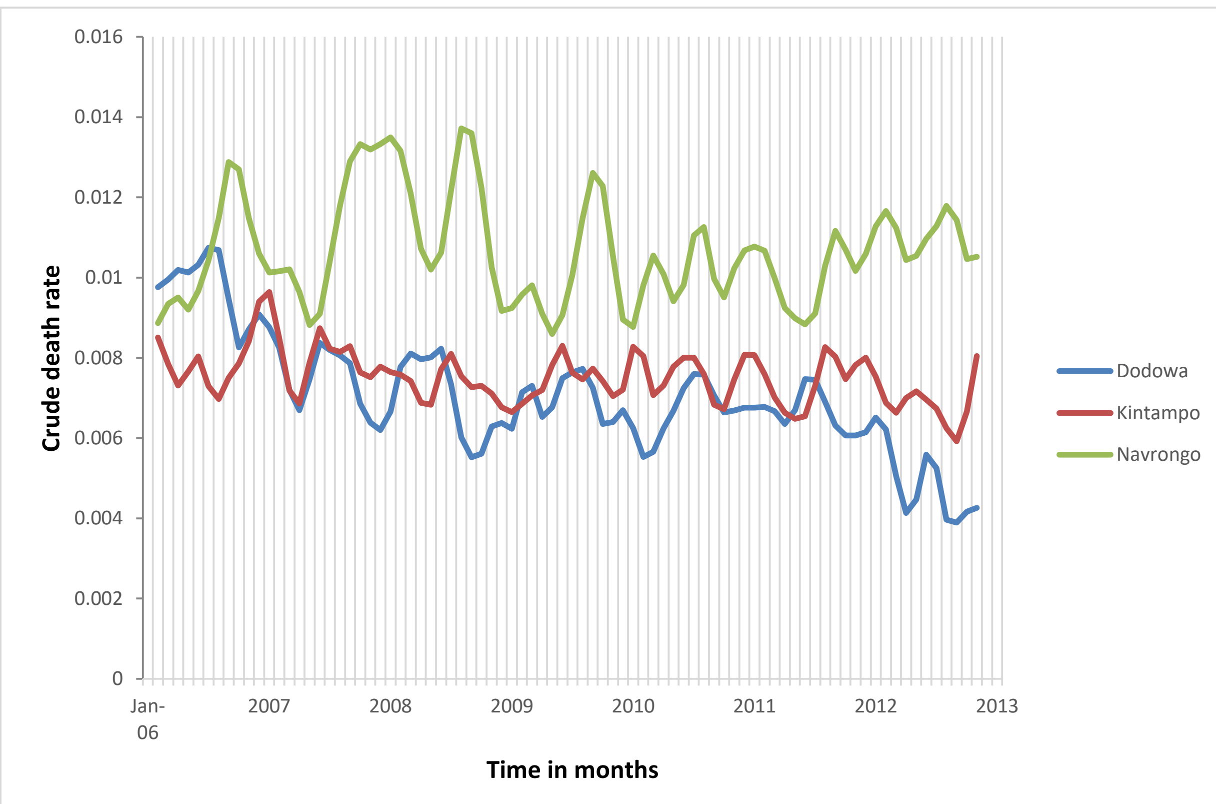

Figure 4: Moving averages of monthly crude death rates for all ages (all deaths) with trend line at all sites

The age-specific moving averages of monthly crude death rates at the HDSS sites, showed that generally, those who were 60 years and above had the highest death rates while the 5-14 years age group had the lowest death rates in all the sites and across the years (Figures 5-7). Seasonality of mortality was evident in each age group. In comparison, the under-five mortality rate in Dodowa was relatively lower than Kintampo and Navrongo, with Navrongo reporting the highest crude death rate.

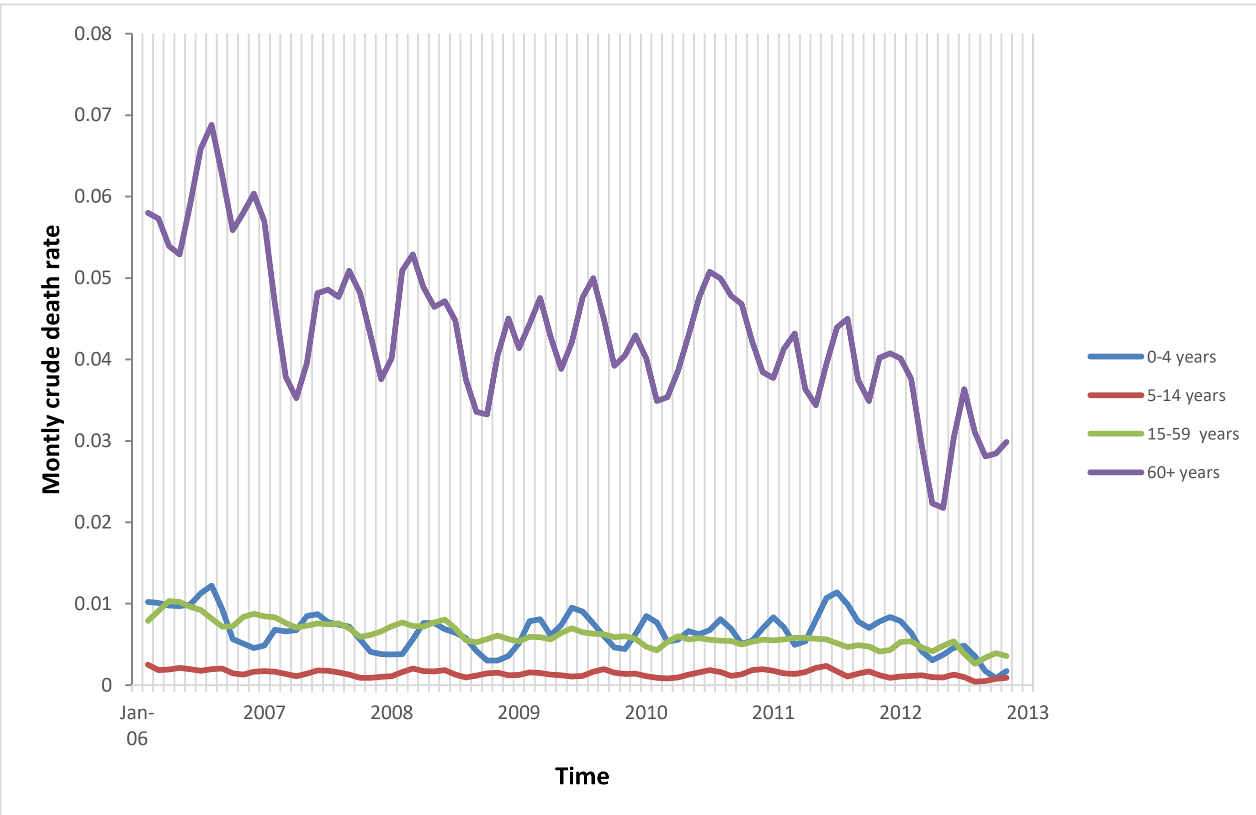

Figure 5: Age specific moving averages of monthly crude death rate (all deaths) at Dodowa HDSS site

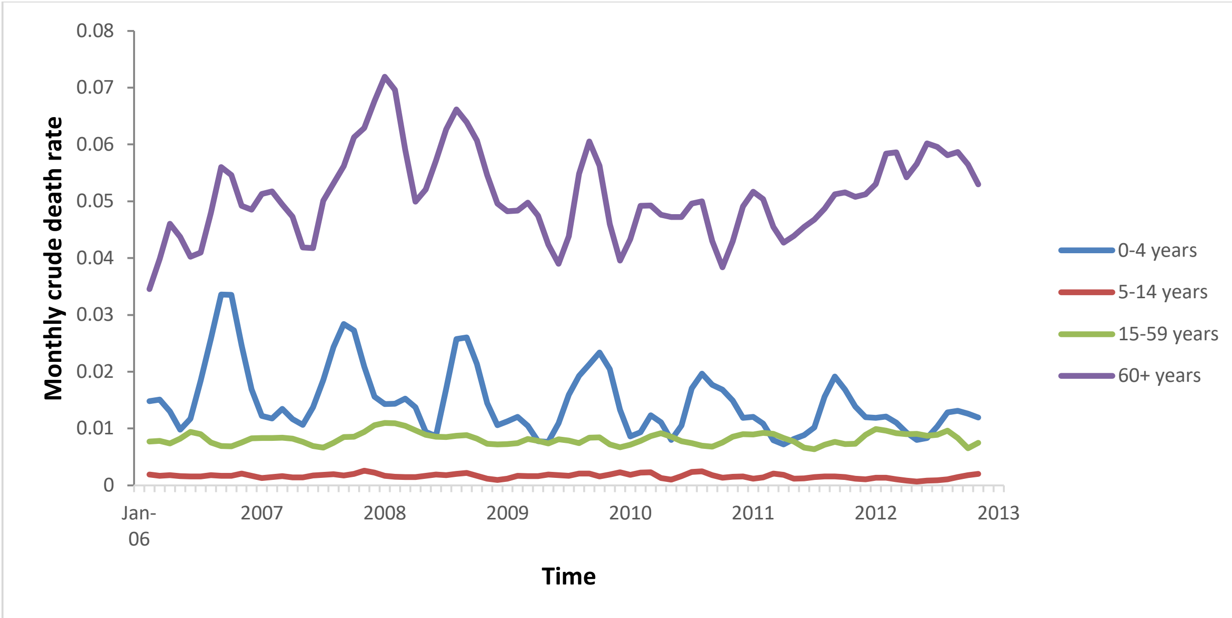

Figure 6: Age-specific moving averages of monthly crude deaths rates (all deaths) at Kintampo HDSS site

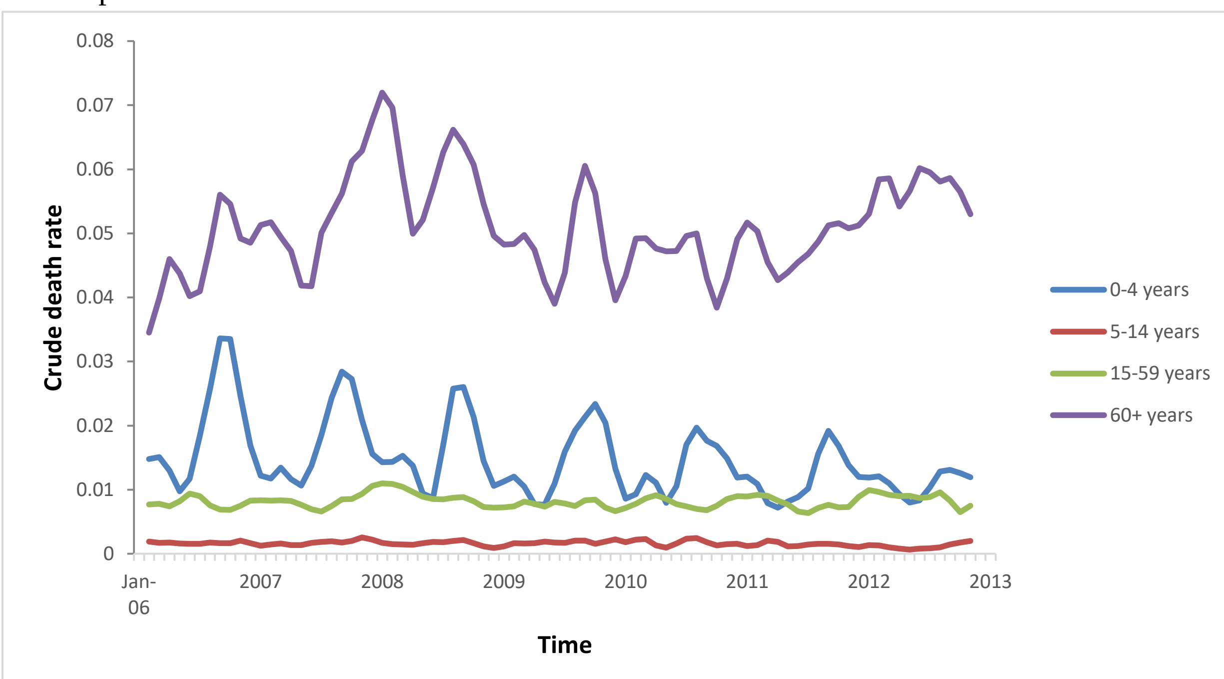

Figure 7: Age-specific moving averages of monthly crude deaths rates (all deaths) at Navrongo HDSS site

4.2.2 Moving averages of monthly malaria specific deaths rates at all study sites

The seasonality of malaria specific mortality at the HDSS sites was more pronounced than that of the all-cause mortality and this was evident through all the years (Figures 8-11). It was observed that the monthly moving averages rates of malaria-specific mortality had different patterns in all the three sites. Generally, in Kintampo malaria specific malaria death rates were higher than the death rates in Navrongo and Dodowa. The three study sites had high peaks of malaria specific deaths in different times (figure 8).

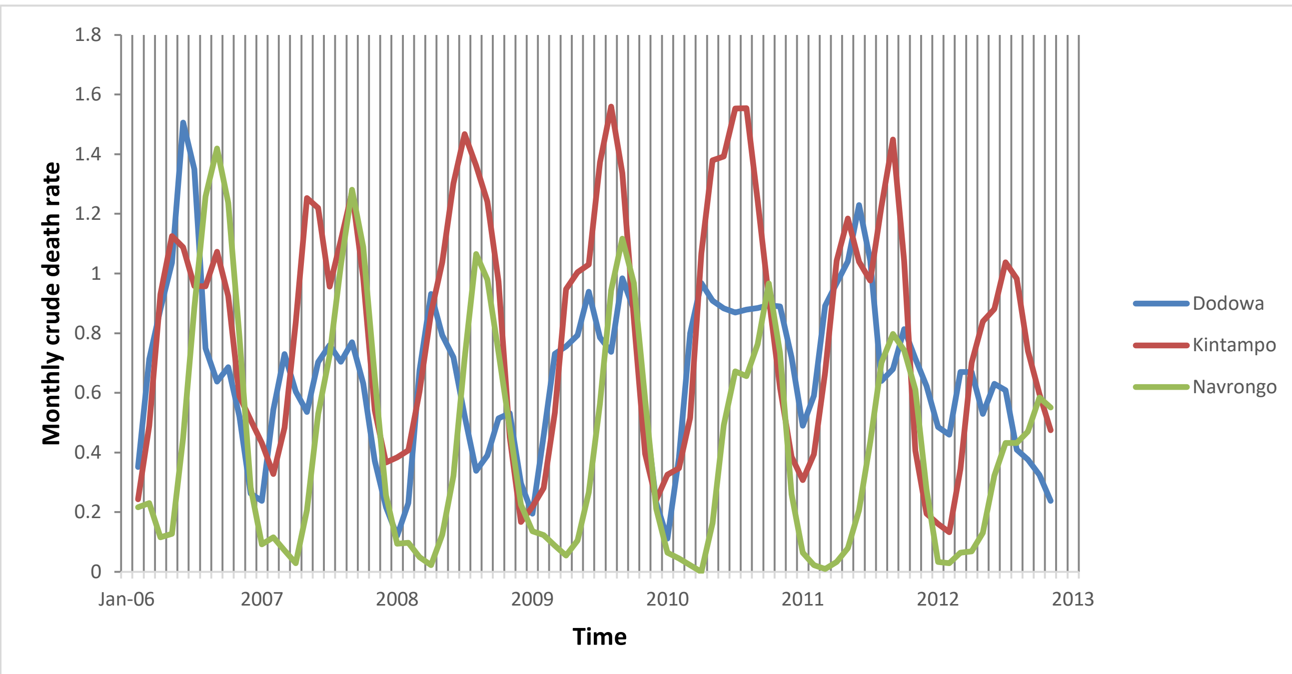

Figure 8: Moving averages of monthly crude death rates for all ages (malaria deaths) line at all sites

The seasonality of malaria specific mortality is also more evident with the age-specific mortality at all the HDSS sites. Each of the age groups showed a slightly different seasonal pattern. As observed in all-cause mortality, those who were 60 years and above had the highest malaria specific mortality rates with those 5-14 years age group reporting the lowest malaria specific rates at the Dodowa and Kintampo HDSSs (Figures 9-10). For Navrongo HDSS, the children under-five years had higher malaria specific death rates than those of 60 years and above except the later years (2010-2012) (Figure 11). Those in the 5-14 years age group however, remained the age group with the lowest malaria specific death rate.

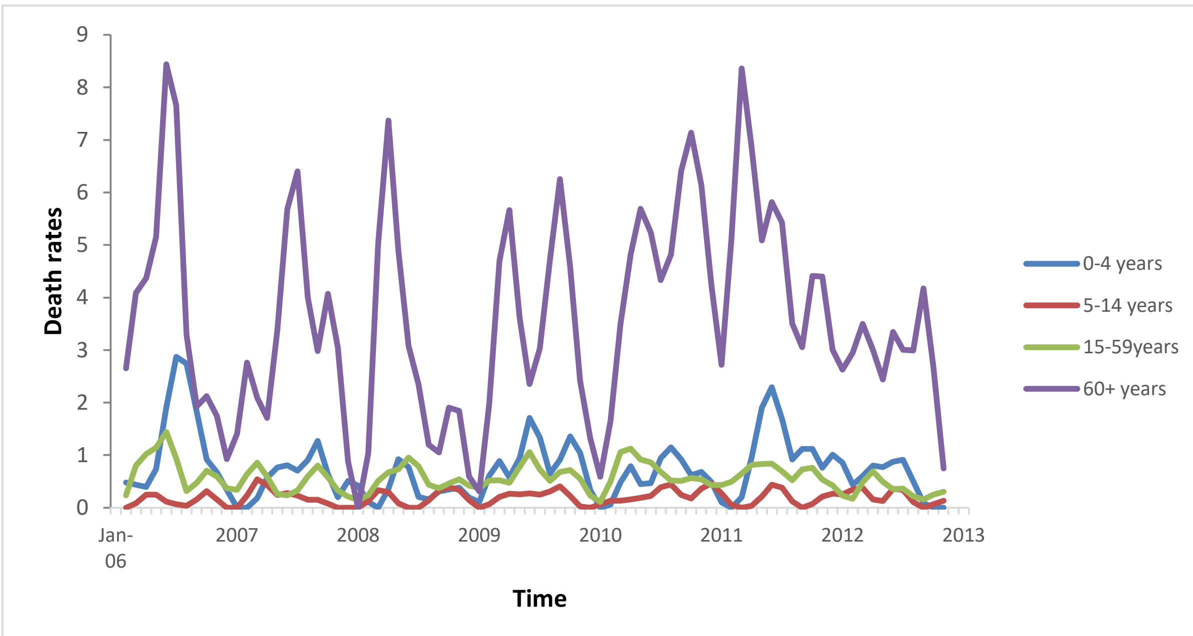

Figure 9: Age specific moving averages of monthly malaria specific death rate/1000 at Dodowa HDSS site

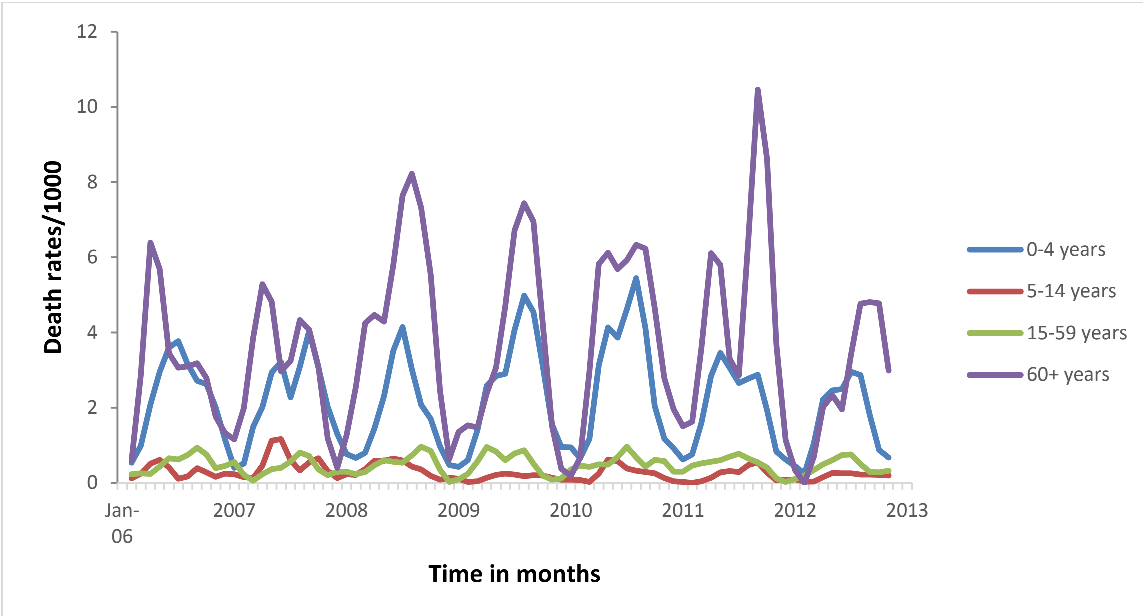

Figure 10: Age specific moving averages of monthly malaria specific death rate/1000 at Kintampo HDSS site

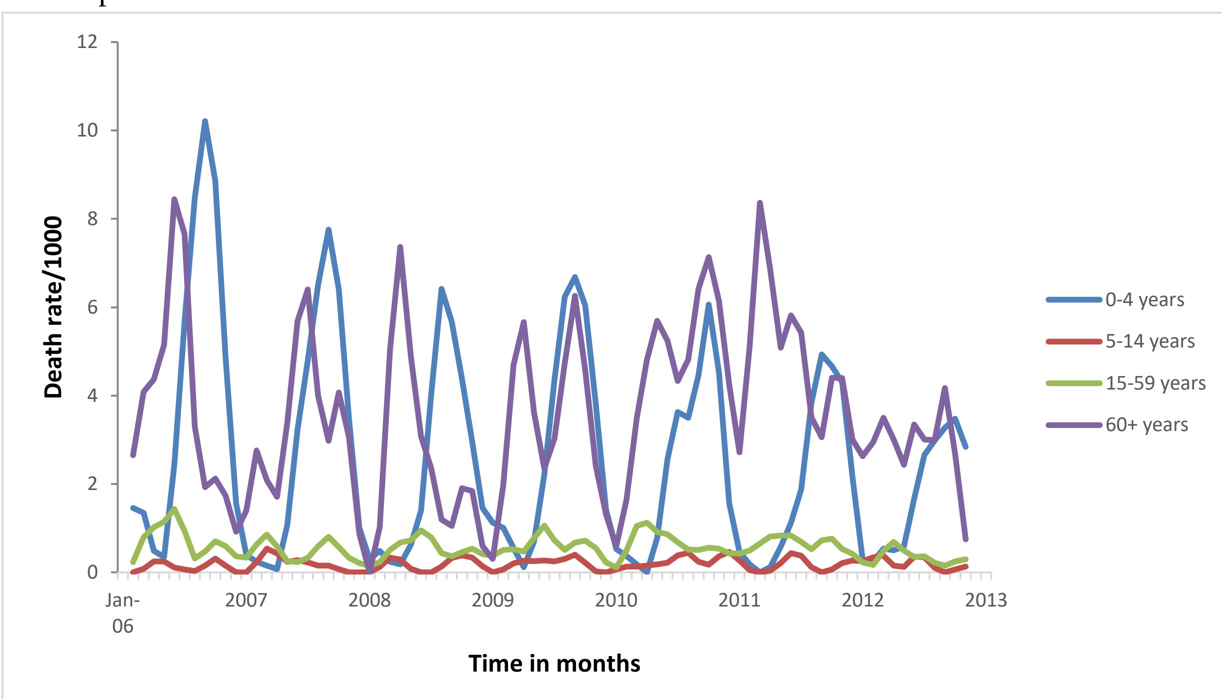

Figure 11: Age specific moving averages of monthly malaria specific death rate/1000 at Navrongo site

4.3.2 Monthly Mortality rate ratios (all deaths) for all study sites

Monthly mortality rate ratios were also calculated to understand the seasonality of mortality using the month of January as the base. This was done for both all-cause and malaria-specific mortality for the three HDSS sites and presented on the log scale. The log rate ratios showed evidence of seasonality of mortality at all the study sites and for age groups. There were no differences in seasonal patterns between the crude and sex-adjusted mortality ratios.

For the Dodowa site, the overall mortality rates fluctuated across the months with the highest peak (LogRR=0.2533) in June and lowest (LogRR=-0.128) in October (Figure 12). High rates of all-cause mortality in Kintampo were in January, June and December with the peak being in June. The lowest rate was observed in March (Figure 13). At the Navrongo HDSS site, higher rate ratios for overall mortality were observed in the months of August, September and October. August had the highest mortality rate ratio with the lowest rate ratio being observed in May (Figure 14).

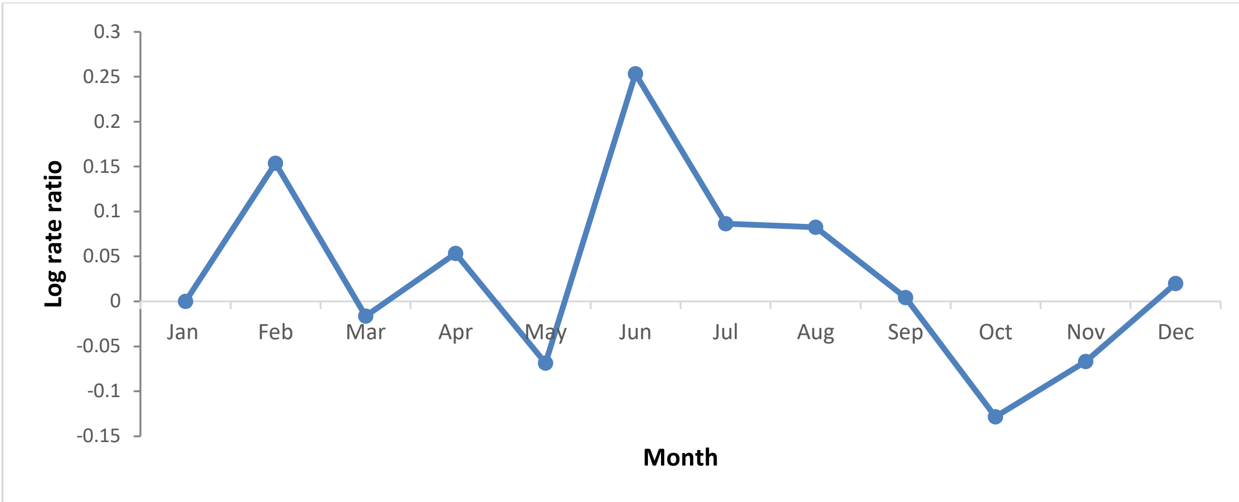

Figure 12: Monthly rate ratio (All deaths) with January as the base month at Dodowa HDSS site

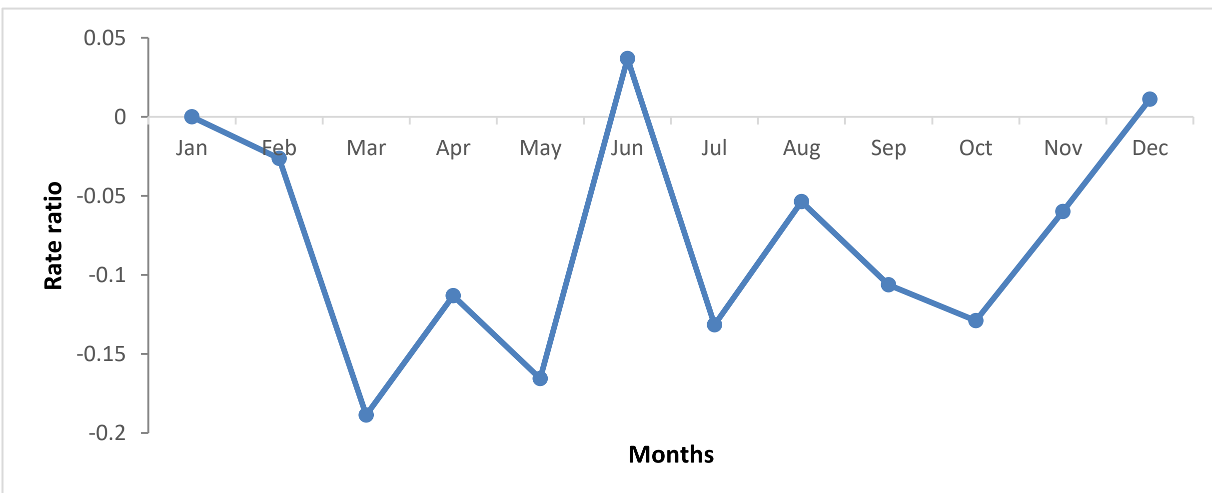

Figure 13: Monthly rate ratio (All deaths) with January as the base month at Kintampo HDSS site

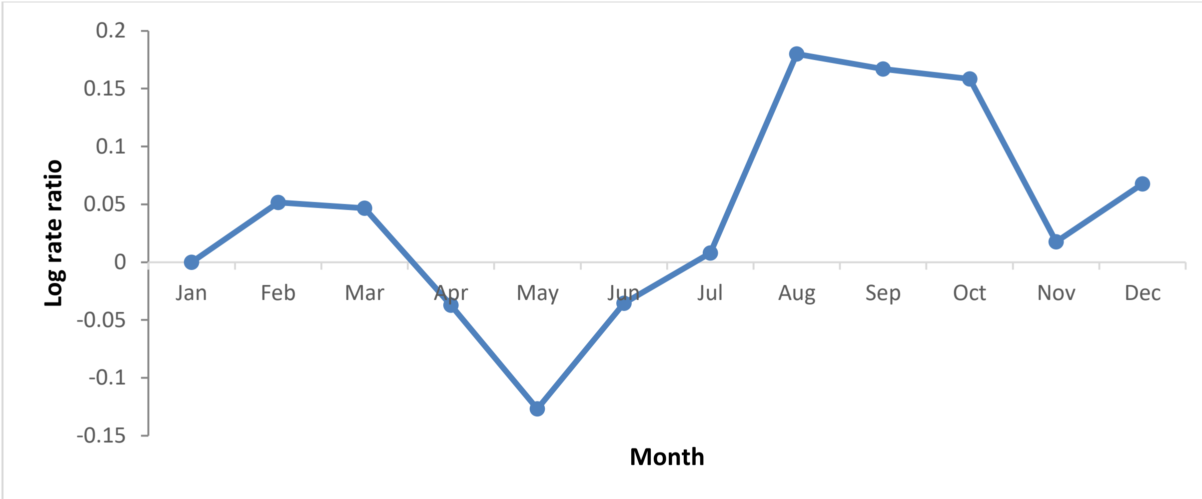

Figure 14: Monthly rate ratio (All deaths) with January as the base month at Navrongo HDSS site

For mortality in the under-five age group, the highest rate ratio was observed in the month of August at the Dodowa HDSS with the lowest rate ratio occurring in October (Figures 15). At the Kintampo HDSS, the highest peak for under-five mortality was in July and the lowest peak was observed in March (Figures 16). Similar to the pattern observed for the overall mortality in the Navrongo HDSS, high mortality rate ratios for those under-five years of age were also observed between the months of August and October, with the highest rate ratio in September and the lowest rate ratio in May (Figure 17).

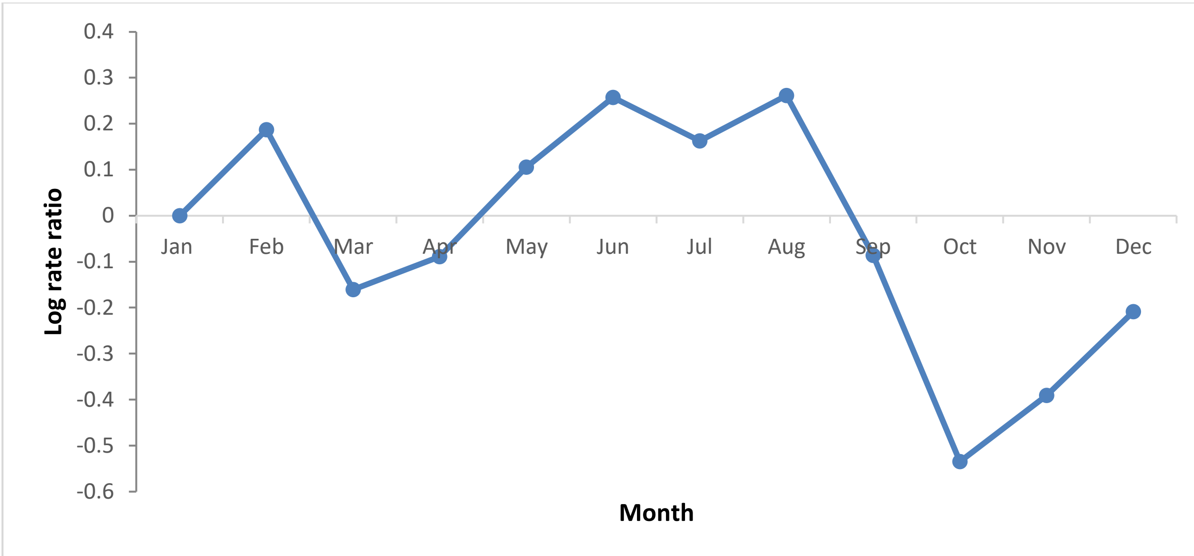

Figure 15: Under-five crude monthly rate ratio with January as the base month at Dodowa HDSS site

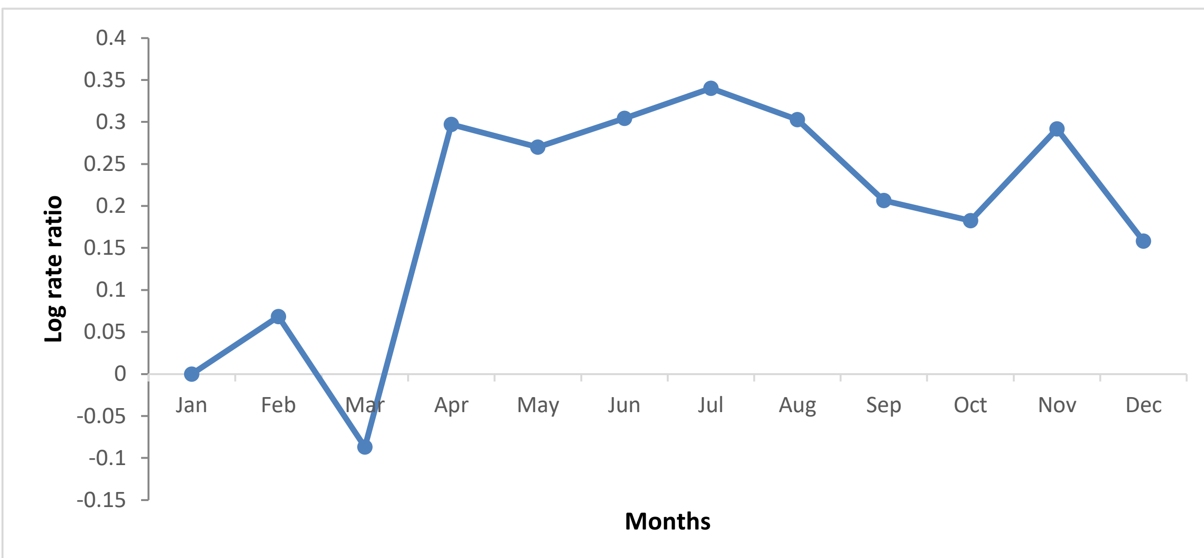

Figure 16: Under-five monthly log rate ratio with January as the base month at Kintampo HDSS site

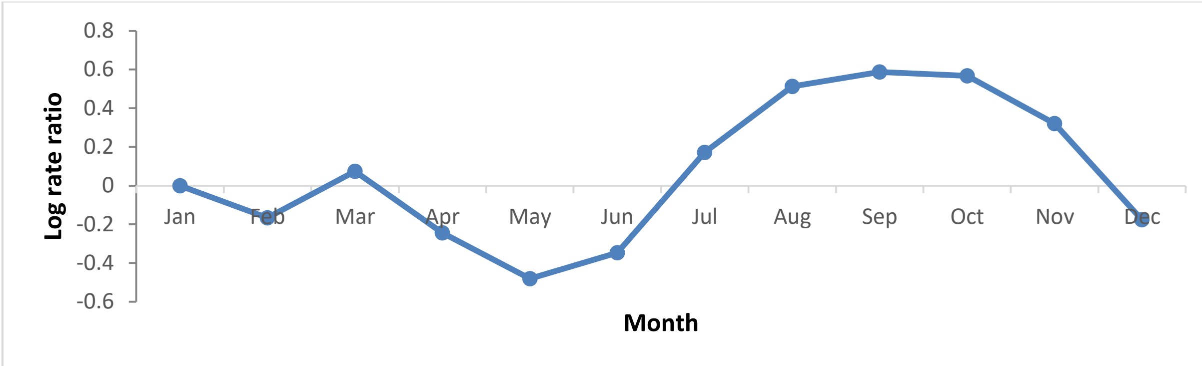

Figure 17: Under-five monthly crude rate ratio with January as the base month at Navrongo HDSS site

Similarly, with the elderly (60+ years), the highest mortality rate ratios were observed in the months of June to August with May having lowest mortality rate ratio at the Dodowa HDSS. For Kintampo HDSS, the highest mortality rate ratio for the same age group was observed in January while the lowest rate ratio was observed in May. High rates of mortality for the elderly (60+ years) were rather observed between August and October at the Navrongo HDSS with the highest being in October and lowest in June.

4.2.4 Monthly rate ratios for Malaria deaths for all the study sites

This section presents monthly rate ratios of malaria deaths at the three sites using January as the base month. The rate ratios revealed seasonality of malaria deaths at the sites.

High monthly mortality rate ratios of malaria deaths for all ages at the Dodowa HDSS site were observed between March and July, then in September to November with the peak mortality in June, one month after the peak of rainfall. Low rates were observed from December to February with the lowest in January (Figure 18). High malaria mortality rates in Kintampo HDSS were from April to October with peak in August. The months of November to March recorded low rates with the lowest rate in November (Figures 19) for

Kintampo. At the Navrongo HDSS, high malaria mortality rates for all ages were observed between June and November with slightly highest peak in September, three months lag the peak of rainfall. Low rates were recorded from December to May with May having the lowest rate (Figures 20).

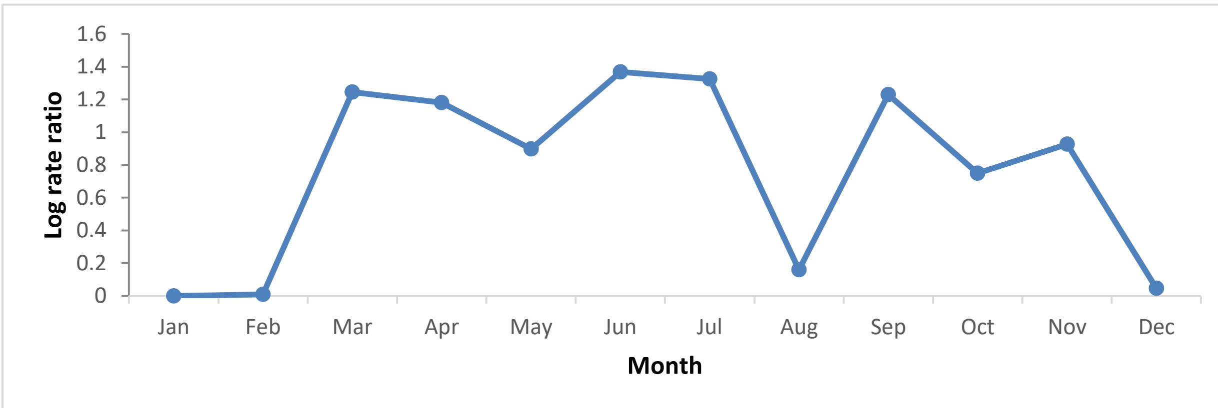

Figure 18: Monthly rate ratio (Malaria deaths) with January as the base month at Dodowa HDSS site

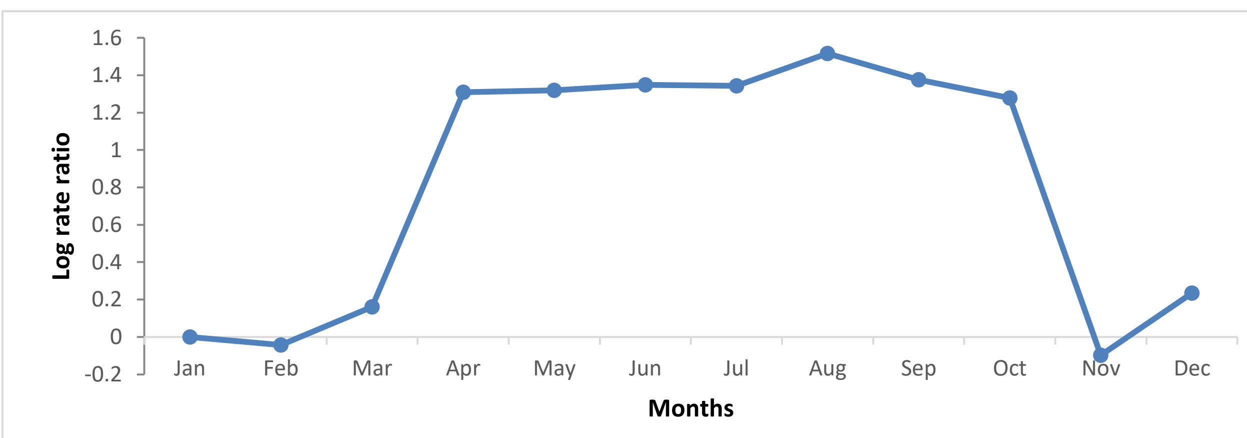

Figure 19: Monthly rate ratio (Malaria deaths) for all ages with January as the base month at Kintampo HDSS site

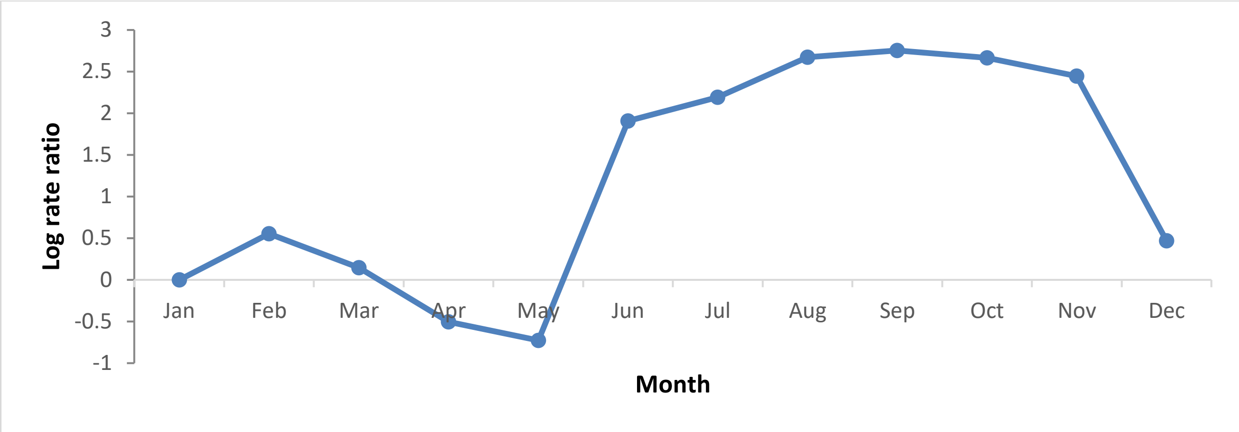

Figure 20: Monthly rate ratio (Malaria deaths) for all ages with January as the base month at Navrongo HDSS site

At the Dodowa HDSS, high rates of under-five malaria mortality were observed from May to July then September. They were two peaks in July and September. Lower rate ratios were observed in January and February (Figure 21).

Kintampo HDSS under-five malaria mortality showed similar patterns as that of all ages. High rates of mortality were between April and October with the highest peak in August. Low under-five malaria mortality rates were observed between November and March with February recording the lowest rate ratio (Figures 22).

Under-five malaria mortality at Navrongo HDSS site had the similar seasonal pattern as the pattern for all ages. The months of June to November had reasonably higher rate ratio of mortality. Low rates were observed between December and May, with May recording the lowest rate (Figures 23).

The malaria deaths for all ages and under-fives were lowest during the dry months and this was observed for all the HDSS sites.

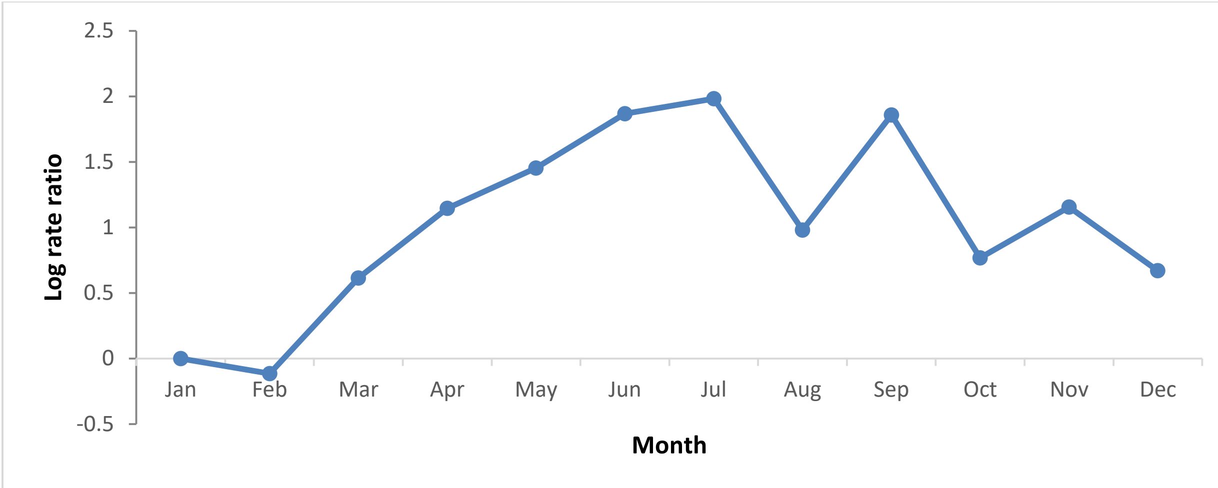

Figure 21: Under-five monthly rate ratio (Malaria deaths) with January as the base month at Dodowa HDSS site

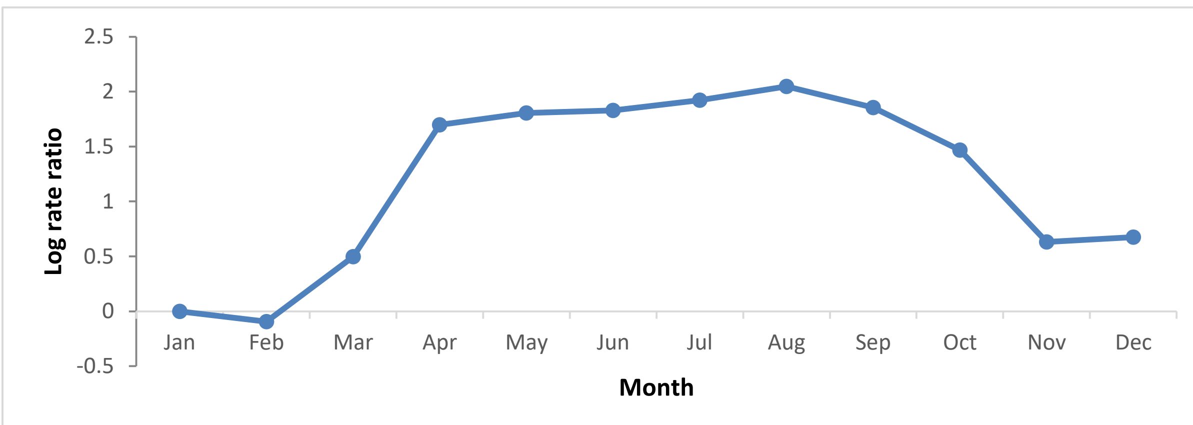

Figure 22: Monthly rate ratios (Malaria deaths) for 0-4 years old with January as the base month at Kintampo HDSS site

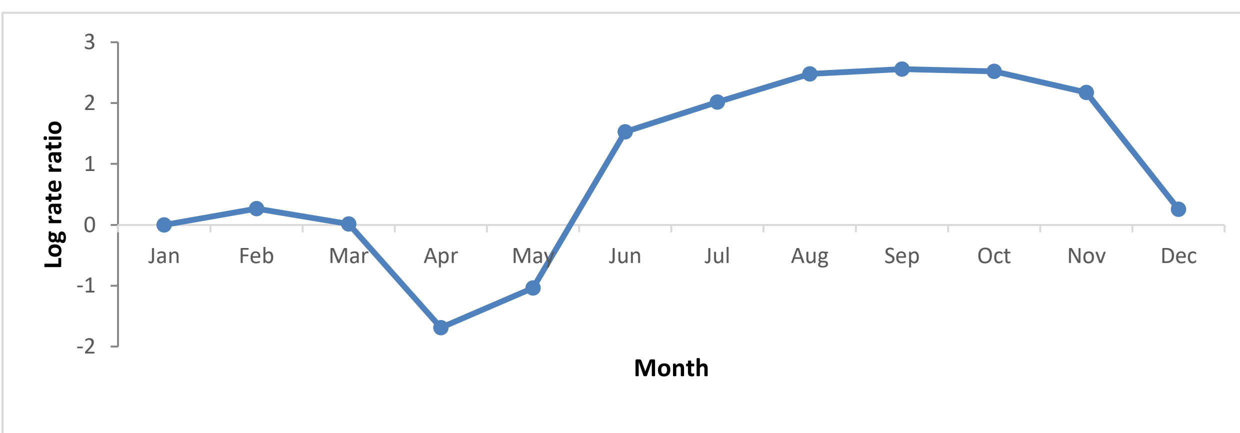

Figure 23: Under-five monthly crude rate ratios (Malaria deaths) with January as the base month at Navrongo HDSS site

For those who were 60 years and above, the highest rate ratio for malaria deaths at DHDSS was observed in July while the lowest rate ratio was in December.

4.2.5 Distribution of weather variables

The mean monthly average maximum temperature for the period 2006-2012 was 33.6 degree celcius (°C) at the DHDSS while the minimum temperature was 23.6. The median total monthly rainfall for DHDSS was 77.3mm. The mean monthly average maximum temperature for NHDSS site for the period 2006-2012 was however 35.2 degree Celsius (°C) with a minimum temperature of 23.1. The site also had a median total monthly rainfall of 59.9mm (Table 3).

Table 3: distribution of Monthly Weather Variables (2006-2012) at the three study sites

Site	**Climate variables**	**Mean**	**SD**	**Min- Max**	**Median**	**25th**	**75th**
Dodowa	Temperature (°C)						
	Maximum	33.6	1.8	30.5-36.8	34.0	31.9	35.1
	Minimum	23.6	0.9	20.0-25.4	23.4	23.1	24.3
	Mean	28.6	1.2	26.6-30.7	28.6	27.6	29.5
	Rainfall (mm)	83.1	58.9	0-245.6	77.3	34.0	129.7
Navrongo	Maximum	35.2	3.1	30.0-40.8	35.3	32.3	37.7
	Minimum	23.1	2.3	18.1-27.4	23.1	22.2	24.5
	Mean	29.1	2.1	25.4-33.8	28.7	27.4	30.7
	Rainfall (mm)	89.7	98.2	0-414.1	59.9	0	105
Kintampo	Maximum	31.3	2.1	27.8-35.4	31.4	29.5	33.1
	Minimum	21.4	1.2	16.4-23.9	21.6	20.8	22.1
	Mean	26.3	1.2	23.9-29.0	26.1	25.5	27.3
	Rainfall (mm)	128.1	105.3	0-447.4	107.0	38.4	195.4

Similarly, the mean monthly average maximum temperature for Kintampo HDSS site for the period 2006-2012 was 31.3 degree celsius (°C) while that of the minimum temperature was 21.4 and the median total monthly rainfall being 107.0 mm.

4.2.6 Seasonality of Rainfall and Temperature

Rainfall pattern at the Dodowa HDSS was inconsistent. It was lowest in January, February, August and December. Rainfall was highest in the month of May followed by June, September, October and April. For mean temperature, July and August were the coldest months, followed by June and September while February and March were the hottest months (Figure 24).

Within the KHDSS however, the peaks of rainfall were in May, September and October. It was lowest between November and February. The mean temperature had considerably similar seasonal pattern like that of the DHDSS. July and August were the coldest months while February and March were the hottest months (Figure 25).

Rainfall in NHDSS is unimodal, it had only one peak which was in June. It was lowest between November and March. For the mean temperature, the coldest month was August, followed by July, September, January and December (Figure 26). There seemed to be a relationship between monthly rainfall, temperature and monthly mortality in all the three sites. Colder months seemed to be associated with higher mortality compared with warmer months. Also, higher mortality seemed to lag behind high temperature months.

Key: For Figures 24 to 26, Month 1=January, 2=February, 3=March, 4=April, 5=May 6=June, 7=July, 8=August, 9=September, 10=October, 11=November, 12=December

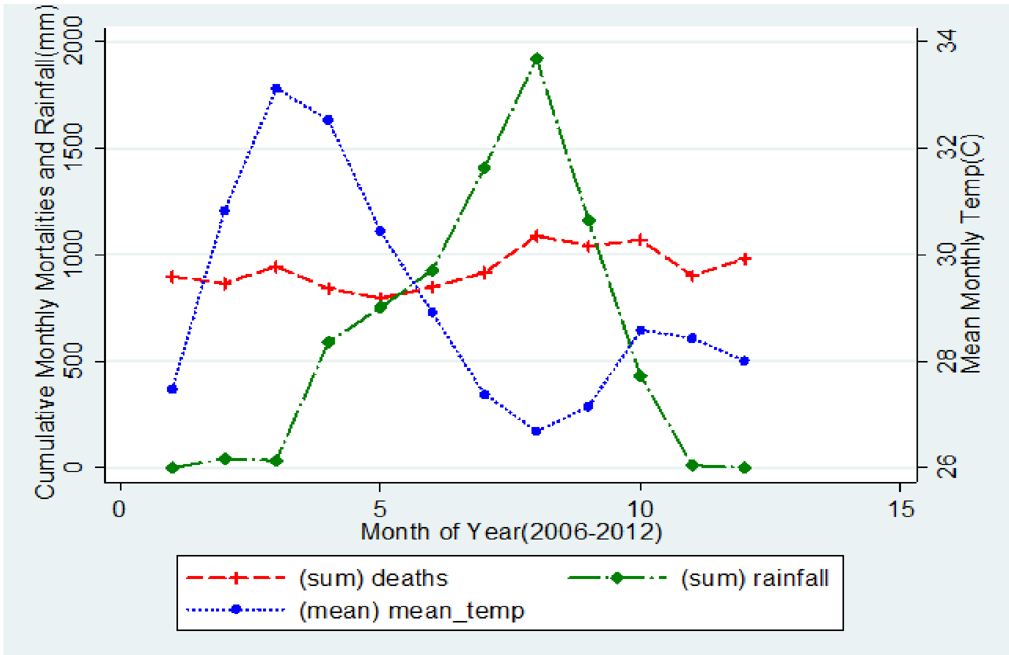

Figure 24: Seasonality of temperature, rainfall and mortality at Dodowa HDSS site

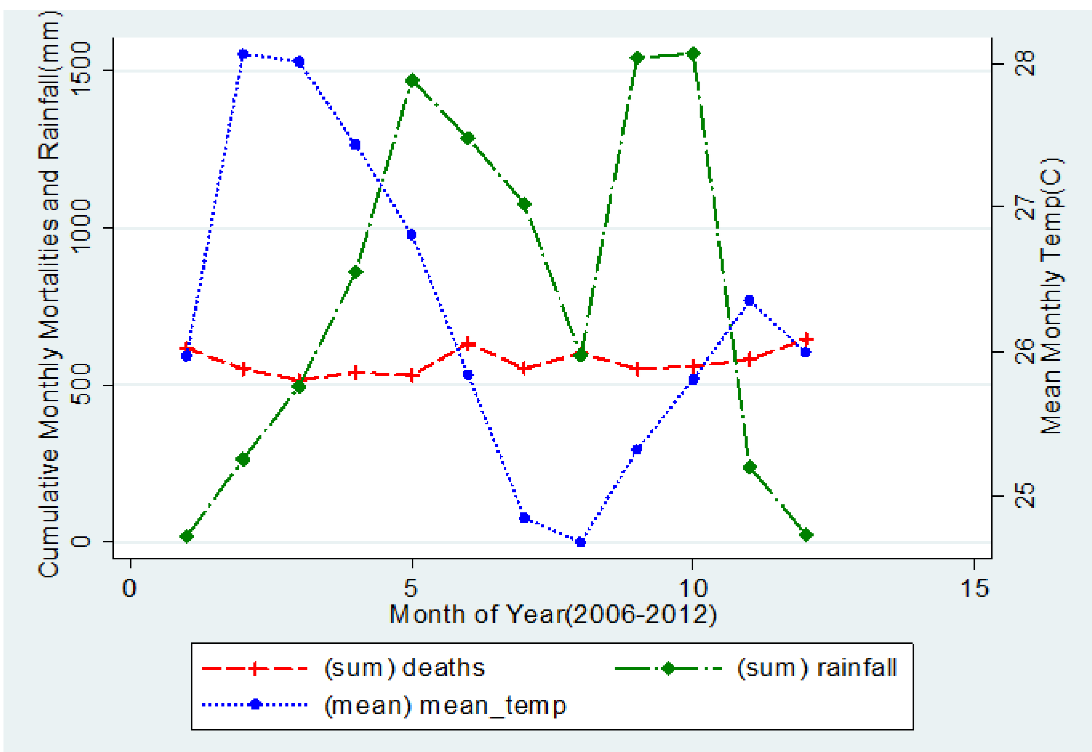

Figure 25: Seasonality of temperature, rainfall and mortality at Kintampo HDSS site

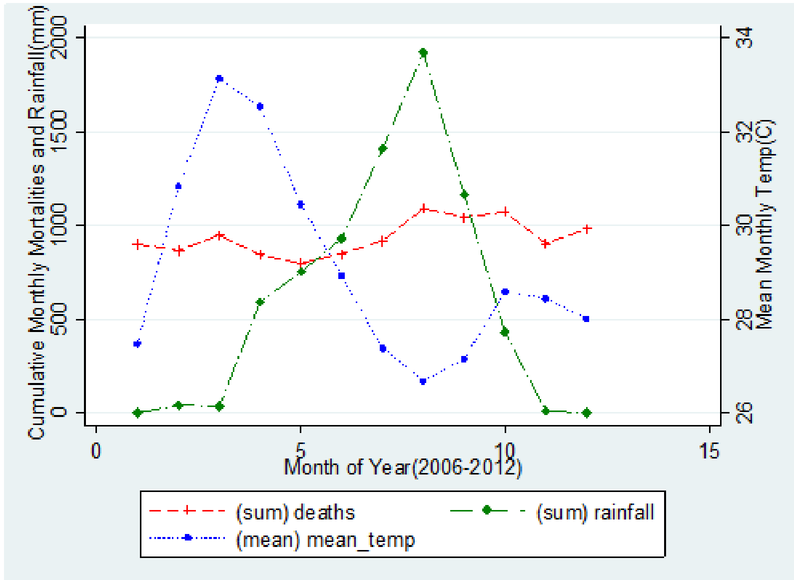

Figure 26: Seasonality of temperature, rainfall and mortality at Navrongo HDSS sites

4.3.1 Relationship between temperature, rainfall and all-cause mortality for all ages at the HDSS sites

Smooth plots of relationships between temperature and all-mortality at the HDSS sites revealed both non-linear and approximate linear relationships. The temperature lag strata had different shapes relationship with all-mortality at the sites. For Dodowa HDSS, temperature in the month of death (lag0) had an inverted J-shape relationship, temperature in the previous one month before occurrence of death (lag1) and two months before occurrence of death (lag2) had approximate linear relationship while temperature in the previous three months before occurrence of death (lag3) had a U-shape relationship when the temperature lags were modeled separately.

With respect to temperature lag0 and lag2, the risk of mortality increased with temperature. For temperature lag1, the risk increased with decreased temperature while for lag3, the risk increased at the extreme ends (Appendix C1). However, when temperature lag0 and lag1 were modeled together, temperature lag0 had approximate U-shape relationship while temperature lag1 maintained the approximate linear relationship with mortality risk decreasing with temperature (Figure 27).

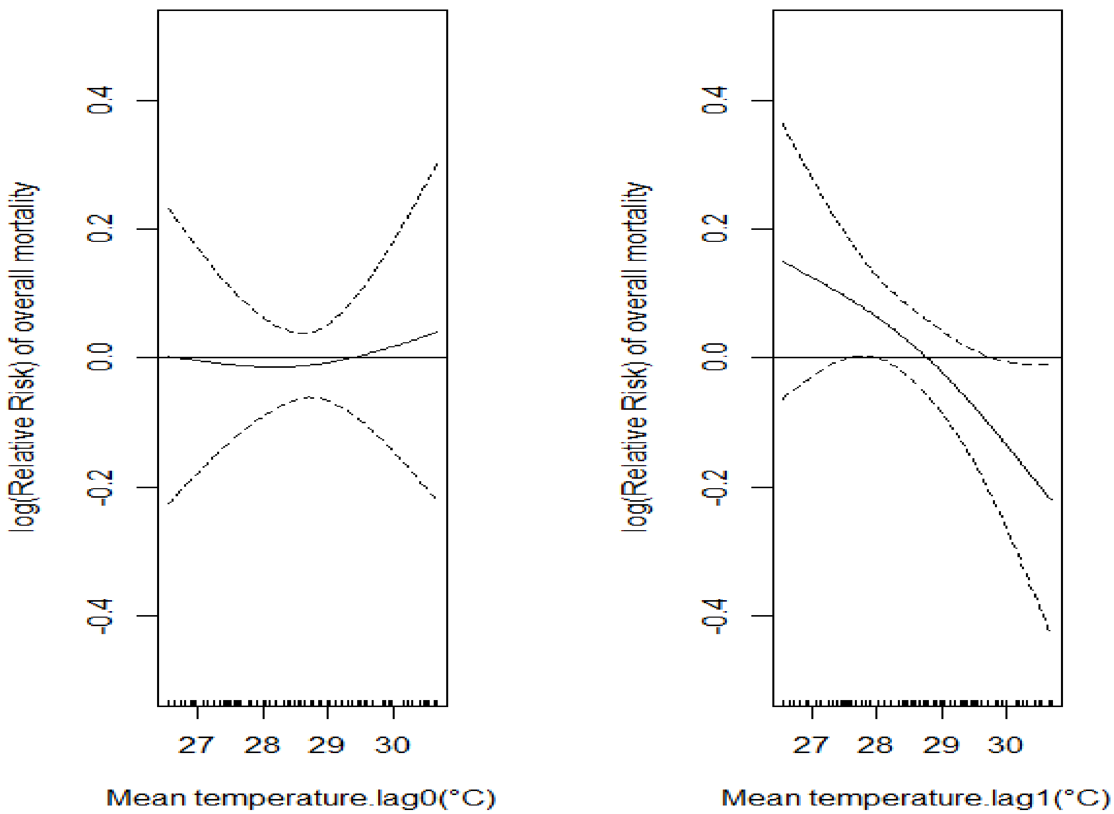

Figure 27: Plot of relationship between mean temperature at lag0 and lag1and all-cause mortality for all ages at the Dodowa HDSS site.

Note: ***For all plots of the relationship between temperature, rainfall and mortality, the solid lines are log relative risks and the broken lines are 95% confidence intervals.***

Plots of the relationship between temperature and mortality at the Kintampo HDSS are shown in Figure 28. For mean temperature lag0, mortality risk increased with temperature. With temperature lag1, mortality risk decreased as temperature increased. For temperature lag2, mortality risk decreased as mean monthly temperature decreased below 25.5°C or increased above 27.0°C and at lag3, mortality risk increased with increase in temperature (Figure 28). The plot for separate temperature lag strata is presented in appendix C2

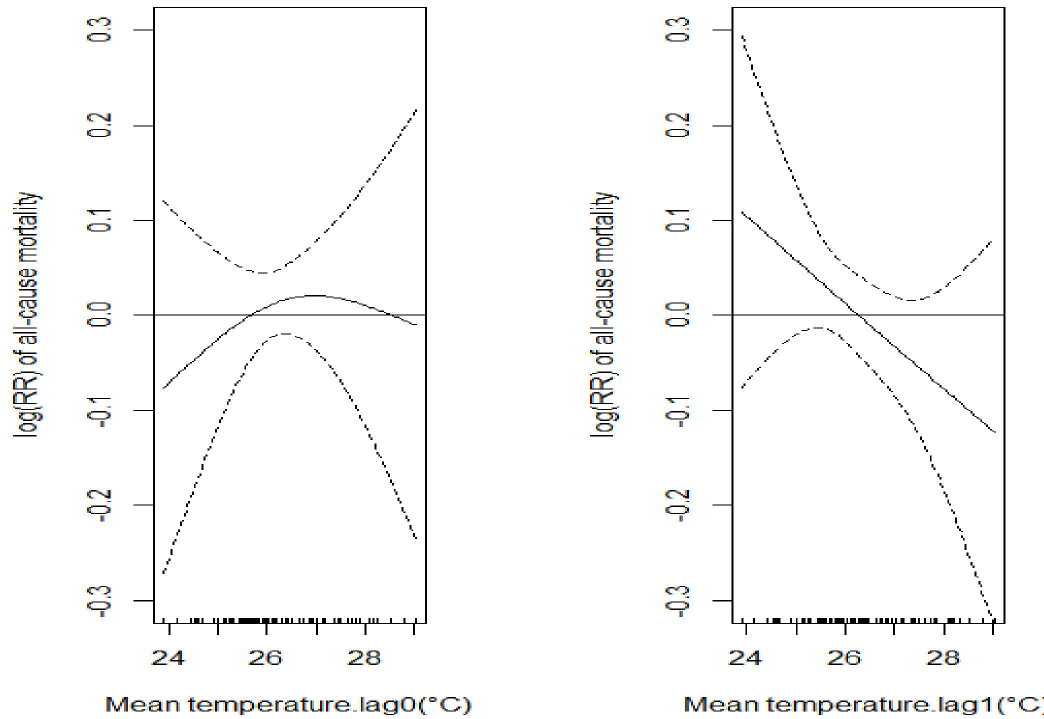

Figure 28: Plot of relationship between temperature and all-cause mortality for all ages at the Kintampo HDSS site.

In Navrongo, temperature in the month of death had a U-shape relationship with mortality. Monthly mortality risk increased as mean temperature in the month of death decreased below a value of about 27.4 degree celcius (°C) or increased above 30.7 °C. Temperature in the previous three months before death, however, had an inverted U-shape relationship while temperature in the previous one month had inverted J-shape (Appendix C3). Temperature in the month of death maintained its U-shape relationship with mortality when it was modeled with temperature lag1 which also maintained inverted J-shape relationship (Figure 29).

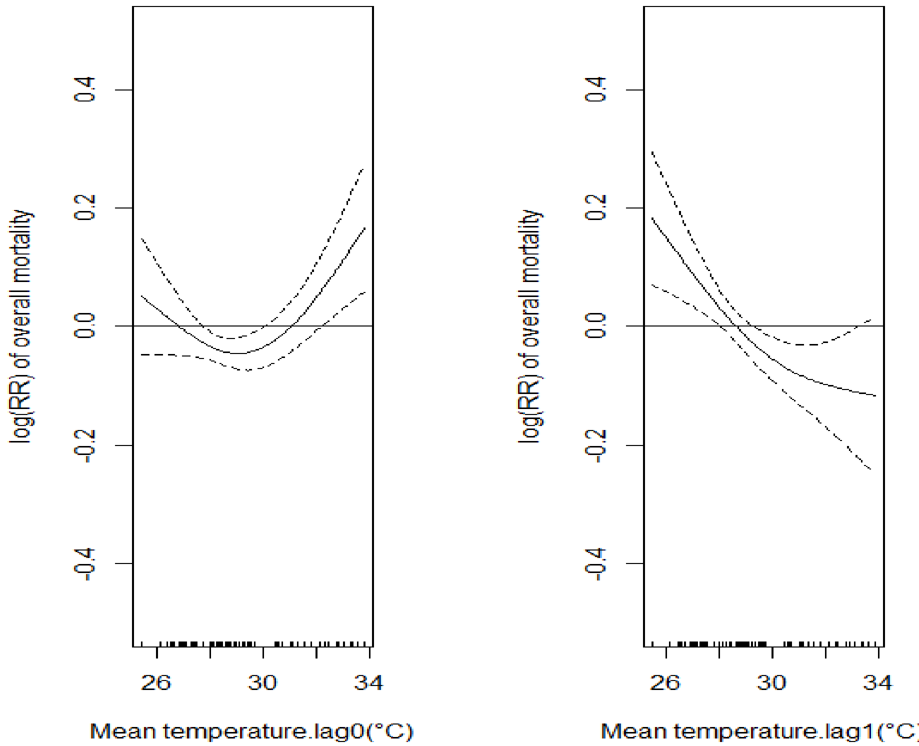

Figure 29: Plot of relationship between mean monthly temperature and overall monthly mortality at the Navrongo HDSS site when the temperature lags were modeled separately.

4.3.1.1 Rainfall and all-cause mortality relationship at HDSS sites

The rainfall-mortality smooth curves also revealed a non-linear relationship with different shape for the different rainfall lag strata and at the HDSS sites. While rainfall lag0 and lag1 had relationships close to linear in Dodowa HDSS, rainfall lag2 had U-shape relationship with rainfall lag3 having inverted U-shape relationships. Overall mortality risk increased as cumulative rainfall lag0 increased. For cumulative rainfall lag1, monthly mortality risk tended to decrease as rainfall increased. For rainfall lag2, mortality risk decreased with increase in rainfall till above 160.5mm and then increased with rainfall beyond 176.5mm.

Mortality risk also increased with a decrease in rainfall below 5.6mm but these changes in risk were not significant. With rainfall lag3, the risk of monthly mortality increased as rainfall increased till 129.3mm and then decreased with rainfall (Appendix C4). When rainfall lag0 and lag1 were put together in the model, mortality risk increased with rainfall lag0 above 129mm or rainfall lag0 below 34mm. For rainfall lag1, mortality risk decreased with rainfall (Figure 30)

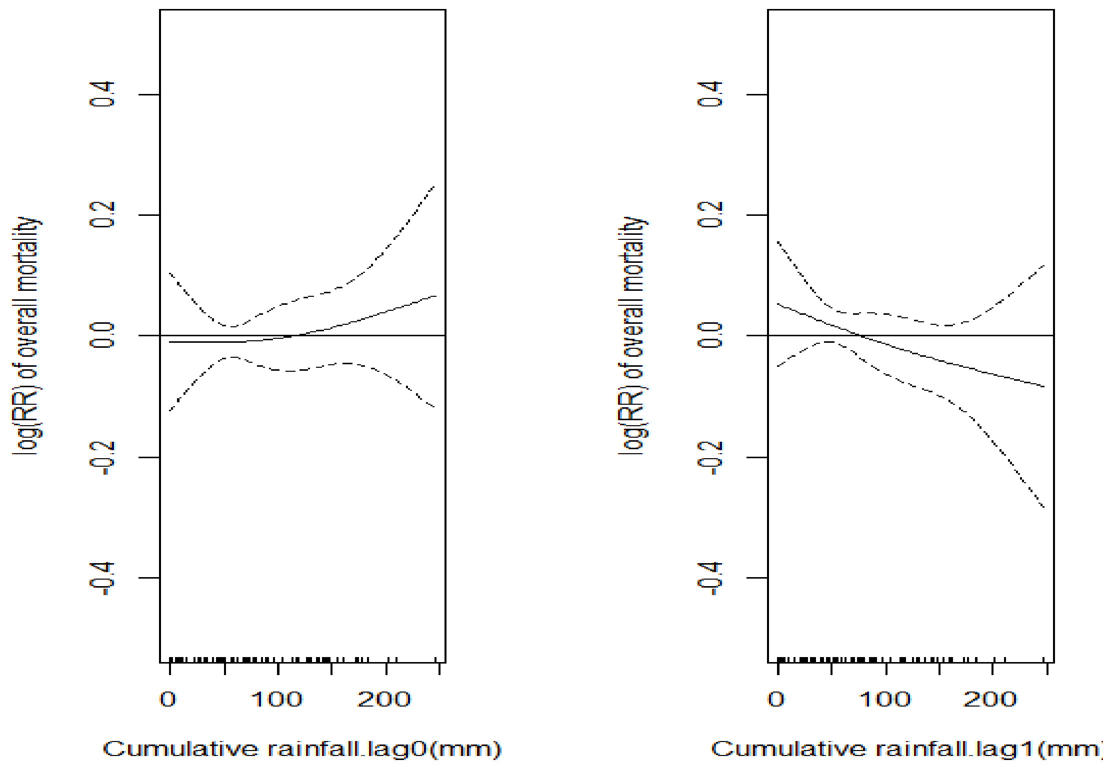

Figure 30: Plot of relationship between cumulative rainfall at lag0 and lag1 and all-cause mortality for all ages at the Dodowa HDSS site.

At the Kintampo HDSS on the other hand, rainfall lag0 and lag2 had inverted U-shape relationship with the risk of mortality while rainfall lag1 had an approximate U-shape relationship. Rainfall lag3 three had approximate linear relationship with the risk of mortality increasing with rainfall. For rainfall lag0, mortality risk increased with rainfall till above 240mm when it started decreasing. For rainfall lag1, mortality risk decreased till a rainfall value of about 350mm at which it started to increase. For temperature lag2, just like lag0, the mortality risk increased slightly and then started decreasing (Appendix C5). Rainfall lag0 and rainfall lag2 maintained their invert U-shape relationship when the three temperature lag strata where combine in the model (Figure31).

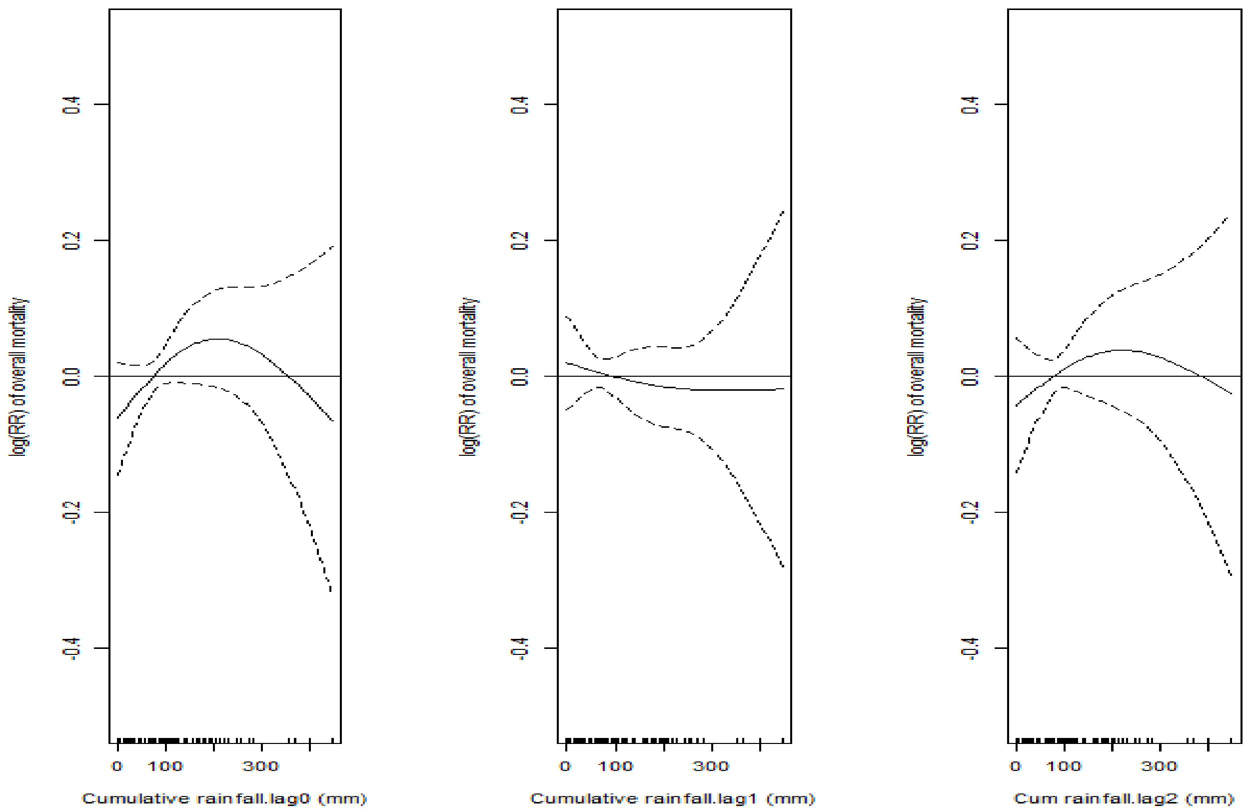

Figure 31: Plot of relationship between rainfall and all-cause mortality for all ages at the Kintampo HDSS site.

However, at the Navrongo HDSS, the plots revealed a linear relationship between rainfall and all-cause mortality. The plots showed that risk of overall monthly mortality increased with increase in monthly rainfall when modeled separately (Appendix C6) or together (Figure 32).

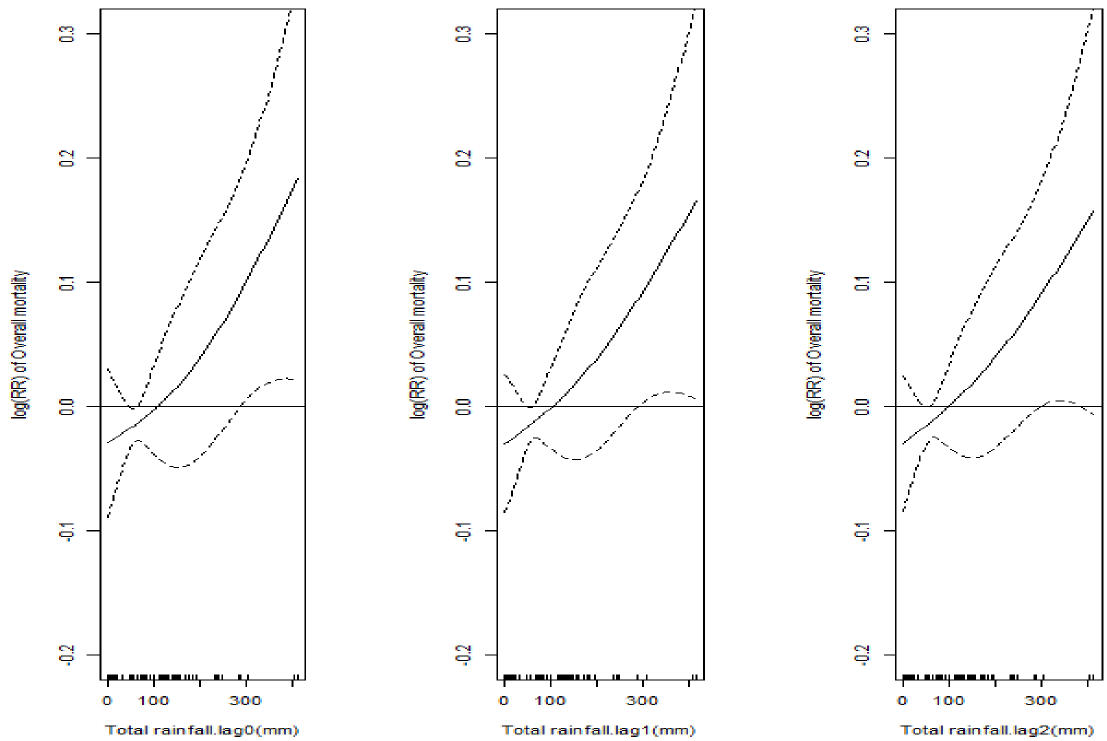

Figure 32: Plot of relationship between rainfall and overall mortality at the Navrongo HDSS Site when the rainfall lags were modeled separately

4.3.1.2 Quantification of the relationship between temperature, rainfall and all-cause mortality for all ages at the HDSS sites

For the overall mortality at the Dodowa HDSS, temperature lag1 was the only lag stratum that was significantly associated with mortality at the 5% significance level when modeled separately. Though mortality risk increased with mean temperature in the month of death, the association was not significant. There was also no significant association between mortality risk and the previous two or three months mean temperature (Appendix D1). For mean temperature lag1, the relative risk was 0.7609 (95% CI, 0.6538, 0.8854) with mean temperature above 29.5°C, which translates to an overall monthly decrease in mortality risk by 23.9%. The risk however, increased with mean temperature below 27.6°C but this was not statistically significant. Linear estimates also indicated decrease in mortality risk with increase in temperature lag1 though the significance level was 10% (Appendix D1).

The effect of mean temperature lag1 on mortality did not change much when modeled with mean temperature lag0. The relative risk was 0.7619 (95% CI, 0.6476, 0.8964) with mean temperature lag1 above 29.5°C, corresponding to monthly decrease in mortality risk by 23.8%. Though, the risk increased by 1.8% with mean temperature below 27.6°C, the change was not statistically significant. For mean temperature lag0, mortality risk increased with mean temperature above 29.5°C or mean temperature below 27.6°C but this was not statistically significant. Linear estimates of relative risk for mean temperatures lag0 and lag1 modeled together indicated increase in mortality risk with mean temperature lag0 and decrease in risk with mean temperature lag1 though the associations were not significant (Table 4a).

When stratified by sex, only the mean temperature lag1 was significantly associated with both male and female mortality risk when the temperature lag strata were modeled separately though the effect size was different. However, when modeled with mean temperature lag0, only male mortality risk was associated at the 5% level of significance with 10% significance level for female mortality. Male monthly mortality risk decreased by 31.8% with mean temperature above 29.5°C while for the females mortality risk decreased by 16.9%.

At the Kintampo HDSS, none of the temperature lag strata was significantly associated with mortality risk. However, for mean temperature lag0, relative risk of mortality was 1.0749 (95% CI, 0.9205, 1.2683), an increase in mortality risk by 7.5% with mean temperature above 27.0°C. The risk decreased by 5.3% with mean temperature below 25.5°C. A linear estimate indicated increased in risk of mortality with temperature by 1.6%. With temperature lag1, relative risk was 0.9082 (0.7821, 1.0524), a decrease in mortality risk by 9.3% with mean temperatures above 27.0°C and increased by 5.2% with mean temperature below 25.5°C. Linear estimate indicated decreased in mortality risk with temperature by 3.85% (Appendix D2). When temperature lag0 and lag1 were modeled together, temperature lag1 was significantly associated with male all-cause mortality. Monthly mortality risk decreased by 15.7% with mean temperature lag1 above 27.0°C and increased by 8.75% with mean temperature below 25.5°C. For female all-cause mortality, none of the temperature lag strata was significantly associated with mortality (Table 4a)

The mean temperature in the previous one month before the occurrence of death was significantly associated with overall mortality when modeled separately (Appendix D3) and in the presence of other temperature lag0 (Table 4b) in Navrongo HDSS. The relative risk of monthly all-cause mortality was 1.1087 (95% CI, 1.0310, 1.1921), corresponding to an increase in mortality risk by 10.9% with mean temperature lag1 below 27.4°C and this was statistically significant. A linear estimate also suggested a decrease in mortality risk with temperature. For the temperature lag0 all-cause mortality risk increased by 2.8% with mean temperature below 27.4°C and by 6.3% with mean temperature above 30.7°C. Linear estimates also suggested increase in mortality with temperature but these were not statistically significant (Table 4b). Just as in the overall mortality results for Navrongo HDSS, temperature lag1 was significantly associated with both male and female mortality when the analysis was stratified by sex. Male and female mortality risk increased by 10.4% and 11.9% respectively with mean temperature lag1 below 27.4°C.

4a : Quantification of relationship between temperature, rainfall and all-cause mortality for all ages for Dodowa and Kintampo HDSS site

	Crude Relative Risk^			Adjusted Relative Risk~		
Factor	**RR (95% CI)**	**% change**	**P value**	**RR (95% CI)**	**% change**	**P value**
Dodowa						
Temp lag 0						
<25th(27.6°C)	1.0091(0.8646,1.1776)	0.91	0.909	0.9938(0.8502, 1.1617)	-0.62	0.938
>75th(29.5°C)	1.0149(0.8541, 1.2060)	1.49	0.867	1.0519(0.8820, 1.2547)	5.19	0.576
Linear	1.0084(0.9019, 1.1275)	0.84	0.883	1.0117(0.8820, 1.1297)	1.17	0.837
Temp lag1						
<25th(27.6°C)	1.0181(0.8755, 1.1838)	1.81	0.817	1.0087(0.8646, 1.1768)	0.87	0.912
>75th(29.5°C)	**0.7619(0.6476, 0.8964)**	**-23.81**	**0.002**	**0.7793(0.6610, 0.9186)**	**-22.07**	**0.004**
Linear	0.9308(0.8493, 1.0200)	-6.93	0.13	0.9272(0.8474, 1.0146)	-7.28	0.105
Rainfall						
Rainfall lag 0						
<25th(34.1mm)	1.0102(0.9037, 1.1292	1.02	0.859	1.0222(0.9189, 1.1371)	2.22	0.687
>75th(129.1mm)	1.0192(0.9348,1.1112)	1.92	0.668	1.0219(0.9405, 1.1103)	2.19	0.611
Linear	1.0003(0.9995,1.0010)	0.03		1.0004(0.9996, 1.0011)	0.04	0.363
Rainfall lag 1						
<25th (34.1mm)	1.0950(0.9889,1.2126)	9.50	0.086	1.0818(0.9800, 1.1942)	8.18	0.125
>75th (129.1mm)	0.9607(0.8778,1.0514)	-3.93	0.387	0.9560(0.8770, 1.0421)	-4.40	0.310
Linear	0.9994(0.9986,1.0002)	-0.06	0.147	0.9994(0.9986, 1.0002)	-0.06	0.136
Kintampo						
Temp lag 0						
<25th(25.5°C)	0.9475(0.8285,1.0835)	-5.25	0.434	0.9165(0.8116, 1.0350)	-8.35	0.166
>75th(27.0°C)	1.0749(0.9110, 1.2683)	7.49	0.395	1.0901(0.9450, 1.2575)	9.01	0.241
Linear	1.0155(0.9505,1.0849)	1.55	0.650	1.0152(0.9485, 1.0867)	1.52	0.665
Temp lag1						
<25th(25.5°C)	1.0517(0.9205,1,2016)	5.17	0.461	1.0597(0.9344, 1.2018)	5.97	0.370
>75th(27.0°C)	0.9073(0.7821, 1.0524)	-9.27	0.204	0.9224(0.8110, 1.0488)	-7.77	0.223
Linear	0.9615(0.9096,1.0163)	-3.85	0.170	0.9602(0.9057, 1.0179)	-3.98	0.177
Rainfall lag 0						
<25th(22.8mm)	0.9459(0.8304,1.0775)	-5.41	0.406	0.9322(0.8162, 1.0646)	-6.78	0.305
>75th(177.5mm)	**1.1285(1.0210,1.2473)**	**12.85**	**0.021**	**1.1350(1.0227, 1.2597)**	**13.50**	**0.021**
Linear	1.0001(0.9996,1.0006)	0.01		1.0001(0.9996, 1.0006)	0.01	0.690
Rainfall lag 1						
<25th(22.8mm)	1.0560(0.9499,1.1740)	5.60	0.317	1.0073(0.8963, 1.1322)	0.73	0.903
>75th	0.9664(0.8843,1.0561)	-3.36	0.453	0.9371(0.8461, 1.0379)	-6.29	0.218
Linear	1.0000(0.9995,1.0004)	-0.003	0.877	1.0000(0.9996, 1.0004)	0.00	0.946
Rainfall lag 2						
<25th (22.8mm)	0.9960(0.8953,1.1082)	-0.40	0.942	0.9752(0.8740, 1.0881)	-2.48	0.655
>75th(177.5mm)	1.1246(0.9992,1.2657)	12.46	0.056	**1.1590(1.0246, 1.3111)**	**15.90**	**0.023**
Linear	1.0000(0.9994,1.0007)	0.005	0.882	1.0000(0.9994, 1.0006)	0.001	0.971

^: Estimates for temperature and rainfall modeled separately

~: Estimates for temperature and rainfall adjusted for each other (modeled together)

4b : Quantification of relationship between temperature, rainfall and all-cause mortality for all ages for Navrongo HDSS site

	Crude Relative Risk^			Adjusted Relative Risk~		
Factor	**RR (95% CI)**	**% change**	**P value**	**RR (95% CI)**	**% change**	**P value**
Navrongo						
Temp lag 0						
<25th(27.4°C)	1.0280(0.9587,1.1024)	2.80	0.441	1.0262(0.9418, 1.1183)	2.62	0.557
>75th(30.7°C)	1.0627(0.9749, 1.1583)	6.27	0.172	1.0532(0.9617, 1.1534)	5.32	0.269
Linear	1.0200(1.0000,1.0404)	2.00	0.055	1.0291(1.0056, 1.0531)	2.91	0.018
Temp lag1						
<25th(27.4°C)	**1.1087(1.0310, 1.1921)**	**10.87**	**0.007**	**1.1100(1.0197, 1.2084)**	**11.00**	**0.019**
>75th(30.7°C)	0.9969(0.9048, 1.0984)	-0.31	0.950	0.9910(0.8968, 1.0950)	-0.90	0.859
Linear	0.9726(0.9477,0.9981)	-2.74	0.039	0.9768(0.9513, 1.0030)	-2.32	0.087
Rainfall						
Rainfall lag 0	1.0005(0.9999,1.0010)	0.05	0.107	1.0002(0.9996, 1.0008)	0.02	0.497
Rainfall lag 1	1.0004(0.9999,1.0010)	0.04	0.156	1.0000(0.9994, 1.0007)	0.004	0.895
Rainfall lag 2	1.0004(0.9998,1.0010)	0.04	0.166	1.0002(0.9997, 1.0008)	0.02	0.384

^: Estimates for temperature and rainfall modeled separately

~: Estimates for temperature and rainfall adjusted for each other (modeled together)

4.3.1.3 Quantification of the relationship between rainfall and all-cause mortality for all ages at the HDSS sites

With rainfall, estimates of relative risk of mortality at Dodowa HDSS suggested that there was no statistically significant association between the rainfall lag strata and all-cause mortality for all ages. Though mortality risk was higher with rainfall lag0 below 34.1mm and above 129.3mm and lower with rainfall lag1 above 129.3mm, the association was not statistically significant. Sex stratified estimates also revealed similar results (Table 4a).

Rainfall in the month of death was significantly associated with all-cause mortality for all ages at Kintampo HDSS. The relative risk of mortality with rainfall lag0 above 177.5mm was 1.1285 (95% CI, 1.0220, 1.2473), an increase in mortality risk by 12.9%. The risk decreased by 5.4% with rainfall lag0 below 22.8mm. A linear estimate of relative risk also suggested increase in mortality with rainfall. The risk increased by 0.1% per 10mm increase in rainfall lag0. With rainfall lag1, mortality risk decreased by 3.4% with rainfall above 177.5mm and increased by 4.9% with rainfall below 22.8mm. With linear estimate, the risk decreased by 0.03% per 10mm increase in rainfall. For rainfall lag month two, mortality risk increased by 12.5% with rainfall above 177.5mm but this was at the 10% level of significance (Table 4a).

When the analysis was stratified by sex, none of the rainfall lag strata was significantly associated with male mortality risk. However, for the female mortality, rainfall in the month of death had a significant association with mortality risk. Mortality risk increased by 13.2% with rainfall lag0 above 177.5mm. With linear estimate, the risk increased by 0.5% per 10mm increased in rainfall but this was not significant.

Though none of the rainfall lags strata was significantly associated with overall mortality at the Navrongo HDSS site, monthly mortality however increased with cumulative rainfall. Mortality risk also increased by 0.5% per 10mm increase in rainfall lag0. The risk also increased by 0.4% each per 10mm increase in the rainfall lag1 and lag2. The cumulative effect of the rainfall lags was 1.3% increase in mortality per 10mm increase in rainfall (Table 4b). As observed in the overall mortality, none of the rainfall lag strata was significantly associated with male or female mortality risk when the analysis was stratified by sex though mortality increased with rainfall.

4.3.1.4 Association between temperature and all-cause mortality adjusted for the effect of rainfall and association between rainfall and all-cause mortality adjusted for the effect of temperature at the HDSS sites

When temperature and rainfall were modeled together, temperature lag1 had a significant association with all-cause mortality for all ages at Dodowa HDSS. The relative risk was 0.779 (95% CI, 0.661, 0.919), a decrease in mortality risk by 22.1% with mean temperatures lag1 above 29.5 °C. Though the risk increased with the mean temperature lag1 below 27.4 °C, it was not significant. Mortality risk also increased with mean temperature lag0 but this was not statistically significant (Table 4a above). At the Kintampo HDSS, rainfall lag0 and rainfall lag2 were significantly associated with mortality when temperature and rainfall were modeled together. The relative risks for monthly rainfall above 177.5mm in the month of death was 1.135(955 CI, 1.023, 1.260) and the previous two months was 1.159(955 CI, 1.025, 1.311). These correspond to increase in mortality risks by 13.5% and 15.9% respectively with rainfall lag0 and rainfall lag2 above 177.5mm (Table 4a). Mean temperature lag1 was significantly associated with all-cause mortality for all ages at Navrongo HDSS site when temperature and rainfall were adjusted for each other. The relative risk associated with mean temperature lag1 below 27.4°C was 1.110(95% CI, 1.020, 1.208), an increase in mortality risk by 11.0% with mean temperature below 27.4°C (Table 4b).

4.3.2 Relationship between temperature, rainfall and under-five all-cause mortality at the HDSS sites

With the relationship between temperature and under-five all-cause mortality, temperature lag0 had approximate linear relationship with mortality when modeled separately (Appendix E1) or with other temperature lags strata at Dodowa HDSS (Figure 33). Under-five mortality risk increased as mean temperature lag0 increased. Temperature lag1 however, had approximate inverted J-shape relationship when modeled with temperature lag0. Under-five all-cause mortality risk also increased with temperature lag1 (Figure 33).

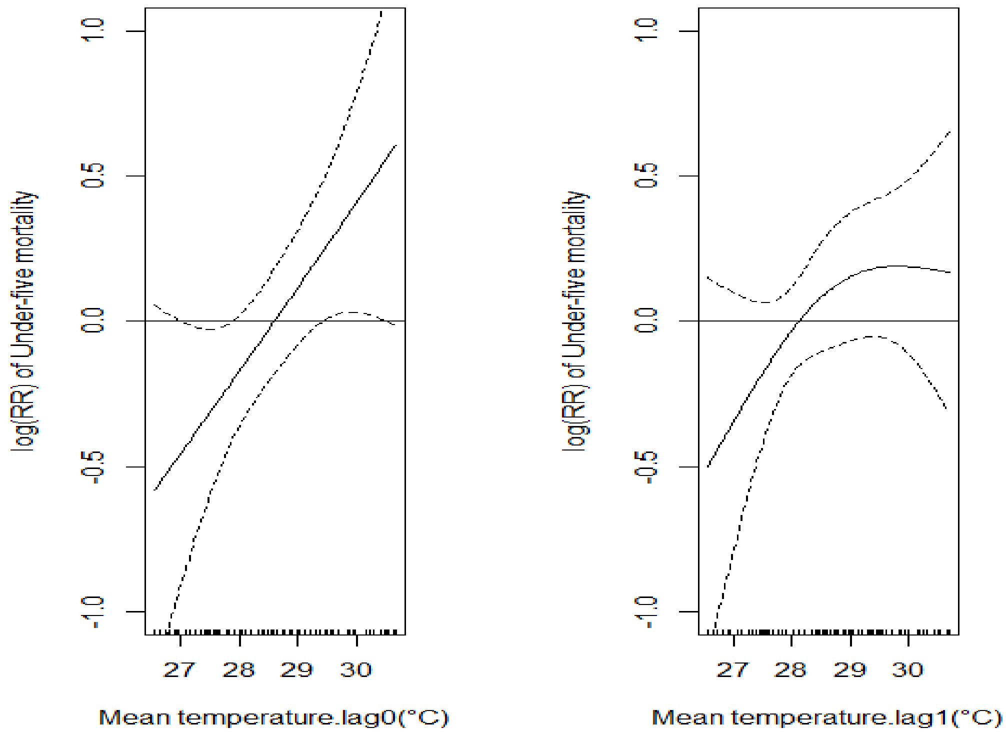

Figure 33: Plot of relationship between mean temperature at lag0 and lag1 and under-five mortality for all ages at the Dodowa HDSS site.

At the Kintampo HDSS, mean temperature lag1 had inverted J-shape relationship with under-five all-cause mortality while the rest had approximate linear relationship. For temperature lag0, mortality risk increased as temperature increased. With temperature lag1, monthly mortality risk increased as mean temperature increased to about 25.5°C and then decreased. For temperature lag2 and lag3, mortality risk increased as mean temperature increased Appendix (E2). For temperature lag0 and lag1 together, temperature lag lag0 had approximate linear relationship while temperature lag1 had inverted J-shape relationship (Figure 34).

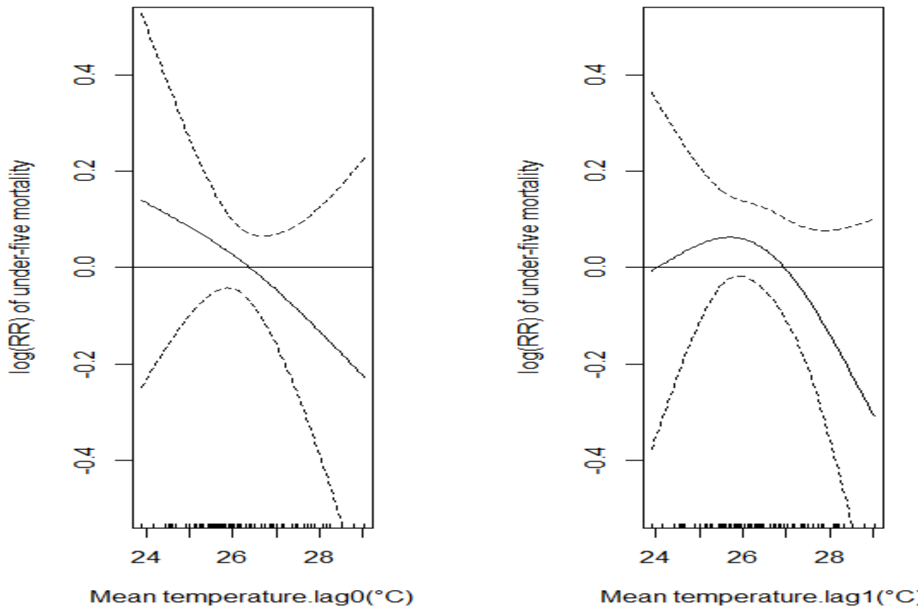

Figure 34: Plot of relationship between temperature lag strata and under-five mortality at the Kintampo HDSS site.

For Navrongo HDSS, temperature lag0 had a J-shape relationship while temperatureblag1 had approximate U-shape relationship. The relationship between temperature lag2 and lag3 were approximate linear. For temperature lag0, mortality risk increased with mean temperature. For temperature lag1 to lag3, the risk of under-five mortality decreased with temperature (Appendix E3). When temperature lag0 and lag1 were modeled together, temperature lag0 maintained its J-shape relationship with under-five mortality. Mortality risk increased significantly with temperature above 30.6 °C (Figure 35).

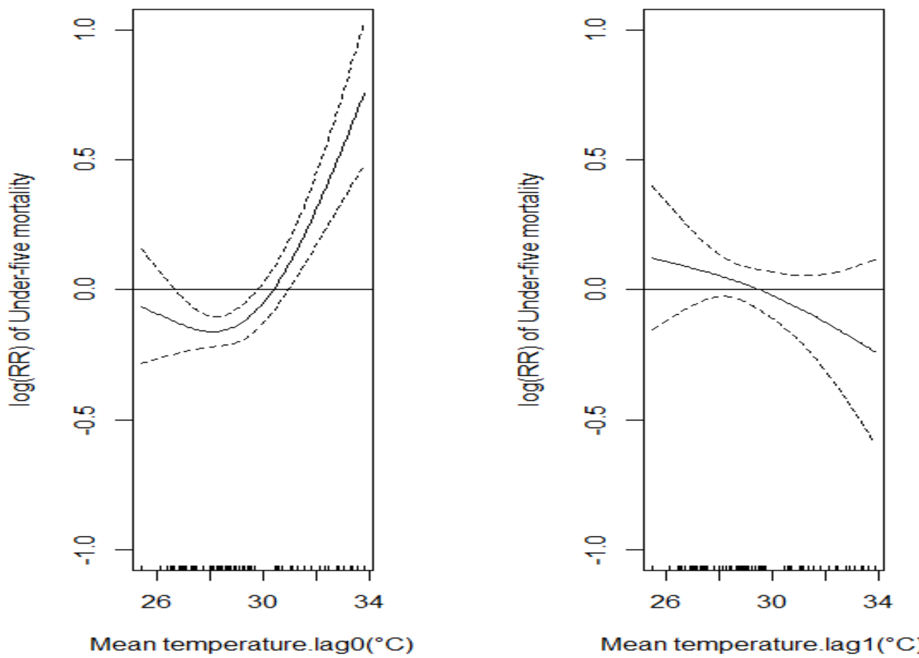

Figure 35: Plot of relationship between mean monthly temperature and under-five monthly mortality at the Navrongo HDSS site when the temperature lags were modeled separately.

4.3.2.1 Relationship between rainfall and under-five all-cause mortality at the HDSS sites

With children under-five years at Dodowa HDSS, mortality risk increased with increasing rainfall lag0. For cumulative rainfall lag1, the risk of under-five mortality tended to decrease as rainfall increased. The risk, however, increased as rainfall lag1 decreased below 34.1mm. The risk of mortality increased with increased rainfall lag2. With rainfall lag3, there was virtually no relationship between risk of under-five mortality and rainfall (Appendix E4). When rainfall lag0 and lag1 were modeled together, rainfall lag0 had approximate linear relationship while rainfall lag1 had an inverted J-shape relationship with mortality (Figure 36).

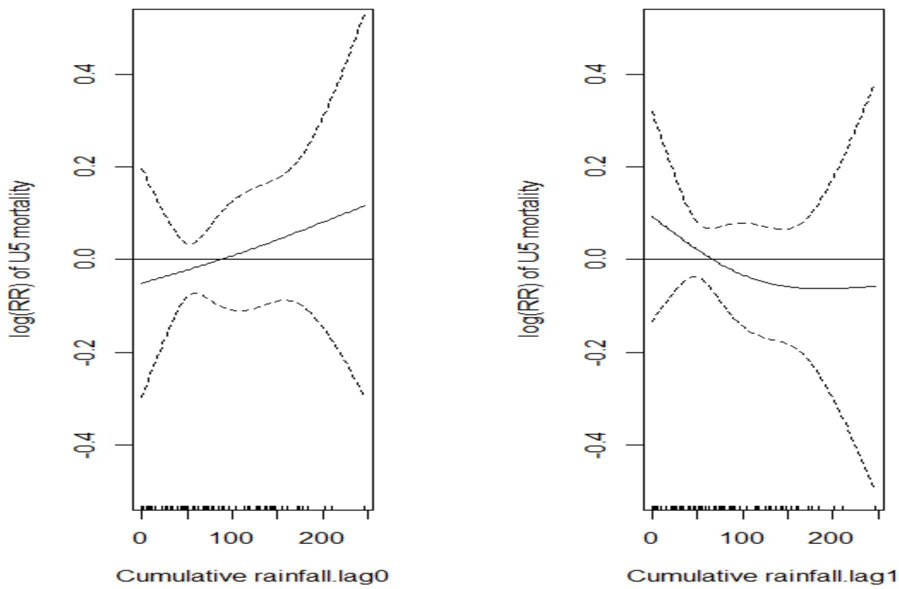

Figure 36: Plot of relationship between cumulative rainfall at lag0 and lag1 and under-five mortality at the Dodowa HDSS site.

For Kintampo HDSS, under-five mortality risk increased with increasing rainfall lag0 till a rainfall value of about 178mm, the 75th percentile when the mortality risk started decreasing. Under-five mortality risk also increased with rainfall lag1. With rainfall lag2, mortality risk increased to around 240mm and then decreased. For rainfall lag3 mortality risk decreased till rainfall value above 300mm when the risk started increasing (Figure 37, Appendix E5).

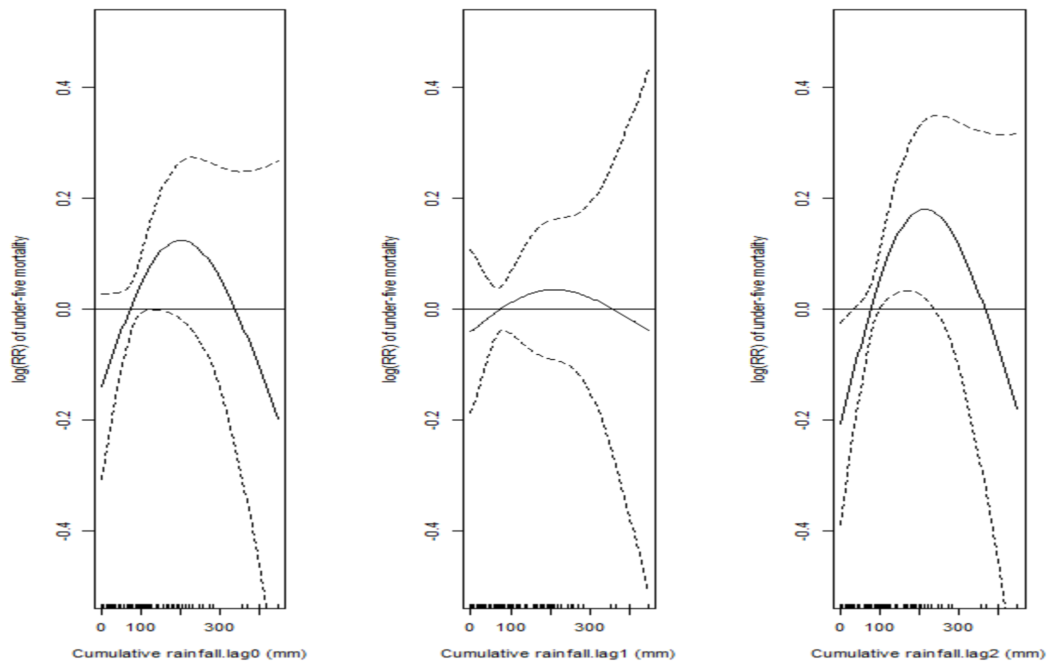

Figure 37: Plot of relationship between rainfall and under-five mortality at the Kintampo HDSS site.

Rainfall was positively related to under-five all-cause mortality at Navrongo HDSS when the lags were modeled separately (Appendix E6) or together (Figure 38). Monthly under-five mortality risk increased with rainfall

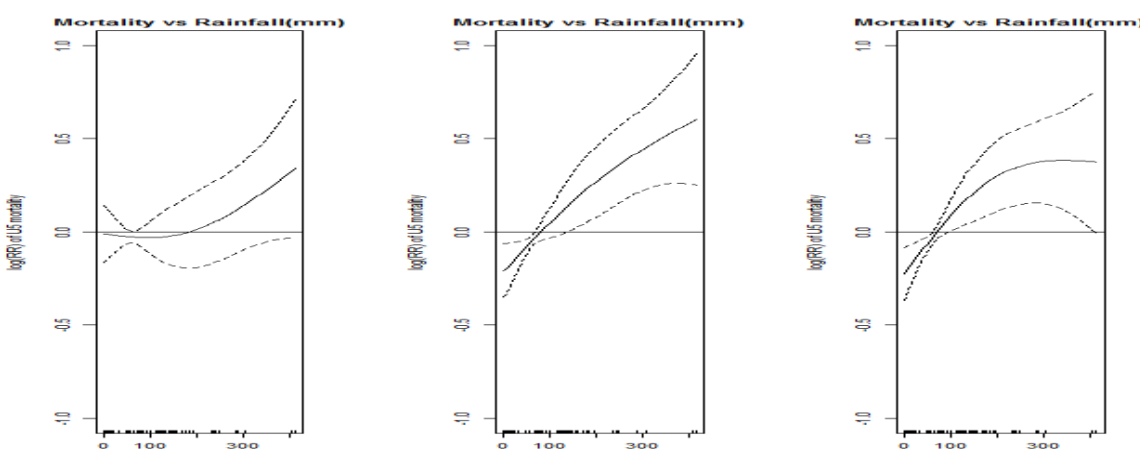

Figure 38: Plot of relationship between rainfall and under-five mortality at the Navrongo HDSS Site.

4.3.2.2 Quantification of the relationship between temperature and under-five all-cause mortality at the HDSS sites

None of the temperature lags strata was significantly associated with under-five mortality risk when modeled using the percentiles though mortality risk increased with temperature (Table 4a). However, when linear effect was estimated, under-five mortality risk was significantly associated with mean temperature lga0. The relative risk was 1.3012 (95% CI, 1.0117, 1.6736) which corresponds to an increase in mortality risk by 30.12% with mean temperature lag0. The risk of mortality increased by 5.93% with mean temperature lag1 but this was not statistically significant (Table 4a). For Kintampo HDSS, none of the temperature lag strata was significantly associated with under-five mortality (Table 5a).

5a : Quantification of relationship between temperature, rainfall and under-five all-cause mortality for Dodowa and Kintampo HDSS sites

	Crude Relative Risk^			**Adjusted Relative Risk~**		
Factor	**RR (95% CI)**	**% change**	**P value**	**RR (95% CI)**	**% change**	**P value**
Dodowa						
Temp lag 0						
<25th(27.6°C)	0.9179(0.6056, 1.3907)	-8.21	0.888	0.9909(0.6756, 1.4532)	-0.91	0.963
>75th (29.5°C)	1.0280(0.7019, 1.5055)	2.80	0.687	0.9926(0.6538, 1.5070)	-0.74	0.972
Linear	**1.3012(1.0117, 1.6736)**	**30.12**	**0.045**	**1.3146(1.0215, 1.6917)**	**31.46**	**0.038**
Temp lag1						
<25th (27.6°C)	0.9219(0.6260,1.3576)	-7.81	0.682	0.8510(0.5710, 1.2681)	-14.90	0.431
>75th(29.5.4°C)	1.0593(0.7081,1.5848)	5.93	0.78	1.1184(0.7458, 1.6771)	11.84	0.591
Linear	1.1354(0.9239, 1.3954)	13.54	0.232	1.1239(0.9154, 1.3799)	12.39	0.269
Rainfall						
Rainfall lag 0						
25th (34.1mm)	1.0448(0.8105,1.3468)	4.48	0.736	1.0473(0.8028, 1.3663)	4.73	0.735
75th (129.3mm)	1.0740(0.8863,1.3015)	7.40	0.469	1.0824(0.8859, 1.3225)	8.24	0.442
Linear	1.0007(0.9991,1.0024)	0.07	0.392	1.0009(0.9993, 1.0026)	0.09	0.285
Rainfall lag 1						
<25th (34.1mm)	**1.2696(1.0070,1.6007)**	**26.96**	**0.048**	**1.2941(1.0144, 1.6509)**	**29.41**	**0.043**
>75th (129.3mm)	1.0376(0.8482,1.2692)	3.76	0.721	1.0470(0.8503, 1.2892)	4.70	0.667
Linear	0.9993(0.9976,1.0010)	-0.07	0.438	0.9994(0.9977, 1.0011)	-0.06	0.500
Kintampo						
Temp lag0						
<25th (25.5°C)	1.0273(0.8395, 1.2571)	2.73	0.795	1.1411(0.9058, 1.4376)	14.11	0.267
>75th(27.0°C)	1.0759(0.8148, 1.4207)	7.59	0.608	1.1325(0.8662, 1.4806)	13.25	0.367
Linear	0.9598(0.8401, 1.0965)	-4.02	0.548	0.9510(0.8315, 1.0877)	-4.90	0.467
Temp lag1						
<25th(25.5°C)	0.9082(0.7342, 1.1234)	-9.18	0.378	1.0345(0.8117, 1.3185)	3.45	0.785
>75th(27.0°C)	0.9800(0.7645,1.2562)	-2.00	0.874	0.9607(0.7530, 1.2258)	-3.93	0.748
Linear	0.9510(0.8486,1.0657)	-4.90	0.391	0.9387(0.8344, 1.0561)	-6.13	0.297
Rainfall lag 0						
<25th (22.8mm)	0.8032(0.6325,1.0201)	-19.68	0.077	**0.7666(0.5961, 0.9858)**	**-23.34**	**0.043**
>75th (177.5mm)	1.0653(0.8934,1.2701)	6.53	0.084	1.1231(0.9267, 1.3611)	12.31	0.242
Linear	1.0001(0.9999,10002)	0.01	0.885	1.0001(0.9992, 1.0010)	0.01	0.861
Rainfall lag 1						
<25th (22.8mm)	1.0475(0.8591,1.2771)	4.75	0.648	0.9894(0.7936, 1.2337)	-1.06	0.925
>75th (177.5mm)	1.0489(0.8956,1.2284)	4.89	0.558	1.0861(0.8982, 1.3133)	8.61	0.398
Linear	1.0005(0.9997,1.0012)	0.047	0.244	1.0006(0.9998, 1.0014)	0.06	0.168
Rainfall lag 2						
<25th (22.8mm)	**0.7219(0.5942, 0.8770)**	**-27.81**	**0.002**	**0.6940(0.5639, 0.8542)**	**-30.60**	**0.001**
>75th (177.5mm)	1.1865(0.9624,1.4628)	18.65	0.115	1.1750(0.9340, 1.4783)	17.50	0.174
Linear	1.0004(0.9993,1.0016)	0.04	0.482	1.0004(0.9992, 1.0015)	0.04	0.538

^: Estimates for temperature and rainfall modeled separately

~: Estimates for temperature and rainfall adjusted for each other (modeled together)

5b : Quantification of relationship between temperature, rainfall and under-five all-cause mortality for Navrongo HDSS site

	Crude Relative Risk^			Adjusted Relative Risk~		
Factor	**RR (95% CI)**	**% change**	**P value**	**RR (95% CI)**	**% change**	**P value**
Navrongo						
Temp lag 0						
<25th (27.4°C)	1.0187(0.8700, 1.1928)	1.87	0.819	1.0588(0.8696, 1.2892)	5.88	0.571
>75th (30.6°C)	**1.5759(1.2567, 1.9762)**	**57.59**	**<0.001**	**1.5491(1.2190, 1.9686)**	**54.91**	**0.001**
Linear	1.0928(1.0414, 1.1467)	9.28	<0.001	1.1155(1.0518, 1.1830)	11.55	0.001
Temp lag1						
<25th (27.4°C)	1.0946(0.9276, 1.2917)	9.46	0.288	1.0845(0.8907, 1.3205)	8.45	0.422
>75th (30.6°C)	0.9678(0.7558, 1.2392)	-3.22	0.796	0.9546(0.7385, 1.2339)	-4.54	0.724
Linear	0.9733(0.9104, 1.0405)	-2.67	0.430	0.9905(0.9235, 1.0625)	-0.95	0.791
Rainfall						
Rainfall lag 0	1.0012(1.0002,1.0022)	0.12	0.017	1.0010(0.9997, 1.0023)	0.10	0.154
Rainfall lag 1	1.0020(0.0011,1.0029)	0.20	<0.001	1.0009(0.9997, 1.0021)	0.09	0.143
Rainfall lag 2	1.0017(1.0008,1.0026)	0.17	<0.001	1.0001(0.9988, 1.0014)	0.01	0.845

^: Estimates for temperature and rainfall modeled separately

~: Estimates for temperature and rainfall adjusted for each other (modeled together)

Under-five monthly mortality risk in Navrongo HDSS was significantly associated with mean temperature lag0 above 30.7°C with a relative risk of 1.5759 (95% CI, 1.2567, 1.9762), an increase in mortality risk by 59.59%. Mortality risk increased by 1.9% with mean temperature below 27.4°C but this was not statistically significant. A linear estimate also indicated increase in mortality risk with mean temperature lag0. Under-five mortality risk increased by 9.5% with mean temperature lag1 below 27.4°C and decreased by 3.2% with mean temperature lag1 above 30.7°C but this relationship was not statistically significant. A linear estimate also indicated a non-significant decrease of mortality risk with mean temperature lag1 (Table 5b).

4.3.2.3 Quantification of the relationship between rainfall and under-five all-cause mortality at the HDSS sites

Rainfall lag1 was significantly associated with under-five all-cause mortality risk at Dodowa HDSS. The relative risk of under-five mortality with rainfall lag1 below 34.1mm was 1.2696 (95% CI, 1.0070, 1.6007) which translates to an increase of under-five mortality risk by 27.0%. Under-five mortality risk also increased by 3.8% with rainfall lag1 above 129.3mm but this was not statistically significant. A linear estimate also suggested a slight decrease in risk with rainfall lag1. The risk decreased by 0.7% per 10mm increase in rainfall. Though the risk of under-five mortality increased by 4.5% with rainfall lag0 below 34.1mm and by 7.4% with rainfall lag0 above 129.3mm, the association was not significant (Table 5a).

Estimates of relative risk of under-five mortality at Kintampo HDSS showed that mortality risk significantly decreased with rainfall lag0 or lag2 below 22.8mm when modeled separately. The relative risk was 0.7774 (95% CI, 0.626, 0.995) with rainfall lag0 below 22.8mm. For rainfall lag2, the relative risk was 0.7151 (95% CI, 0.5918, 0.8641) with rainfall below 22.8mm. The risk however, increased with rainfall above 177.5mm but these changes were not significant. With the linear estimates, mortality risk increased by 0.03% per 10mm increase in rainfall lag0 and 0.3% per 10mm increase in rainfall lag1 but these associations were not also significant (Appendix F2). However, when the lags were modeled together, only rainfall lag2 was statistically significant with relative risk of 0.7219 (95% CI, 0.594, 0.877), a reduction of mortality risk of 27.8% with rainfall below 22,8mm. For rainfall lag0, mortality risk decreased by 19.68% with rainfall below 22.8mm but this was significant at the 10% level (Table 5a).

Rainfall significantly associated with under-five mortality at the Navrongo HDSS sites. Relative risks for rainfall lag0 was 1.0012 (95% CI, 1.0002, 1.0022). The relative risk of mortality associated with rainfall lag1 was 1.0020 (95% CI, 1.0011, 1.0029) while the relative risk associated with rainfall lag2 was 1.0017 (95% CI, 1.0008, 1.0026). These translate into increase in under-five mortality risk by 1.2%, per 10mm increase in rainfall lag0, 2.0% per 10mm increase in rainfall lag1 and 1.7% per 10mm increase in rainfall lag2. The cumulative change in monthly under-five mortality per 10mm increase in rainfall was 4.9% (Table 5b).

4.3.2.4 Association between temperature and under-five mortality adjusted for the effect of rainfall and the association between rainfall and under-five mortality adjusted for the effect of temperature at the HDSS sites

Temperature lag0 and rainfall lag1 were significantly associated with under-five mortality at Dodowa HDSS when temperature and rainfall were adjusted for each other in the model. Temperature lag0 was associated with under-five mortality with relative risk of 1.315(95% CI, 1.022, 1.692). Rainfall lag1 below 34.1mm was associated with a relative risk of 1.294 (95% CI, 1.014, 1.651). These correspond to mortality risks increase of 31.5% and 29.4% respectively (Table 5a). Monthly under-five mortality at Kintampo was also significantly associated with rainfall lag0 and lag2. Mortality risk decreased by 23.3% with rainfall lag0 and by 30.6% with rainfall lag2 below 22.8mm (Table 5a)

With under-five mortality at Navrongo HDSS, temperature lag0 was significantly associated with mortality with a relative risk of 1.549 (95% CI, 1.219, 1.969). That is an increase in under-five mortality risk by 54.9% with mean temperature above 30.7°C. A linear estimate also indicated a significant increase in under-five mortality risk with temperature (Table 5a).

4.3.3.2 Quantification of the relationship between temperature, rainfall and all-cause mortality in the elderly (60+ years) at the HDSS sites

At Dodowa HDSS, mortality in the elderly (60+ years), was associated with lower mean temperature of the previous one month. Mortality risk significantly decreased by 31.4% with a mean temperature lag1 above 29.5°C. For the linear estimates, the decrease was 9.37% but this was not significant (Table 6a). Mortality risk in the elderly (60+ years) at Kintampo HDSS increased by 17.9% with mean temperature lag0 above 27.0°C and decreased by 15.4% with mean temperature lag0 below 25.5°C (Table 6a). For Navrongo HDSS, there was no significant association between any of the temperature lags and risk of monthly mortality in the elderly (60+) though mortality risk increased with temperature in the month of death (Table 6b). None of the rainfall lags was significantly associated with mortality risk in the elderly in the HDSS sites (60+ years) (Table 6).

When temperature and rainfall were adjusted for each other in the model mean temperature lag1 was significantly associated with mortality in the elderly (60+ years) in Dodowa HDSS (Table 6a). At Kintampo HDSS, temperature lag0 was significantly associated with mortality risk in the elderly (Table 6a). For Navrongo HDSS, none of the rainfall or temperature lags was significantly associated with mortality in the elderly (table 6b).

6a : Quantification of relationship between temperature, rainfall and under-five all-cause mortality for Dodowa and Kintampo HDSS sites

	Crude Relative Risk^			Adjusted Relative Risk~		
Factor	**RR (95% CI)**	**% change**	**P value**	**RR (95% CI)**	**% change**	**P value**
Dodowa						
Temp						
<25th (27.6°C)	1.1169(0.9082, 1.3735)	11.69	0.299	1.1026(0.8921, 1.3627)	10.26	0.370
>75th ((29.5°C)	1.0170(0.8024, 1.2888)	1.70	0.89	1.0476(0.8196, 1.3389)	4.76	0.712
Linear	0.8842(0.7617, 1.0264)	-11.58	0.111	0.8878(0.7640, 1.0316)	-11.22	0.125
Temp lag1						
<25th (27.6°C)	1.1381(0.9324, 1.3893)	13.81	0.208	1.1406(0.9281, 1.4017)	14.06	0.216
>75th (29.5.0°C)	0.6861(0.5494, 0.8569)	-31.39	0.002	0.7009(0.5578, 0.8807)	-29.91	0.003
Linear	0.9063(0.7999, 1.0268)	-9.37	0.128	0.9034(0.7969, 1.0240)	-9.66	0.117
Rainfall						
Rainfall lag 0						
25th (34.1mm)	0.9949(0.8567, 1.1554)	-0.51	0.947	0.9995(0.8670, 1.1523)	-0.05	0.995
75th (129.5mm)	1.0336(0.9186, 1.1630)	3.36	0.585	1.0266(0.9170, 1.1492)	2.66	0.650
Linear	1.0005(0.9994, 1.0015)	0.05	0.368	1.0005(0.9994, 1.0015)	0.05	0.374
Rainfall lag 1						
<25th (34.1mm)	1.0808(0.9418, 1.2404)	8.08	0.273	1.0538(0.9222, 1.2041)	5.38	0.445
>75th (129.5mm)	0.9465(0.8365, 1.0709)	-5.35	0.386	0.9369(0.8328, 1.0539)	-6.31	0.282
Linear	0.9997(0.9987, 1.0008)	-0.03	0.618	0.9997(0.9987, 1.0008)	-0.03	0.595
Kintampo						
Temp lag0						
<25th (25.5°C)	0.8456(0.7206, 0.9923)	-15.44	0.044	0.7507(0.6207, 0.9080)	-24.93	0.005
>75th (27.0°C)	1.1792(0.9430, 1.4746)	17.92	0.153	1.1485(0.9134, 1.4443)	14.85	0.241
Linear	1.0733(0.9666, 1.1917)	7.33	0.190	1.0759(0.9667, 1.1974)	7.59	0.186
Temp lag1						
<25th(25.5°C)	1.0403(0.8812, 1.2280)	4.03	0.643	0.9712(0.7977, 1.1825)	-2.88	0.772
>75th (27.0°C)	1.0429(0.8534, 1.2746)	4.29	0.683	1.0444(0.8483, 1.2858)	4.44	0.684
Linear	0.9996(0.9158, 1.0910)	-0.04	0.993	1.0033(0.9155, 1.0995)	0.33	0.944
Rainfall lag 0						
<25th (22.8mm)	1.1363(0.9204, 1.4029)	13.63	0.239	1.1680(0.9453, 1.4431)	16.80	0.156
>75th (177.5mm)	1.0859(0.9213, 1.2799)	8.59	0.330	1.0459(0.8852, 1.2358)	4.59	0.600
Linear	0.9997(0.9989, 1.0004)	-0.03	0.403	0.9997(0.9989, 1.0004)	-0.03	0.395
Rainfall lag 1						
<25th (22.8mm)	1.0605(0.8900, 1.2636)	6.05	0.514	1.0783(0.8927, 1.3025)	7.83	0.437
>75th (177.5mm)	0.9898(0.8568, 1.1434)	-1.02	0.889	0.9011(0.7670, 1.0585)	-9.89	0.210
Linear	0.9999(0.9993, 1.0006)	-0.01	0.806	0.9999(0.9992, 1.0005)	-0.01	0.723
Rainfall lag 2						
<25th (22.8mm)	1.1006(0.9233, 1.3120)	10.06	0.289	1.1258(0.9448, 1.3413)	12.58	0.191
>75th (177.5mm)	1.0793(0.8914, 1.3068)	7.93	0.437	1.1122(0.9155, 1.3511)	11.22	0.289
Linear	0.9997(0.9988, 1.0007)	-0.03	0.563	0.9997(0.9987, 1.0007)	-0.03	0.540

^: Estimates for temperature and rainfall modeled separately

~: Estimates for temperature and rainfall adjusted for each other (modeled together)

6b : Quantification of relationship between temperature, rainfall and under-five all-cause mortality for Navrongo HDSS site

	Crude Relative Risk^			Adjusted Relative Risk~		
Factor	**RR (95% CI)**	**% change**	**P value**	**RR (95% CI)**	**% change**	**P value**
Navrongo						
Temp lag 0						
<25th (27.4°C)	1.0458(0.9534, 1.1472)	4.58	0.346	1.0377(0.9263, 1.1626)	3.77	0.525
>75th (30.6°C)	0.9859(0.8799, 1.1047)	-1.41	0.807	0.9777(0.8677, 1.1016)	-2.23	0.712
Linear	1.0053(0.9797, 1.0315)	0.53	0.691	1.0129(0.9827, 1.0441)	1.29	0.410
Temp lag1						
<25th (27.4°C)	1.0782(0.9790, 1.1874)	7.82	0.131	1.0954(0.9792, 1.2254)	9.54	0.117
>75th(30.6°C)	1.0146(0.8923, 1.1536)	1.46	0.826	1.0117(0.8872, 1.1537)	1.17	0.863
Linear	0.9712(0.9394, 1.0042)	-2.88	0.091	0.9707(0.9378, 1.0048)	-2.93	0.097
Rainfall						
Rainfall lag 0	1.0004(0.9998, 1.0011)	0.04	0.208	1.0002(0.9994, 1.0010)	0.02	0.587
Rainfall lag 1	1.0000(0.9993, 1.0007)	0.00	0.918	1.0002(0.9994, 1.0010)	0.02	0.614
Rainfall lag 2	1.0003(0.9996, 1.0010)	0.003	0.433	1.0003(0.9996, 1.0010)	0.03	0.431

^: Estimates for temperature and rainfall modeled separately

~: Estimates for temperature and rainfall adjusted for each other (modeled together)

4.3.4 Relationship between temperature, rainfall and all-cause mortality in the poorest and richest socioeconomic groups at the HDSS sites

Mean temperature lag1 and lag2 had approximate linear relationship with mortality in the poorest socioeconomic group in DHDSS where risk of mortality increased from RR<1 to RR>1 as temperature increased from 27.6°C to 29.5°C (Appendix G1). Temperature lag0 had a J-shape relationship with mortality in the poorest socioeconomic group where the risk decreased as mean temperature increased to 27.6°C. It then increased with temperature as mean temperature increased from 27.6°C to 29.5°C. Temperature lag3 had inverted U-shape relationship with mortality where mortality risk decreased below RR=1 at the extreme ends of mean temperature. When temperature lag0 and lag1 were modeled together, temperature lag0 had an approximate linear relationship with mortality risk decreasing as temperature increased. Temperature lag1, however, maintained its linear relationship (Figure 39).

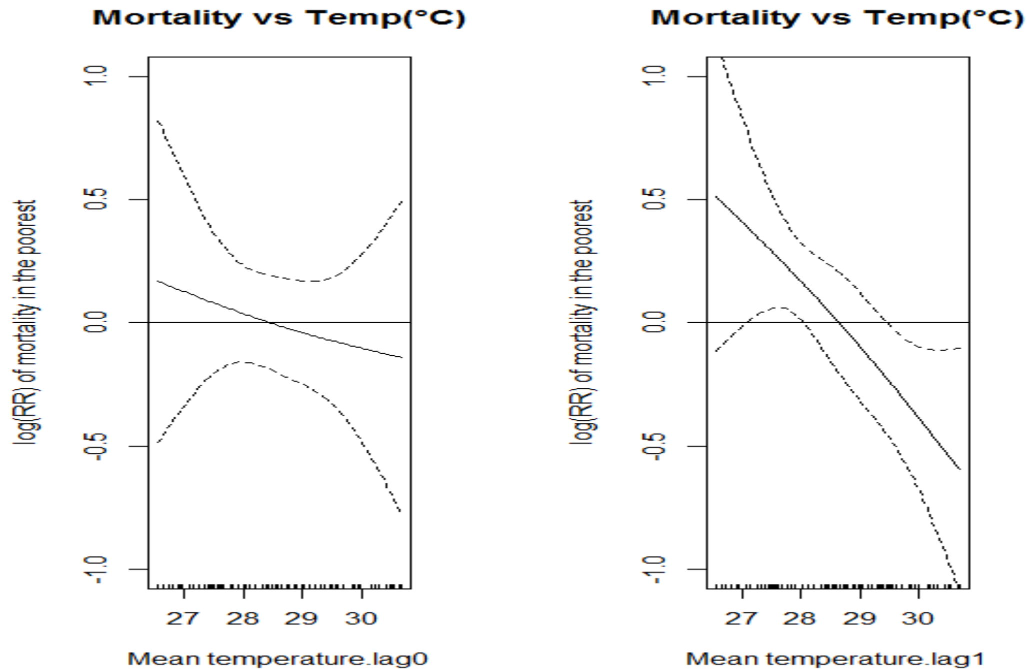

Figure 39: Plot of relationship between temperature and mortality in the poorest wealth quintile at the Dodowa HDSS.

Smooth curves for those in the richest group indicated approximate linear relationship for temperature lag0 and temperature lag3 when modelled separately. Temperature lag1 had inverted U-shape while lag2 had approximate inverted J-shape relationship. For temperature lag0 and temperature lag3, mortality risk decreased as temperature increased while for lag2 mortality risk increased as temperature increased. With temperature lag1, mortality risk decreased at the extreme ends. Temperature lag0 and lag1 maintained their relationship with mortality risk when modeled together (40).

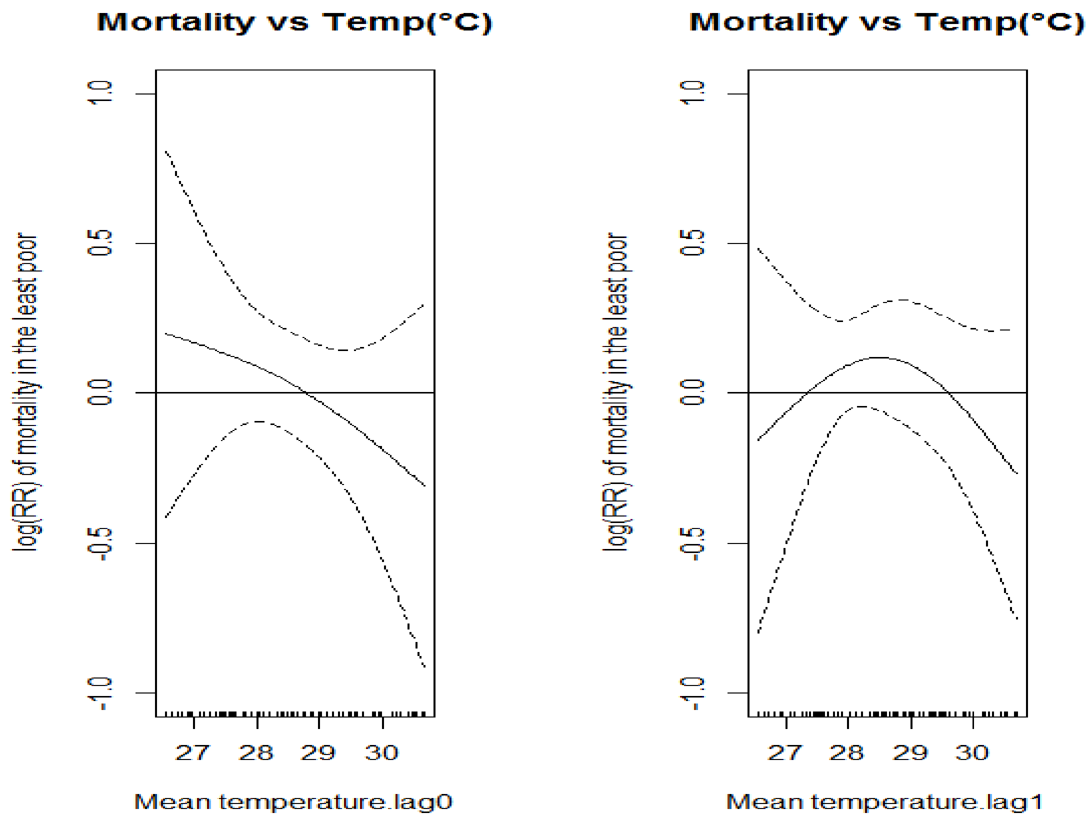

Figure 40: Plot of relationship between temperature and mortality in the richest wealth quintile at the DHDSS.

Temperature lag0 had virtually no relationship with mortality risk in the poorest socioeconomic group in KHDSS (Figure 41). The log relative risk lies approximately on the horizontal axis, logRR=0 (RR=1). Temperature lag1-3 had approximate linear relationships with mortality, which means either mortality risk increased or decreased linearly with mean temperature. For temperature lag1 and lag2, mortality risk decreased as monthly mean temperature increased, however, for temperature below 25.5°C, relative risks increased above 1. With temperature lag3, mortality risk increased as temperature increased.

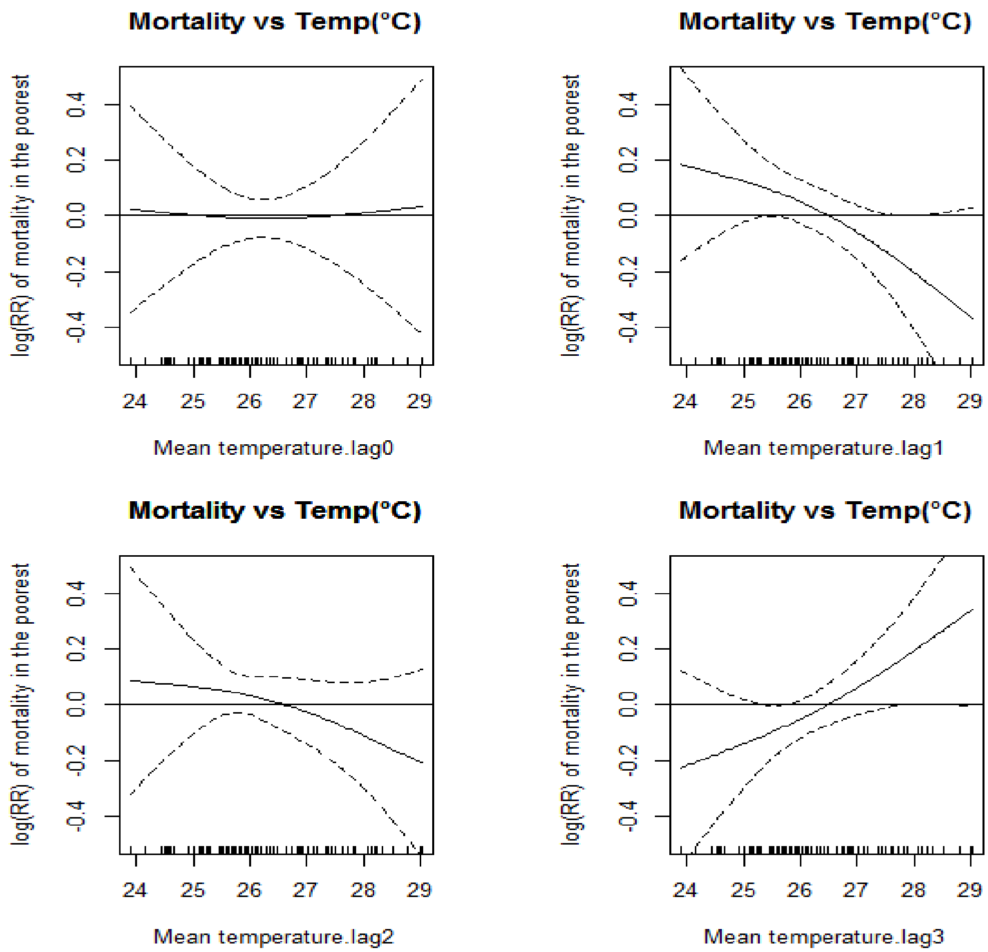

Figure 41: Plot of relationship between temperature and mortality in the poorest quintile at the Kintampo HDSS site when lags were modeled separately.

With those in the richest socioeconomic group at the KHDSS site, temperature lag1 had an inverted U-shape relationship with mortality. Mortality risk increased as mean temperature lag1 increased from 23.5°C to about 25.5°C and then decreased as mean temperature increased from around 27.0°C. Temperatures lag0 and lag3 had approximate linear relationship with mortality where mortality risk increased with temperature. For temperature lag2, there was virtually no relationship between mean temperature and mortality except a slight decrease of mortality above 28.01°C (Figure 42).

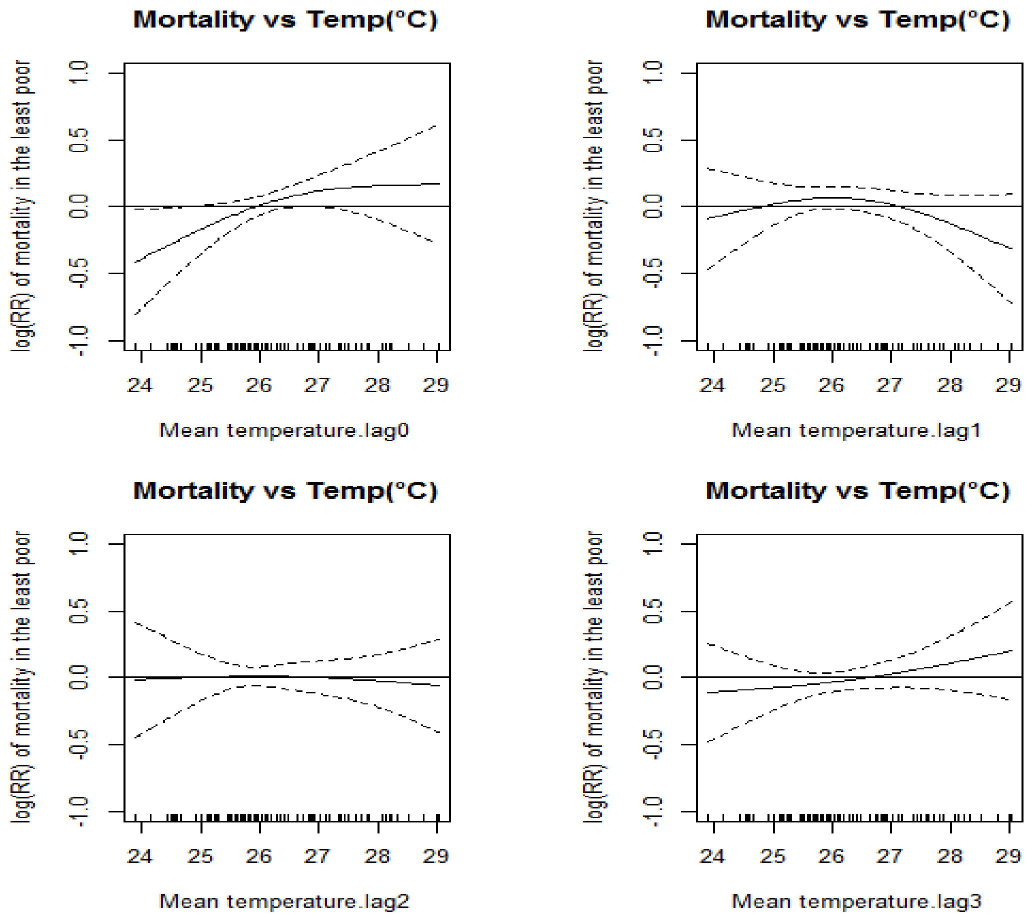

Figure 42: Plot of relationship between temperature and mortality in the least poor quintile (richest) at the Kintampo HDSS site when temperature lags were modeled separately.

Figure 43 presents a plot of relationship between temperature and all-cause mortality for those in the poorest socioeconomic quintile at the Navrongo HDSS site when modeled separately. Temperature lag0 had an approximate U-shape relationship with mortality risk increasing as monthly mean temperature increased above 30.7°C or dropped below 27.4°C while temperature lag3 had an inverted U-shape relationship. For temperature lag1 and lag2, however, the relationships were approximate linear with the risk of mortality decreasing with increasing temperature. A drop of temperature below 27.4°C was however, associated with increased in mortality risk with relative risk greater than one (RR>1). For those in the richest quintile, temperature lag0 had approximate J-shape relationship with mortality. Temperature lag1had U-shape relationship while lag2 and lag3 had approximate linear relationship (figure 44).

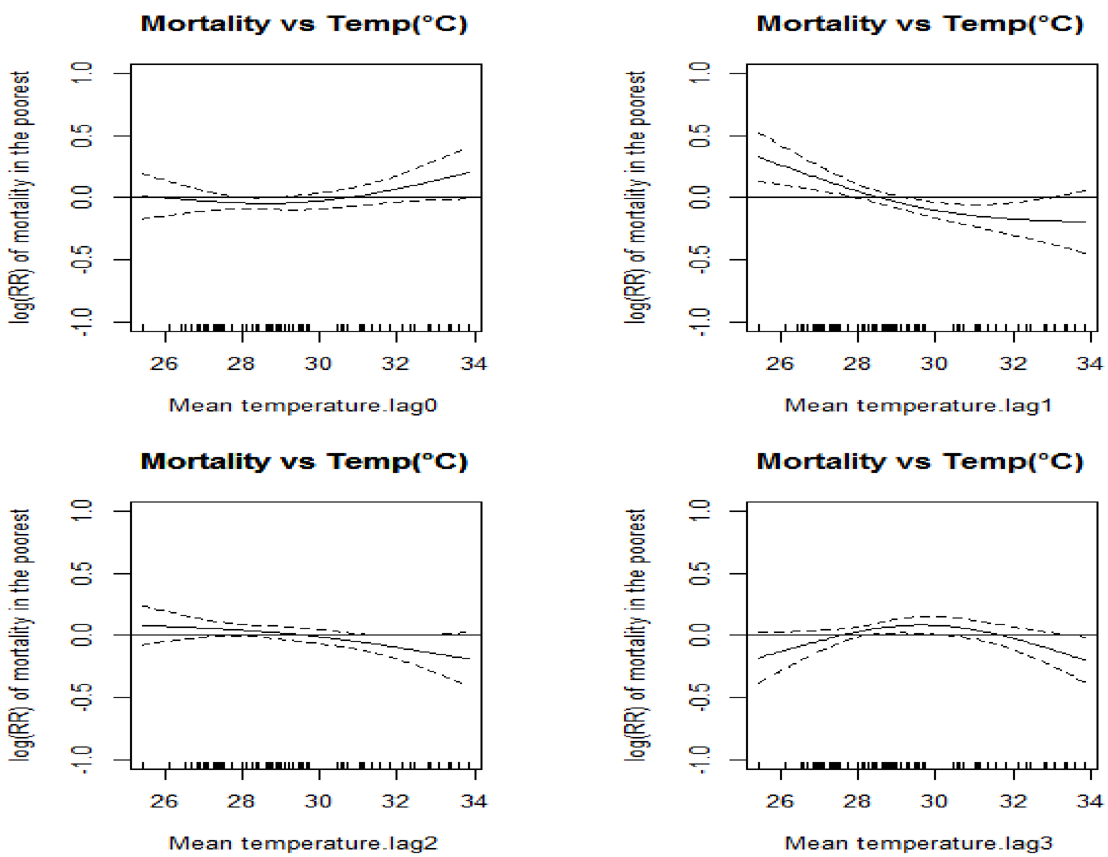

Figure 43: Plot of relationship between mean monthly temperature and mortality in the poorest quintile at the Navrongo HDSS site when the temperature lags were modeled separately.

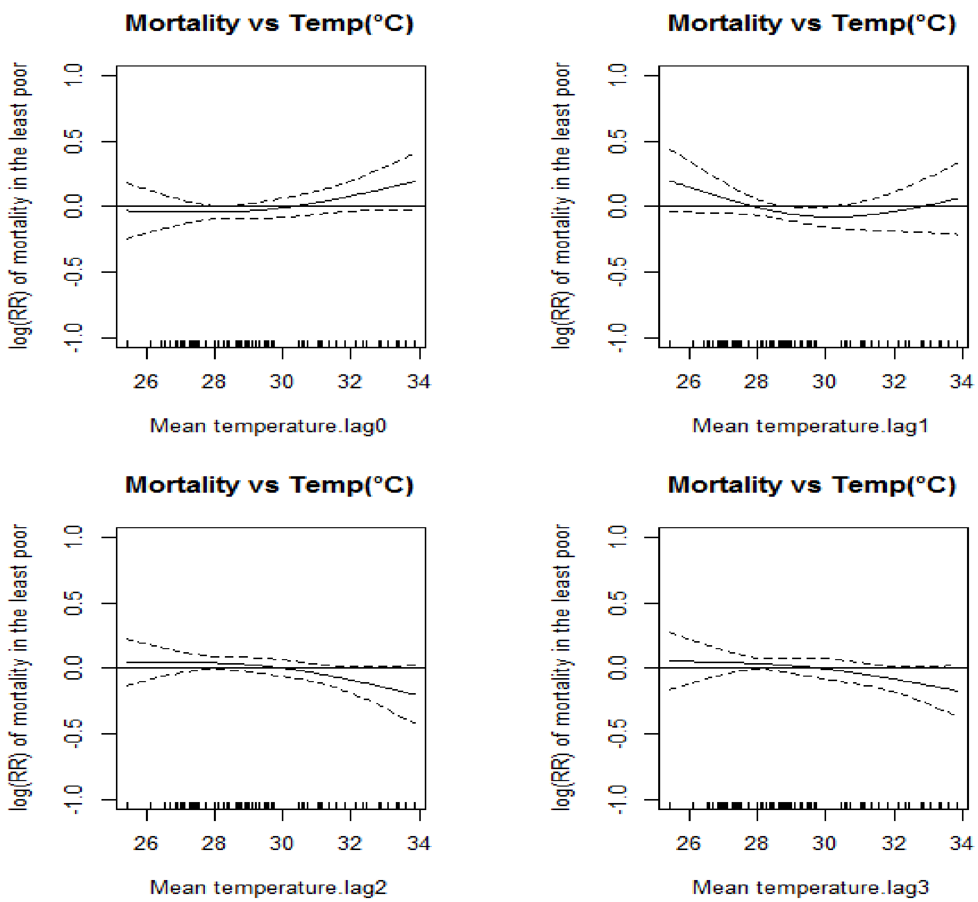

Figure 44: Plot of relationship between mean monthly temperature and mortality in the least poor (richest) quintile at the Navrongo HDSS site when the temperature lags were modeled separately.

4.3.4.1 Relationship between rainfall and all-cause mortality in the poorest and richest socioeconomic groups at the HDSS sites

Smooth curves for the relationship between rainfall and all-cause mortality in the poorest quintile at DHDSS when modelled separately indicated approximate linear relationships for rainfall lag0 and lag2 while rainfall lag1 and lag3 had approximate J-shape and inverted U-shape respectively. For lag0 and lag1, mortality risk increased with monthly rainfall. With lag3, however, mortality risk decreased at the extreme values of rainfall (Figure 45).

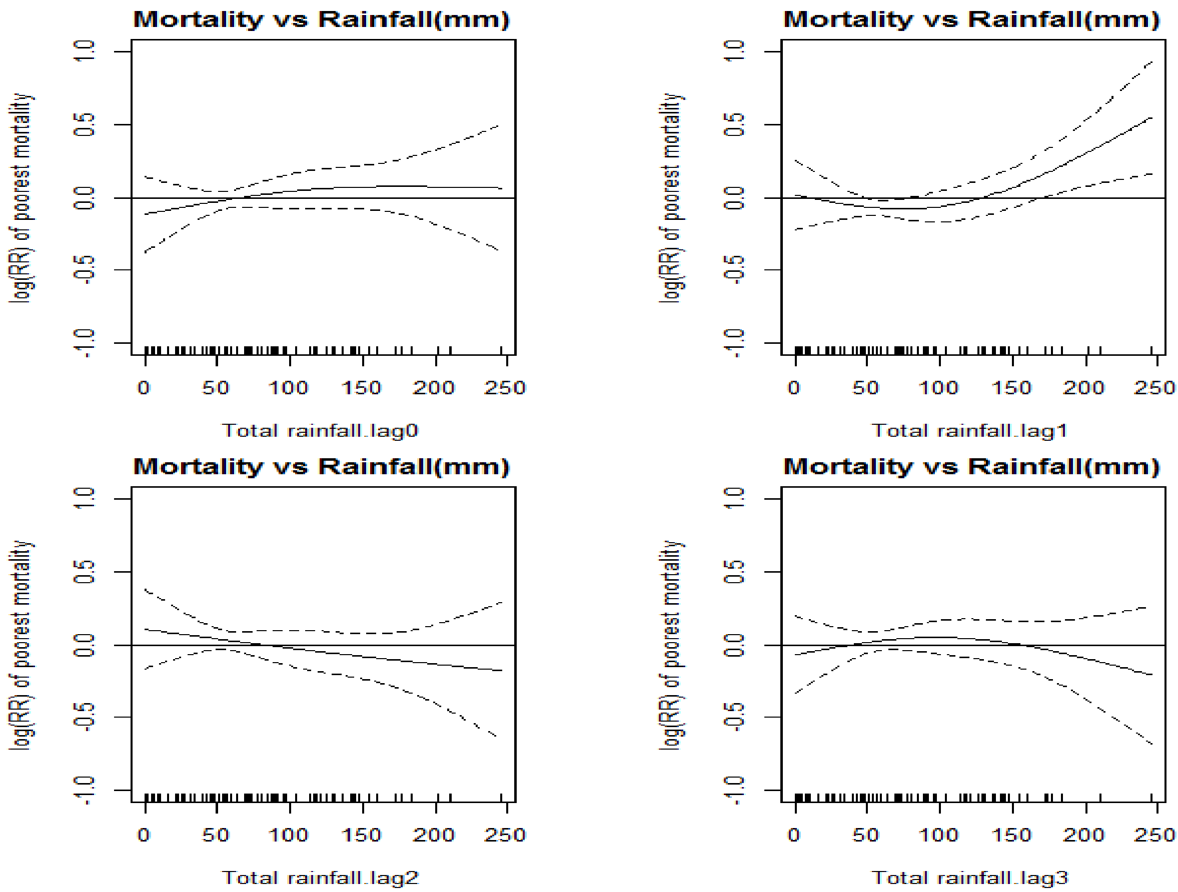

Figure 45: Plot of relationship between rainfall and mortality in the poorest quintile at the Dodowa HDSS site.

With those in the richest quintile, rainfall lag0 and lag3 had inverted U-shape relationship when modelled separately. Mortality risk increased with rainfall to about 160mm and then started decreasing with rainfall. Lag1 had approximate U-shape while lag2 had inverted J-shape with mortality. With lag1, mortality risk increased with temperature from a rainfall value of about 160mm. Mortality risk also decreased with rainfall lag2 (Figure 46).

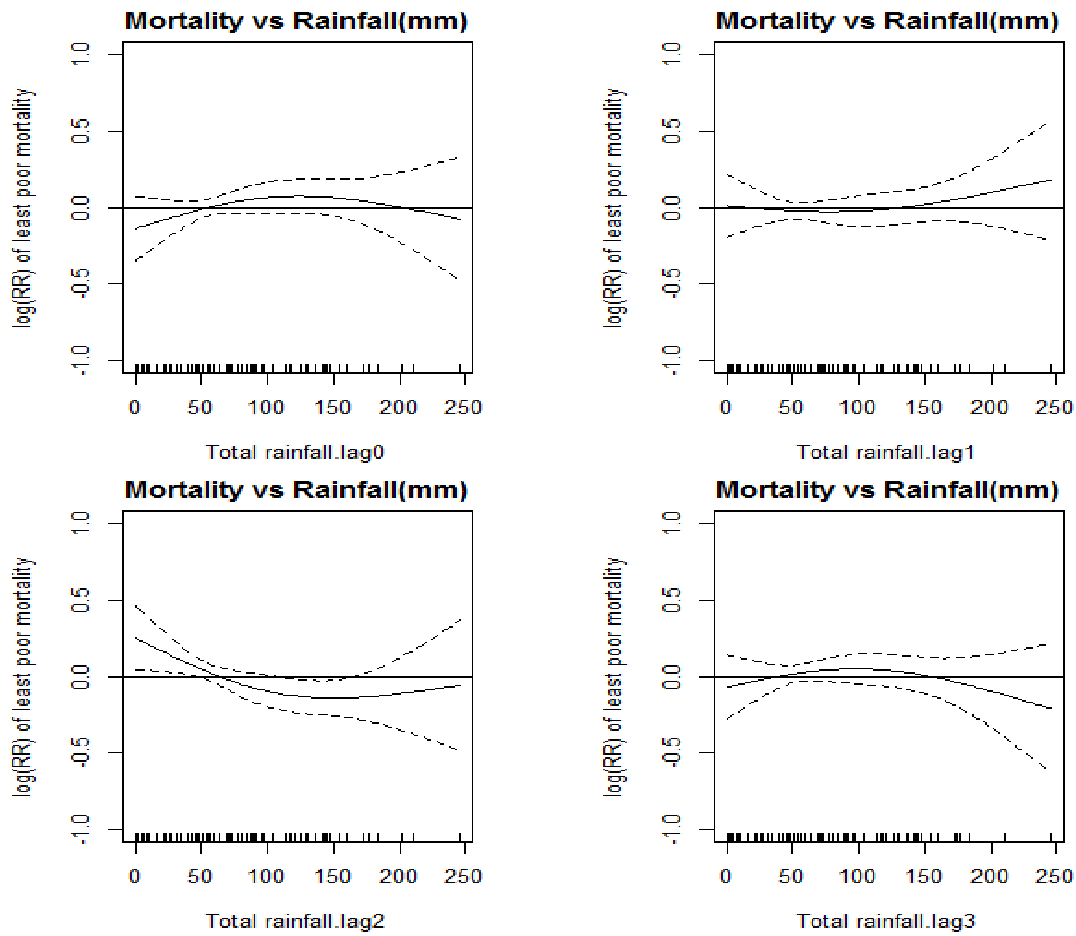

Figure 46: Plot of relationship between rainfall and mortality in the least poor quintile at the DHDSS site.

Rainfall lag0 and lag3 had approximate linear relationship with mortality in the poorest socio-economic group in KHDSS with decreasing mortality risk as monthly rainfall increased. Rainfall lag1 had a J-shape relationship with mortality where mortality risk decreased as rainfall increased from 0.0mm to around 178mm and then increased as monthly rainfall increased. Rainfall lag2 on the other hand had an inverted U-shape relationship with mortality where mortality risk increased with rainfall to around 178mm and then decreased (Figure 47).

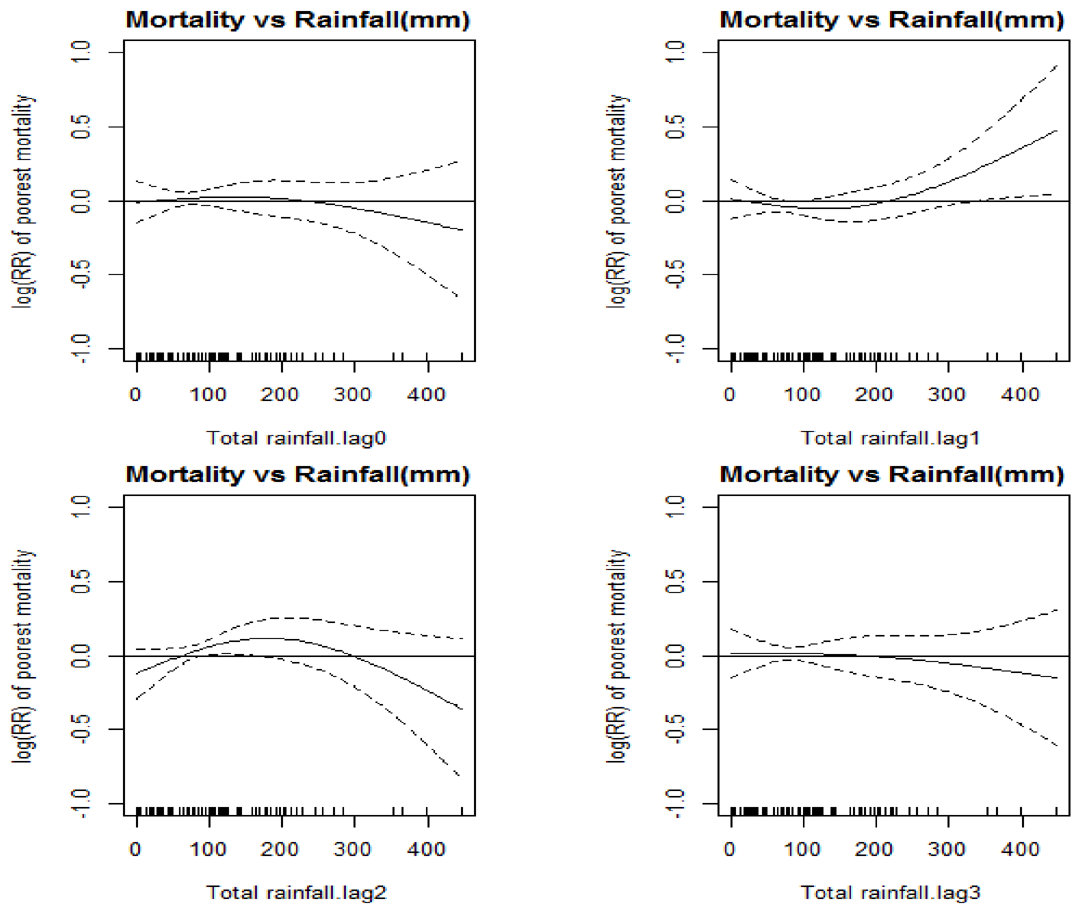

Figure 47: Plot of relationship between rainfall and mortality in the poorest quintile at the KHDSS.

As in the overall analysis, the relationship between rainfall and all-cause mortality in the poorest quintile is approximate linear the NHDSS. Mortality risk in each of the quintiles increased with increased rainfall (Figure 48).

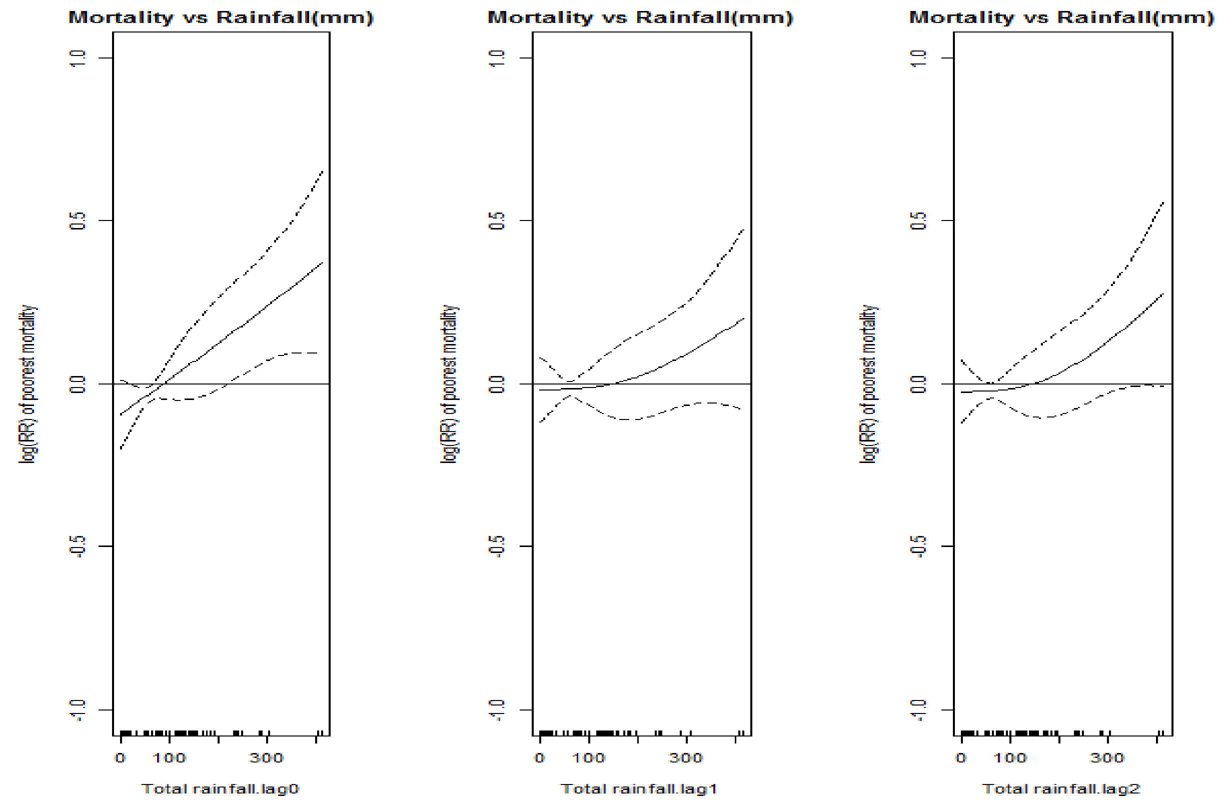

Figure 48: Plot of relationship between rainfall and mortality in the poorest quintile at the NHDSS site.

4.3.4.2 Quantification of the relationship between Temperature and all-cause mortality in the poorest and richest socioeconomic groups at the HDSS sites

When the analysis was stratified by wealth index, both mean temperature lag0 and lag1 were significantly associated with those in the poorest socioeconomic group, when modeled separately at Dodowa HDSS. However, when the mean temperatures lag0 and lag1 were put together in the model, only mean temperature lag1was significant. The mortality risk decreased by 43.38% with mean temperature lag1 above 29.5°C. A linear estimate also indicated significant decrease of mortality risk with increase in mean temperature lag1 in the poorest socioeconomic (Table 7a). With those in the richest socioeconomic quintile, estimates of relative risk of mortality indicated that none of the temperature lag strata was significantly associated with mortality (Table 8a).

Temperature lag0 was significantly associated with mortality in the poorest socioeconomic group in KHDSS when modeled separately. The relative risk was 0.7957 (95% CI, 0.6500, 0.9740), a reduction in mortality risk by 20.4% with mean temperature lag0 above 27.0°C. There was however, an increase in mortality risk by 13.3% with mean temperature lag0 below 25.5°C. However, when it was modeled with mean temperature lag1, the significance level reduced to 10%. Mortality risk decreased by 18.1% with mean temperature in the month of death above 27.0°C and increased by 6.7% with mean temperature below 25.5°C. For the linear estimate, mortality risk decreased by 1.9% with 1°C increase in mean temperature lag1. Mortality risk increased by 11.5% with mean temperature lag1 below 25.5°C and decreased by 14.9% with mean temperature above 27.0°C (Table 7a).

Results of the relationship between temperature and mortality in those in the richest socioeconomic quintile indicated no significant association. The risk of mortality decreased by 9.0% with mean temperature lag0 below 25.5°C and increased by 10.9% with mean temperature above 27.0°C. For temperature in the previous one month, mortality risk increased with mean temperature below 25.5°C and decreased by 14.8% with mean temperature above 27.0°C but these were not statistically significant (Table 8a).

7a : Quantification of relationship between temperature, rainfall and all-cause mortality in the poorest socioeconomic for Dodowa and Kintampo HDSS sites

	Crude Relative Risk^			Adjusted Relative Risk~		
Factor	**RR (95% CI)**	**% change**	**P value**	**RR (95% CI)**	**% change**	**P value**
Dodowa						
Temp lag 0						
<25th(27.4°C)	1.0000(0.6933, 1.4424)	0.00	0.079	0.7301(0.4999, 1.0664)	-26.99	0.109
>75th(29.5°C)	1.2011(0.8057, 1.7904)	20.11	0.372	1.1696(0.7769, 1.7606)	16.96	0.456
Linear	0.9234(0.7189, 1.1860)	-7.66	0.535	0.9432(0.7363, 1.2083)	-5.68	0.645
Temp lag1						
<25th(27.4°C)	1.0585(0.7491, 1.4958)	5.85	0.748	1.0315(0.7198, 1.4781)	3.15	0.866
>75th(29.5°C)	**0.5662(0.3909, 0.8201)**	**-43.38**	**0.004**	**0.5724(0.3931, 0.8335)**	**-42.76**	**0.005**
Linear	0.7591(0.6216, 0.9269)	-24.09	0.009	0.7594(0.6240, 0.9242)	-24.06	0.008
Rainfall lag 0						
<25th(34.1mm)	0.8247(0.6281, 1.0829)	-17.53	0.171	0.8703(0.6767, 1.1194)	-12.97	0.284
>75th(129.1mm)	1.0352(0.8332, 1.2861)	3.52	0.756	1.0713(0.8728, 1.3148)	7.13	0.513
Linear	1.0012(0.9993, 1.0031)	0.12	0.229	1.0014(0.9996, 1.0033)	0.14	0.139
Rainfall lag 1						
<25th(34.1mm)	1.0529(0.8229, 1.3472)	5.29	0.683	1.0336(0.8191, 1.3044)	3.36	0.781
>75th(129.1mm)	1.2207(0.9766, 1.5259)	22.07	0.085	1.1570(0.9395, 1.4250)	15.70	0.175
Linear	1.0018(0.9999, 1.0037)	0.18	0.073	1.0017(0.9999, 1.0036)	0.17	0.069
Kintampo						
Temp lag 0						
<25th(25.5°C)	0.8191(0.6666, 1.0064)	-18.09	0.062	0.7764(0.6045, 0.9972)	-22.36	0.052
>75th(27.0°C)	1.0670(0.7990, 1.4249)	6.70	0.662	1.0456(0.7768, 1.4075)	4.56	0.770
Linear	0.9807(0.8573, 1.1218)	-1.93	0.777	0.9683(0.8466, 1.1075)	-3.17	0.640
Temp lag1						
<25th(25.5°C)	1.1150(0.8994, 1.3822)	11.50	0.325	1.2065(0.9346, 1.5575)	20.65	0.155
>75th(27.0°C)	0.8514(0.6625, 1.0941)	-14.86	0.313	0.8865(0.6807, 1.1544)	-11.35	0.375
Linear	0.8970(0.8024, 1.0027)	-10.30	0.062	**0.8779(0.7834, 0.9837)**	**-12.21**	**0.029**
Rainfall lag 0						
<25th(22.8mm)	0.8788(0.6721, 1.1491)	-12.12	0.349	0.8676(0.6647, 1.1324)	-13.24	0.300
>75th(177.5mm)	1.1006(0.8924, 1.3575)	10.06	0.374	1.0766(0.8703, 1.3319)	7.66	0.499
Linear	0.9997(0.9987, 1.0007)	-0.03	0.536	0.9997(0.9987, 1.0007)	-0.03	0.576
Rainfall lag 1						
<25th(22.8mm)	1.1638(0.9352, 1.4482)	16.38	0.179	1.1014(0.8694, 1.3953)	10.14	0.427
>75th(177.5mm)	1.0727(0.8897, 1.2934)	7.27	0.465	1.0201(0.8278, 1.2571)	2.01	0.853
Linear	1.0006(0.9997, 1.0014)	0.06	0.193	1.0008(0.9999, 1.0016)	0.08	0.084
Rainfall lag 2						
<25th(22.8mm)	0.9616(0.7681, 1.2039)	-3.84	0.734	0.9328(0.7439, 1.1697)	-6.72	0.549
>75th(177.5mm)	1.2195(0.9521, 1.5618)	21.95	0.121	**1.3534(1.0500, 1.7445)**	**35.34**	**0.023**
Linear	0.9998(0.9985, 1.0011)	-0.02	0.744	0.9997(0.9984, 1.0009)	-0.03	0.608

^: Estimates for temperature and rainfall modeled separately

~: Estimates for temperature and rainfall adjusted for each other (modeled together)

7b : Quantification of relationship between temperature, rainfall and all-cause mortality in the poorest socioeconomic group for Navrongo HDSS sites

	Crude Relative Risk^			Adjusted Relative Risk~		
Factor	**RR (95% CI)**	**% change**	**P value**	**RR (95% CI)**	**% change**	**P value**
Poorest						
Temp lag 0						
<25th(27.4°C)	1.1143(0.9871, 1.2580)	11.43	0.085	1.1028(0.9514, 1.2782)	10.28	0.199
>75th(30.6°C)	1.1202(0.9600, 1.3071)	12.02	0.154	0.9747(0.7811, 1.2163)	-2.53	0.822
Linear	1.0215(0.9864, 1.0578)	2.15	0.237	0.9607(0.8849, 1.0431)	-3.93	0.344
Temp lag1						
<25th(27.4°C)	1.1974(1.0552, 1.3587)	19.74	0.007	1.1439(0.9794, 1.3360)	14.39	0.095
>75th(30.6°C)	0.9839(0.8278, 1.1694)	-1.61	0.854	0.9322(0.7768, 1.1187)	-6.78	0.454
Linear	0.9383(0.8967, 0.9817)	-6.17	0.008	0.9335(0.8926, 0.9762)	-6.65	0.004
Rainfall						
Rainfall lag 0	**1.0011(1.0001, 1.0020)**	**0.11**	**0.032**	1.0007(0.9997, 1.0018)	0.07	0.188
Rainfall lag 1	1.0005(0.9995, 1.0015)	0.05	0.305	0.9999(0.9988, 1.0009)	-0.01	0.846
Rainfall lag 2	1.0007(0.9997, 1.0016)	0.07	0.189	1.0002(0.9992, 1.0012)	0.02	0.682

^: Estimates for temperature and rainfall modeled separately

~: Estimates for temperature and rainfall adjusted for each other (modeled together)

Mean temperature lag1 was significantly associated with all-cause mortality in the poorest socioeconomic quintile in NHDSS. Mortality risk decreased by 1.6% with mean temperature lag1 above 30.7%°C and significant increase in mortality risk by 19.7% with mean temperature lag1 below 27.4°C. Linear estimate suggested decrease of mortality risk with temperature. For temperature lag0, the risk of mortality insignificantly increased by 11.4% and 12.0% with mean temperature below 27.4°C and above 30.7°C respectively (Figure 7b). With those in the richest socioeconomic quintile, mortality risk insignificantly increased by 1.3% with mean temperature lag0 below 27.4°C and by 5.3% with mean temperature above 30.7°C. Mortality risk in this socioeconomic group increased by 16.3% with mean temperature lag1 below 27.4°C. The risk also increase by 17.6% with temperature lag1 above 30.7°C. The change with mean temperature below 27.4°C was statistically significant (Table 8b).

8a : Quantification of relationship between temperature, rainfall and all-cause mortality in the richest socioeconomic group for Dodowa and Kintampo HDSS sites

	Crude Relative Risk^			Adjusted Relative Risk~		
Factor	**RR (95% CI)**	**% change**	**P value**	**RR (95% CI)**	**% change**	**P value**
Dodowa						
Temp lag 0						
<25th (27.6°C)	1.0466(0.7350, 1.4903)	4.66	0.801	1.0997(0.7672, 1.5761)	9.97	0.607
>75th (29.5°C)	0.9549(0.6480, 1.4073)	-4.51	0.817	0.8999(0.6014, 1.3466)	-10.01	0.610
Linear	0.8490(0.6650, 1.0839)	-15.10	0.194	0.8505(0.6648, 1.0882)	-14.95	0.203
Temp lag1						
<25th (27.6°C)	0.9130(0.6426, 1.2970)	-8.70	0.613	0.9608(0.6666, 1.3848)	-3.92	0.831
>75th (29.5°C)	0.7891(0.5421, 1.1485)	-21.09	0.221	0.7718(0.5243, 1.1362)	-22.82	0.195
Linear	0.9288(0.7529, 1.1459)	-7.12	0.493	0.9238(0.7470, 1.1425)	-7.62	0.468
Rainfall lag 0						
25th (34.1mm)	0.8359(0.6565, 1.0645)	-16.41	0.151	0.8254(0.6419, 1.0613)	-17.46	0.140
75th (129.3mm)	0.8844(0.7347, 1.0646)	-11.56	0.199	0.8787(0.7270, 1.0622)	-12.13	0.187
Linear	1.0006(0.9989, 1.0022)	0.06	0.516	1.0005(0.9989, 1.0022)	0.05	0.525
Rainfall lag 1						
<25th (34.1mm)	0.9856(0.7913, 1.2276)	-1.44	0.897	0.9652(0.7675, 1.2138)	-3.48	0.763
>75th (129.3mm)	0.9812(0.8099, 1.1887)	-1.88	0.847	0.9925(0.8150,1.2087)	-0.75	0.941
Linear	1.0003(0.9986,1.0020)	0.03	0.729	1.0003(0.9986, 1.0020)	0.03	0.720
Kintampo						
Temp lag0						
<25th	0.9096(0.7282, 1.1363)	-9.04	0.407	0.8904(0.6743, 1.1757)	-10.96	0.416
>75th	1.1090(0.8166, 1.5060)	10.90	0.510	1.1351(0.8195, 1.5721)	13.51	0.449
Linear	1.1165(0.9692, 1.2863)	11.65	0.132	1.1142(0.9656, 1.2857)	11.42	0.144
Temp lag1						
<25th	1.0189(0.8113, 1.2796)	1.89	0.873	1.0444(0.7896, 1.3815)	4.44	0.762
>75th	0.8519(0.6511, 1.1145)	-14.81	0.247	0.8356(0.6273, 1.1130)	-16.44	0.225
Linear	0.9714(0.8650, 1.0909)	-2.86	0.626	0.9603(0.8525, 1.0818)	-3.97	0.508
Rainfall lag 0						
<25th	1.1069(0.8300, 1.4762)	10.69	0.492	1.0787(0.7969, 1.4602)	7.87	0.626
>75th	1.1956(0.9571, 1.4934)	19.56	0.121	1.2080(0.9525, 1.5320)	20.80	0.125
Linear	0.9996(0.9985, 1.0006)	-0.04	0.397	0.9996(0.9986, 1.0006)	-0.04	0.401
Rainfall lag 1						
<25th	1.0684(0.8468, 1.3479)	6.84	0.579	0.9800(0.7503, 1.2800)	-2.00	0.883
>75th	1.0394(0.8546, 1.2641)	3.94	0.700	0.9783(0.7769, 1.2318	-2.17	0.853
Linear	1.0001(0.9993, 1.0010)	0.01	0.734	1.0002(0.9993, 1.0010)	0.02	0.727
Rainfall lag 2						
<25th	1.0537(0.8309,1.3362)	5.37	0.668	1.0186(0.7927, 1.3088)	1.86	0.886
>75th	1.1631(0.8978,1.5066)	16.31	0.257	**1.2039(0.8151, 1.7783)**	**20.39**	**0.018**
Linear	1.0000(0.9975,1.0003)	0.000	0.147	0.9990(0.9977. 1.0003)	-0.10	0.126

^: Estimates for temperature and rainfall modeled separately

~: Estimates for temperature and rainfall adjusted for each other (modeled together)

8b : Quantification of relationship between temperature, rainfall and all-cause mortality in the richest socioeconomic group for Navrongo HDSS site

	Crude Relative Risk^			Adjusted Relative Risk~		
Factor	**RR (95% CI)**	**% change**	**P value**	**RR (95% CI)**	**% change**	**P value**
Navrongo						
Temp lag 0						
<25th (27.4°C)	1.0126(0.8822, 1.1624)	1.26	0.859	1.0425(0.8816, 1.2327)	4.25	0.629
>75th(30.6°C)	1.0526(0.8939, 1.2394)	5.26	0.541	0.9488(0.7446, 1.2091)	-5.12	0.673
Linear	1.0297(0.9892, 1.0718)	2.97	0.158	0.9647(0.8747, 1.0641)	-3.53	0.475
Temp lag1						
<25th(27.6°C)	1.1629(1.0072, 1.3426)	16.29	0.044	1.1305(0.9473, 1.3492)	13.05	0.179
>75th(30.6°C)	1.1758(0.9748, 1.4183)	17.58	0.095	1.1226(0.9140, 1.3789)	12.26	0.275
Linear	0.9881(0.9371, 1.0419)	-1.19	0.660	0.9845(0.9308, 1.0414)	-1.55	0.588
Rainfall						
Rainfall lag 0	1.0006(0.9995, 1.0017)	0.06	0.304	1.0002(0.9990, 1.0014)	0.02	0.702
Rainfall lag 1	1.0010(0.9999, 1.0021)	0.10	0.088	1.0003(0.9990, 1.0015)	0.03	0.655
Rainfall lag 2	1.0008(0.9997, 1.0019)	0.08	0.171	1.0003(0.9991, 1.0016)	0.03	0.586

^: Estimates for temperature and rainfall modeled separately

~: Estimates for temperature and rainfall adjusted for each other (modeled together)

4.3.4.3 Quantification of the relationship between rainfall and all-cause mortality in the poorest and richest socioeconomic groups at the HDSS sites

Estimates of relative risk for mortality in the poorest wealth quintile indicated that none of the rainfall lag strata was associated with mortality at 5% significance level at Dodowa HDSS. Rainfall lag1 was however, associated with mortality in this quintile at the 10% level. Mortality risk increased by 22.1% with rainfall lag1 above 129.3mm with the significance level of 10%. The risk also increased by 5.3% with rainfall lag1 below 34.1mm but this was not significant. For linear estimates, mortality increased by 1.8% per 10mm increase in rainfall lag1 which was also significant at the 10% level. Mortality risk also increased by 3.5% with rainfall lag0 above 129mm. With the linear estimate, mortality risk increased by 1.2% per 10mm increase in rainfall lag1 but these were not statistically significant (Table 7a). For those in the richest wealth quintile, none of the rainfall lags was significantly associated with mortality (Table 8a).

Results in Table 7 shows that none of the rainfall lag strata had a significant association with mortality in the poorest socio-economic group at the Kintampo HDSS. Mortality risk decreased by 7.6% with rainfall lag0 below 22.8mm and by 4.5% with rainfall above 177.5mm for poorest socio-economic group. For the linear estimate, mortality risk decreased by 0.2% per 10mm increase in cumulative rainfall in the month of death. With the previous one month's rainfall, mortality risk increased by 15.4% with rainfall below 22.8mm and by 23.9% with rainfall above 177.5mm but this was significant at the 10% level. With linear estimate, the risk increased by 0.6% per 10mm increase in rainfall (Table 7a). With those in the richest socioeconomic groups, none of the rainfall lag strata was significantly associated with mortality (Table 8a).

Rainfall lag0 was significantly associated with mortality in the poorest socio-economic group at Navrongo HDSS. Mortality risk increased by 1.1% per 10mm increase in rainfall lag0 for the poorest socio-economic group. The risk also increased by 0.5% per 10mm increase in rainfall lag1 but this was not statistically significant (Table 7b). For those in the richest quintiles, none of the rainfall lags strata was significantly associated with mortality (Table 8b).

4.3.4.4 Association between temperature and mortality in the poorest and the richest socioeconomic groups adjusted for the effect of rainfall and the association between rainfall and mortality in the poorest and richest groups adjusted for the effect of temperature at the HDSS sites

When rainfall and temperature were adjusted for each other in the model, temperature lag1 was significantly associated with mortality in those in the poorest socioeconomic quintile at Dodowa HDSS (Table 7a). For those in the richest quintiles, none of the temperature or rainfall lags was significant (Table 8a).

For Kintampo HDSS, rainfall lag2 was significantly associated with mortality in the poorest socioeconomic quintile while temperature lag0 was associated at the 10% level of significance. With a linear estimate, rainfall in the previous one month was also associated with mortality (Table 7a). For the richest, none of the rainfall or temperature lags was significantly associated with mortality (Table 8a).

Temperature lag1was associated with mortality in the poorest socioeconomic quintile at the 10% level when temperature and rainfall were modeled together at Navrongo HDSS. However, the linear estimate indicated association at the 5% level (Table 7b). None of the temperature or rainfall lags was significantly associated with mortality in the richest socioeconomic quintiles, (Table 8b).

4.4.1 Relationship between temperature, rainfall and malaria mortality for all ages at the HDSS sites

Figure 49 shows the relationships between monthly mean temperature lag strata and monthly malaria mortality at Dodowa HDSS. Mean temperature lag0 and lag1 had approximate inverted J-shape relationship with monthly malaria mortality. Monthly malaria mortality risk increased as mean temperature increased. The risk increased from RR<1 to RR>1 as temperature increased from 27.6°C to 29.5°C, then decreased between mean temperatures of 29.5°C and 30.7°C but still with RR>1. Mean temperature lag2 had approximate linear relationship while mean temperature lag3 had approximate U-shape relationship with malaria mortality.

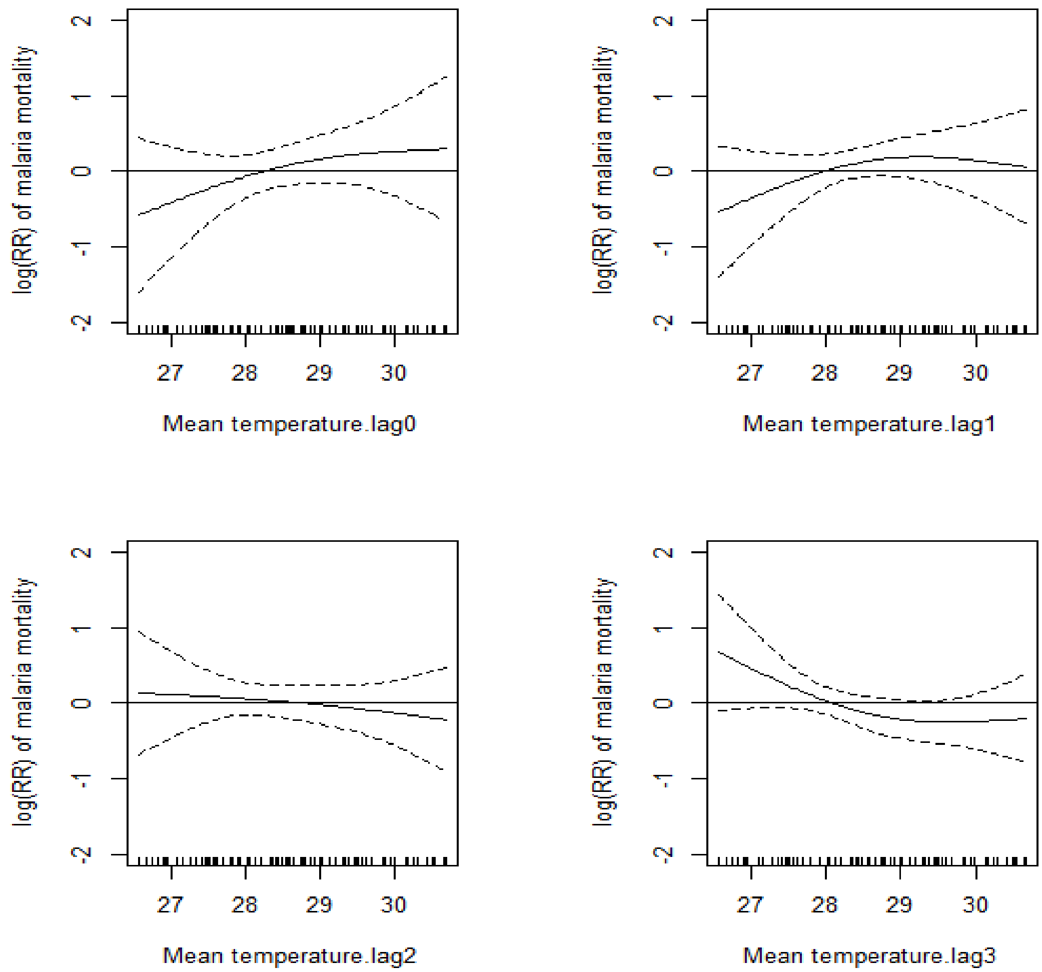

Figure 49: Plot of relationship between temperature and malaria mortality for all ages at the DHDSS site.

Temperature lag0 had an approximate inverted U-shape relationship with malaria mortality at KHDSS when modelled separately while temperature lag1 and lag2 had U-shape relationship. Temperature lag3, had an approximate linear relationship with monthly malaria mortality. For temperature lag month zero, malaria mortality risk decreased as mean temperature dropped below 25.5°C or rose above 27.0°C. For temperature lag2, mortality risk increased as mean temperature dropped below 25.5°C or rose above 27.0°C (Figure 50).

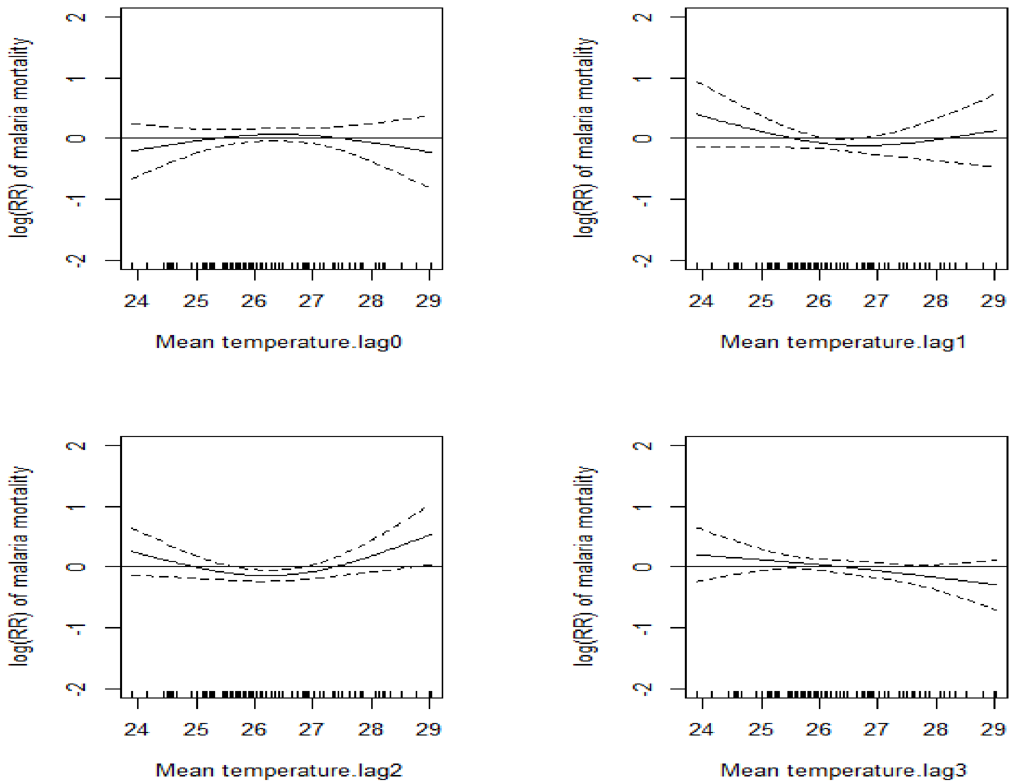

Figure 50: Plot of relationship between temperature and malaria mortality for all ages at the KHDSS Site

With NHDSS, Temperature lag0 and lag1 had invented U-shape relationship when modelled separated. Mean temperature lag3 had a U-shape relationship with monthly malaria mortality while mean temperature lag2 had virtually no relationship with malaria mortality (Appendix H). Figure (Figure 51) presents the plot for the temperature malaria mortality relationships when the temperature lag strata were modeled together. Temperature lag0 had nearly a J-shape relationship. Monthly malaria mortality risk decreased, as temperature decreased below 27.4°C and increased as temperature increased above 30.7°C. For mean temperature lag1, the risk of malaria mortality increased as temperature dropped below 27.4 °C and decreased as mean temperature rose above 30.7°C. Mean temperature lag3, however, maintained the U-shape relationship. The risk of monthly malaria mortality increased as monthly mean temperature dropped below 27.4C or rose above 30.7°C.

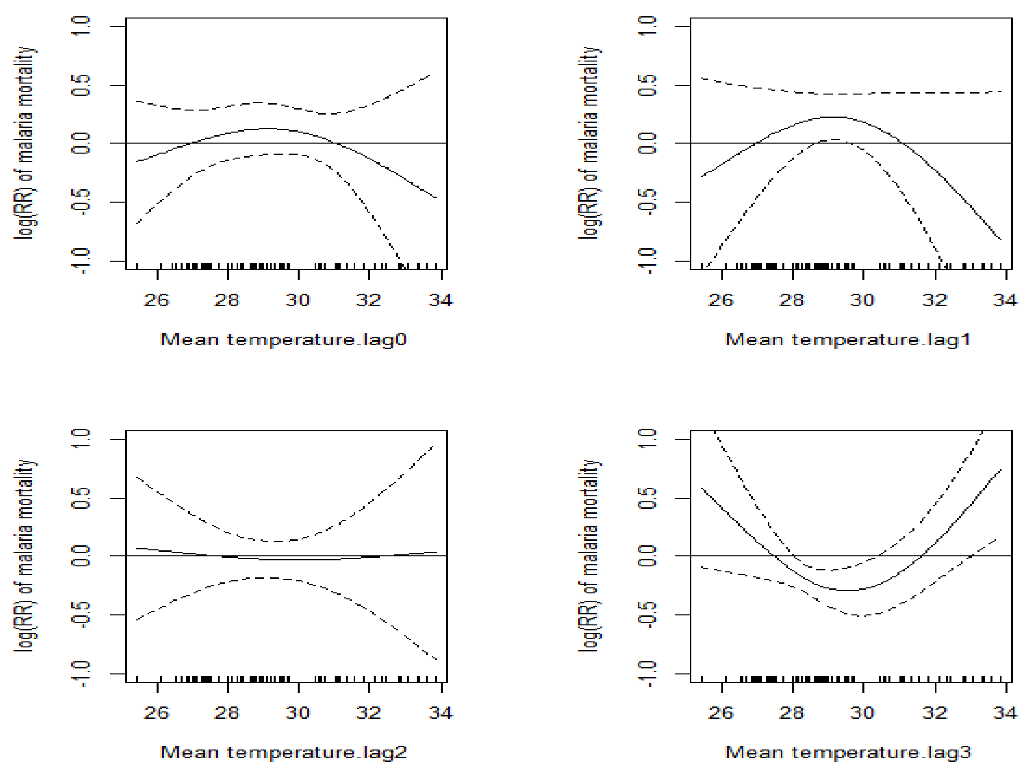

Figure 51: Plot of relationship between temperature and malaria mortality for all ages at the Navrongo HDSS Site when temperature lags were modeled separately.

4.4.1.1 Relationship between rainfall and malaria-specific mortality for all ages at the HDSS sites

The relationship between rainfall and malaria mortality also had non-linear relationship. For rainfall lag0 and lag1 at Dodowa HDSS, mortality risk increased as rainfall increased while for lag2 and lag3, mortality risk decreased as rainfall dropped below 34.1mm or increased above 129.3mm. Malaria mortality risk however, decreased when rainfall lag0, rose above the 75th percentile (129.3mm). Malaria mortality risk also increased as rainfall lag2 dropped below the 5th percentile (2.13mm) (Figure 52).

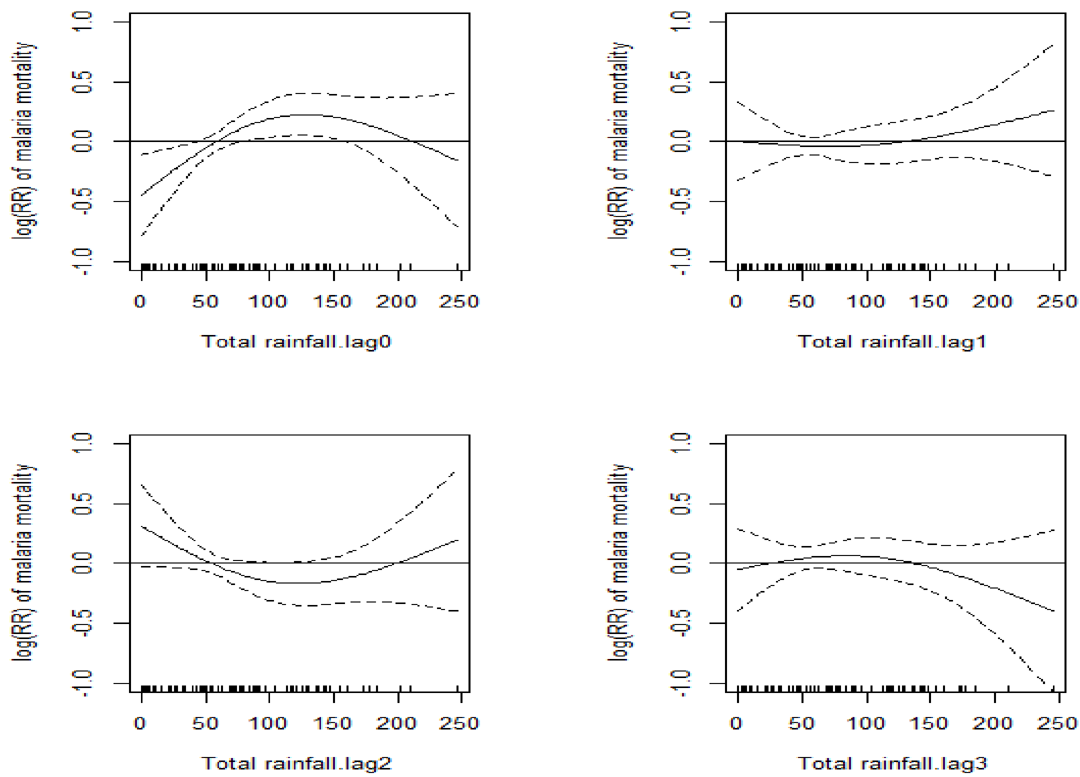

Figure 52: Plot of relationship between rainfall and malaria mortality for all ages at the Dodowa HDSS site.

Rainfall lag0 and lag2 had somewhat non-linear relationships. For rainfall lag1 and lag2, mortality risk decreased as monthly mean rainfall increased while for lag0 and lag3, mortality increased as monthly mean rainfall increased (Figure 53).

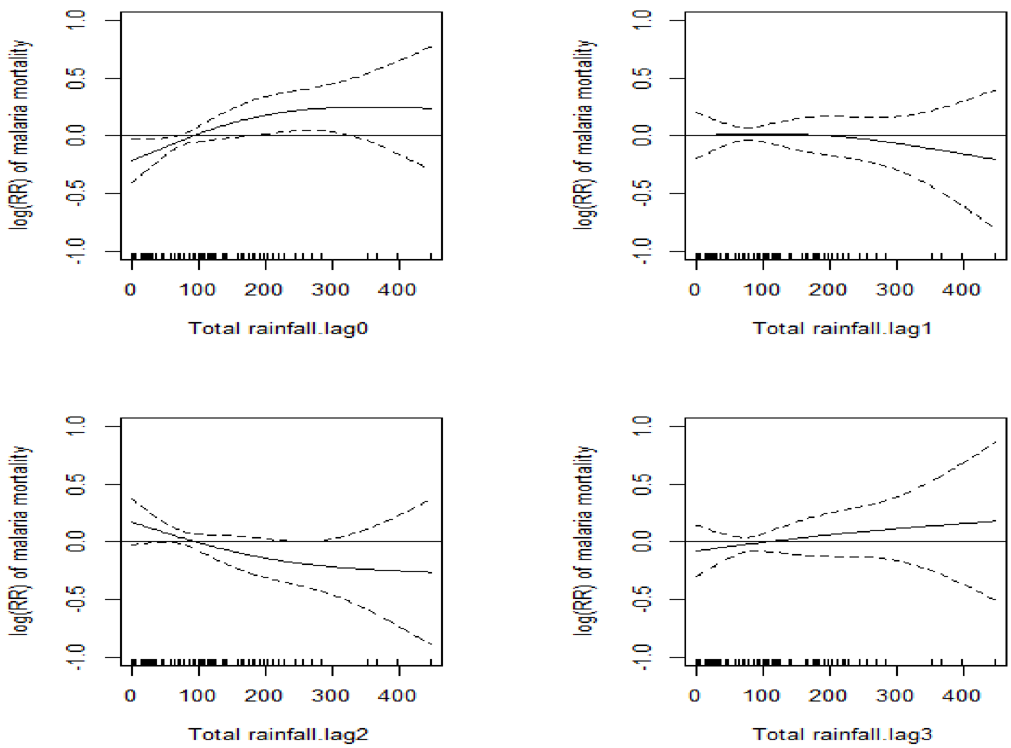

Figure 53: Plot of relationship between rainfall and malaria mortality for all ages at the Kintampo HDSS Site.

Unlike all-cause mortality the plots for rainfall and malaria mortality at the Navrongo HDS sites suggest non-linear relationship and suggested that malaria mortality risk increased with rainfall (Figure 54).

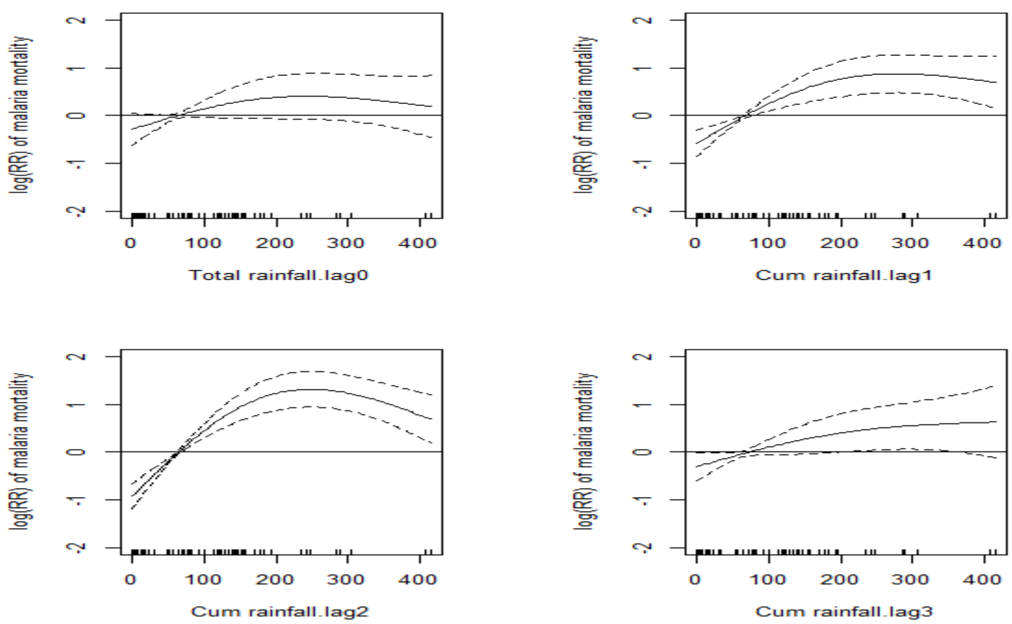

Figure 54: Plot of relationship between rainfall and malaria mortality for all ages at the Navrongo HDSS Site when rainfall lags were modeled separately.

4.4.1.2 Quantification of the relationship between temperature and malaria mortality for all ages at the HDSS site

Temperature in the previous one month before death was significantly associated with malaria mortality for all ages at the Dodowa HDSSS site. The relative risk of malaria mortality with mean temperatures lag1below 27.6 °C was 0.6065 (95% CI, 0.3773, 0.9750), a decrease in malaria mortality risk by 39.4%. For temperature lag0, mortality risk decreased by 17.6% with mean temperature below 27.6 °C but this was not statistically significant (Table 9a).

Temperature lag strata for the previous two and three months were significantly associated with malaria mortality at the Kintampo HDSS site. For temperature lag2, the relative risk of mortality with mean temperature above 27.0°C was 1.5695 (95% CI, 1.0875, 2.2651), an increase of mortality risk by 56.95%. With temperature in the previous three months, malaria mortality decreased by 30.97% with mean temperature above 27.0°C. Temperature in the month of death was however, not significantly associated with malaria mortality at the site (9a).

Estimates of relative risk of malaria mortality at Navrongo HDSS showed that temperature lag3 e was the only strata that was statistically significant at the 5% level for both the separate temperature lags and when modeled together. This significant association was with change in risk below the 27.4°C with relative risk of 1.5410 (95% CI, 1.0380, 2.2877). Monthly malaria mortality risk increased by 54.1% with mean temperature of the previous three months below 27.4°C (Table 9b).

Table 9a : Estimation of the relationship between temperature, rainfall and malaria-specific mortality for all ages for Dodowa and Kintampo HDSS site

	Crude Relative Risk^			Adjusted Relative Risk~		
Factor	**RR(95% CI)**	**% change**	**P value**	**RR(95% CI)**	**% change**	**P value**
Dodowa						
Temp lag 0						
<25th(27.6°C)	0.8236(0.5026,1.349)	-17.64	0.445	0.9080(0.5543, 1.4873)	-9.20	0.703
>75th(29.5°C)	1.2105(0.6473,2.2635)	21.05	0.552	1.1079(0.6374, 1.9255)	10.79	0.718
Linear	1.0904(0.7470,1.5919)	9.04	0.325	1.0909(0.7451, 1.5973)	9.09	0.656
Temp lag1						
<25th (27.6°C)	**0.6065(0.3773,0.9750)**	**-39.35**	**0.044**	0.6374(0.3835, 1.0593)	-36.26	0.088
>75th (29..5°C)	1.0415(0.5696,1.9044)	4.15	0.895	0.9623(0.5847, 1.5836)	-3.77	0.880
Linear	1.1462(0.8299,1.5830)	14.62	0.655	1.0877(0.7759, 1.5249)	8.77	0.628
Rainfall lag 0						
<25th (34.1mm)	**0.6262(0.4198,0.9340)**	**-37.38**	**0.025**	0.6973(0.4427, 1.0981)	-30.27	0.126
>75th (129.mm)	1.0114(0.7714,1.3214)	1.14	0.934	1.0111(0.7322, 1.3963)	1.11	0.947
Linear	1.0018(0.9994,1.0042)	0.18	0.144	1.0016(0.9990, 1.0042)	0.16	0.243
Rainfall lag 1						
<25th (34.1mm)	0.8756(0.6011,1.2756)	-12.44	0.492	0.9693(0.6377, 1.4735)	-3.07	0.885
>75th(129.3mm)	0.9447(0.7180,1.2430)	-5.53	0.686	0.9242(0.6614, 1.2913)	-7.58	0.646
Linear	1.0011(0.9988,1.0034)	0.11	0.356	1.0014(0.9989, 1.0038)	0.14	0.273
Kintampo						
Temp lag 0						
<25th(25.5°C)	1.0524(0.7409,1.4949)	5.24	0.776	1.2041(0.8271, 1.7530)	20.41	0.337
>75th(27.0°C)	0.9515(0.6166,1.4683)	-4.85	0.823	0.9498(0.6172, 1.4615)	-5.02	0.816
Linear	0.9619(0.7811,1.1845)	-3.81	0.716	0.8664(0.6960, 1.0784)	-13.36	0.204
Temp lag 2						
<25th(25.5°C)	1.0774(0.8127,1.4284)	7.74	0.606	0.9729(0.7136, 1.3263)	-2.71	0.863
>75th(27.0°C)	**1.5695(1.0875,2.2651)**	**56.95**	**0.019**	1.3577(0.9116, 2.0223)	35.77	0.138
Linear	1.0436(0.8727,1.2479)	4.36	0.642	1.0172(0.8528, 1.2133)	1.72	0.850
Temp lag 3						
<25th(25.5°C)	1.1402(0.877,1.6097)	14.02	0.459	1.2484(0.8802, 1.7707)	24.84	0.219
>75th(27.0°C)	**0.6903(0.5178,0923)**	**-30.97**	**0.014**	0.6921(0.5174, 0.9260)	-30.79	0.016
Linear	0.8836(0.7705,1.0134)	-11.64	0.082	0.8826(0.7714, 1.0098)	-11.74	0.074
Rainfall						
Rainfall lag 0 mm						
<25th (22.8mm)	1.0390(0.7030,1.5357)	3.90	0.848	1.0094(0.6799, 1.4983)	0.94	0.963
>75th (177.5mm)	1.2682(0.9618,1.6721)	26.82	0.097	1.2999(0.9712, 1.7398)	29.99	0.083
Linear	1.0010(0.9998,1.0023)	0.10	0.111	1.0012(0.9999, 1.0025)	0.12	0.074
Rainfall lag 2 mm						
<25th (22.8mm)	0.9675(0.6914,1.3538)	-3.25	0.848	0.9904(0.7025, 1.3964)	-0.96	0.956
>75th (177.5mm)	0.8536(0.6058,1.2027)	-14.64	0.369	0.8902(0.6274, 1.2629)	-10.98	0.517
Linear	0.9994(0.9980,1.0009)	-0.06	0.459	0.9993(0.9978, 1.0009)	-0.07	0.408

^: Estimates for temperature and rainfall modeled separately

~: Estimates for temperature and rainfall adjusted for each other (modeled together)

9b : Estimation of the relationship between temperature, rainfall and malaria-specific mortality for all ages for Navrongo HDSS site

	Crude Relative Risk^			Adjusted Relative Risk~		
Factor	**RR (95% CI)**	**% change**	**P value**	**RR (95% CI)**	**% change**	**P value**
Navrongo						
Temp lag 0 °C)						
<25th(27.4°C)	0.8751(0.6485,1.1809)	-12.49	0.386	0.9211(0.6363, 1.3335)	-7.89	0.665
>75tth(30.7°C)	0.8053(0.3563,1.8204)	-19.47	0.605	0.7729(0.3397, 1.7587)	-22.71	0.542
Linear	1.1497(0.9647,1.3702)	14.97	0.124	1.0687(0.8438, 1.3535)	6.87	0.583
Temp lag 3 °C)						
$<25^{th}$ (27.4°C)	**1.5410(1.0380,2.2877)**	**54.10**	**0.036**	**1.5539(1.0239, 2.3585)**	**55.39**	**0.043**
$>75^{th}$ (30.6°C)	1.3944(0.8952,2.1720)	39.44	0.146	1.4598(0.8740, 2.4384)	45.98	0.154
Linear	1.2003(1.0063,1.4318)	20.03	0.047	1.1553(0.9499, 1.4051)	15.53	0.153
Rainfall						
Rainfall lag 0 mm						
$>75^{th}$ (147mm)	1.1334(0.7618,1.6862)	13.34	0.539	1.0243(0.6321, 1.6599)	2.43	0.923
Linear	1.0019(0.9995,1.0044)	0.19	0.125	0.9994(0.9967, 1.0021)	-0.06	0.665
Rainfall lag 1 mm						
$>75^{th}$ (147mm)	1.3016(0.8792,1.9271)	30.16	0.193	1.1183(0.7151, 1.7488)	11.827	0.626
Linear	1.0022(1.0000,10045)	0.22	0.056	0.9997(0.9975, 1.0020)	-0.03	0.817
Rainfall lag 2 mm						
$>75^{th}$ (147mm)	**1.5340(1.0824,2.1740)**	**53.40**	**0.019**	1.2257(0.8818, 1.7038)	22.57	0.231
Linear	1.0035(1.0012,1.0057)	0.35	0.003	1.0006(0.9983, 1.0029)	0.06	0.619

^: Estimates for temperature and rainfall modeled separately

~: Estimates for temperature and rainfall adjusted for each other (modeled together)

4.4.1.3 Quantification of the relationship between rainfall and malaria-specific mortality for all ages at the HDSS sites

Estimates of relative risk of malaria mortality in all ages and rainfall indicated that rainfall lag0 was significantly associated with mortality at the Dodowa HDSS. The relative risk was 0.6262 (95% CI, 0.4198, 0.9340) with rainfall lag0 below 34.1mm, a decrease of malaria mortality risk by 37.4%. Mortality risk increased by 1.14% with rainfall lag0 above 129.7mm. The risk increased by 1.8% per 10mm increased in rainfall when linear effect was estimated. These associations were however, not statistically significant. With rainfall lag1, malaria mortality risk decreased by 12.4% with rainfall below 34.1mm. For linear estimate, mortality risk increased by 1.1% per 10mm increase temperature lag1 (Table 9a).

Rainfall lag0 and lag2 were significantly associated with malaria mortality when modeled separately at Kintampo HDSS. The relative risk for rainfall lag0 was 1.3740 (95% CI, 1.1077, 1.7042) with rainfall above 177.5mm, an increase in mortality risk by 37.4%. With rainfall lag2, malaria mortality risk decreased by 27.23% when modeled separately (Appendix). However, when these rainfall lags were modeled together, neither of them was significant at the 5% level. Though malaria mortality risk increased by 26.82% with rainfall in the month of death above 177.5mm, it was significant at the 10% level (Table 9a).

Estimates of monthly malaria mortality relative risk at the NHDSS indicated that rainfall lag2 was significantly associated with malaria mortality either when modeled separately or together (Appendix G, Table 9b). The relative risk was 1.5340 (95% CI, 1.0824, 2.1740), an increase in malaria mortality risk by 53.4% with rainfall lag2 above 149.1mm. For rainfall lag0 and lag1, though mortality risks increased with mean rainfall above 149.1mm, they were not statistically significant. Linear estimate of rainfall lag2 was also significant and indicated increase in malaria mortality risk with rainfall. The risk increased by 3.5% per 10mm increase in rainfall lag2 (Table 9b).

4.4.1.4 Association between temperature and malaria-specific mortality adjusted for the effect of rainfall and association between rainfall and malaria-specific mortality adjusted for the effect of temperature at the HDSS sites

When temperature and rainfall were modeled together, temperature in the previous one month before death was associated with malaria mortality at the 10% significance level DHDSS. Though mortality risk increased with temperature in the month of death, it was not statistically significant (Table 9a). Temperature in the previous three months was significantly associated with monthly malaria mortality risk when modeled with rainfall in KHDSS. The association was however, at the 10% level when estimated linearly. Malaria mortality was also associated with rainfall in the months of death at the 10% significance level (Table 9a). In NHDSS, temperature in the previous three months before death was significantly associated with malaria mortality when modeled together with rainfall. The relative risk was 1.554 (95% CI, 1.024, 2.359) with mean temperature below 27.4°C. Though malaria mortality risk also increased with mean temperature above 30.7°C, the change was not statistically significant (Table 9b).

4.4.2 Relationship between temperature and under-five malaria mortality at the HDSS sites

For under-five malaria mortality at Dodowa HDSS, temperature lag0 had inverted J-shape relationship while temperature lag1 had approximate linear relationship (Figure 55).

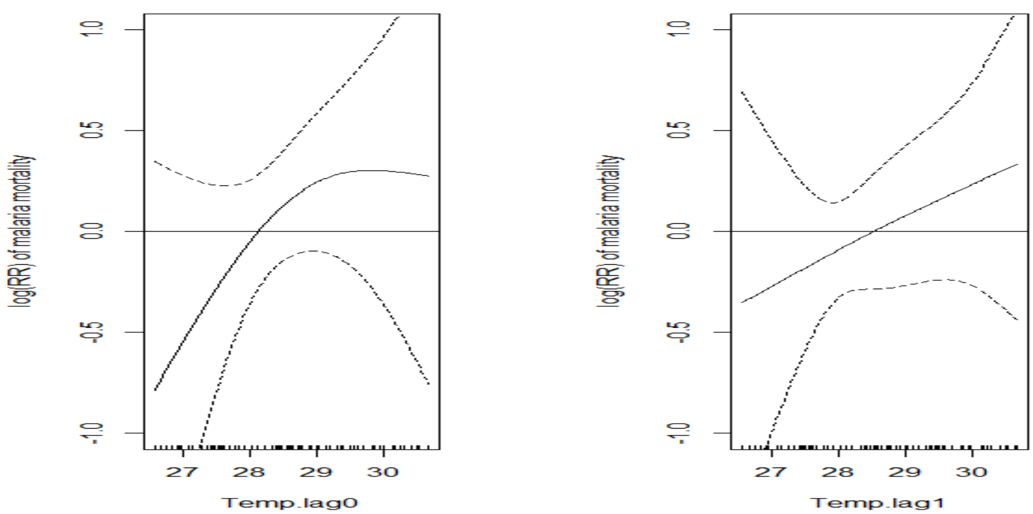

Figure 55: Plot of relationship between temperature and under-five malaria mortality at the DHDSS site.

With KHDSS site, temperature lag0 had approximate linear relationship with under-five malaria mortality when modelled separately. Temperature lag1 and lag2 had approximate U-shape while temperature lag3 had an inverted U-shape relationship with under-five malaria mortality (Figure 56).

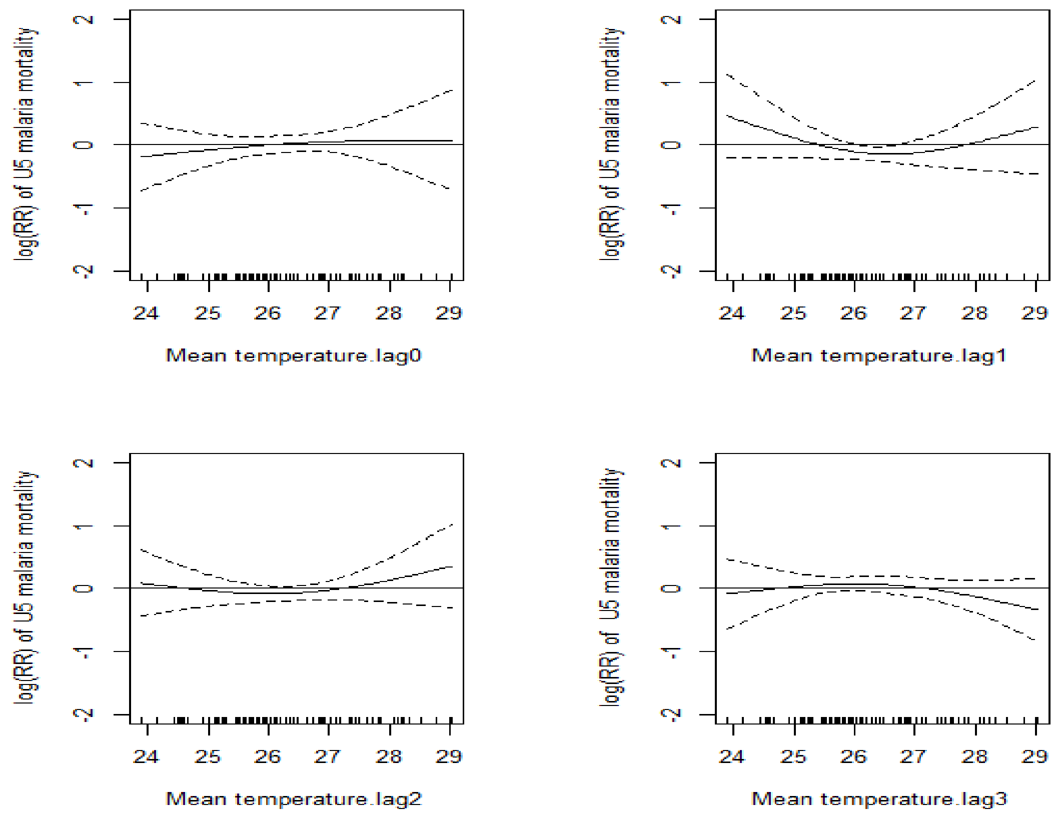

Figure 56: Plot of relationship between temperature and under-five malaria mortality at the KHDSS.

In NHDSS, temperature lag0 and lag1 had inverted U-shape relationship with malaria mortality. Temperature lag3 had a U-shape relationship while lag2 had virtually no relationship with malaria mortality (Figure 57)

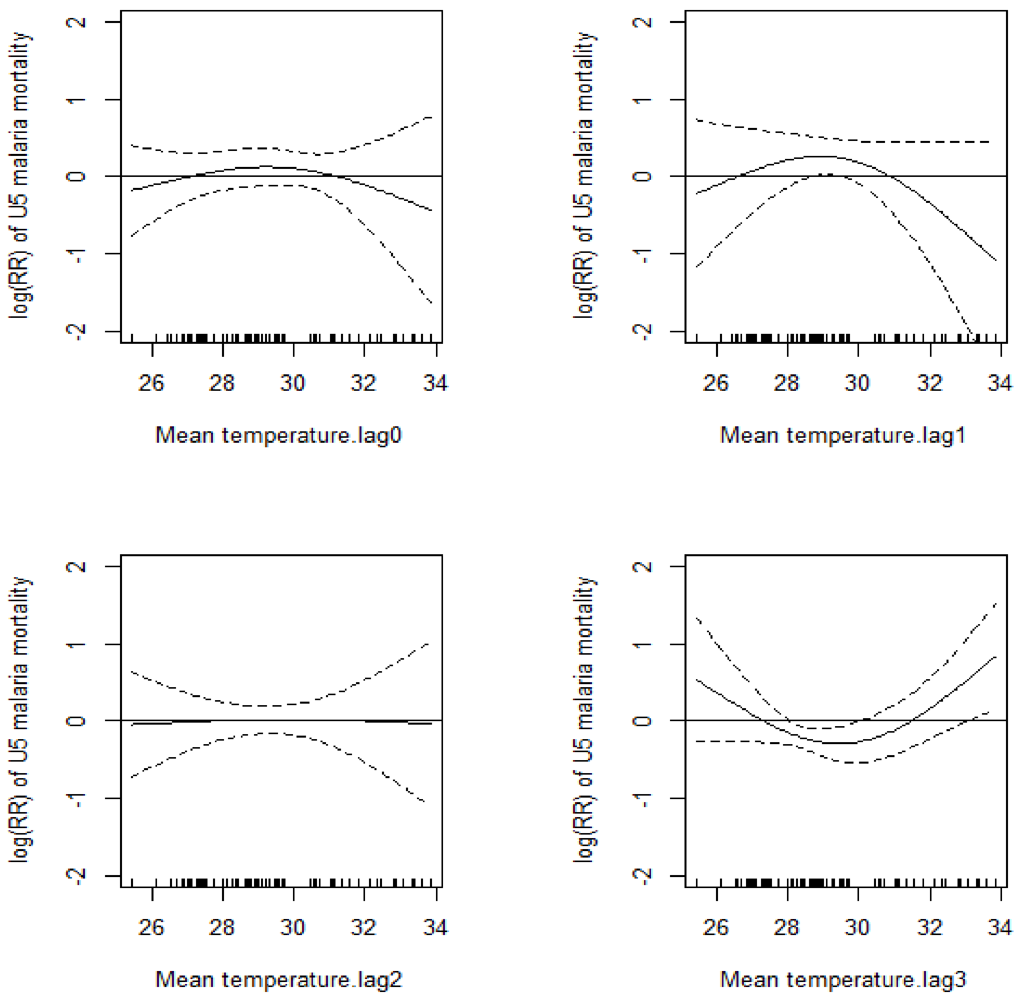

Figure 57: Plot of relationship between temperature and under-five malaria mortality at the Navrongo HDSS Site when temperature lags were modeled separately.

4.4.2.1 Relationship between rainfall and under-five malaria mortality at the HDSS sites

Figure 58 shows plot of the relationship between rainfall and under-five malaria mortality risk at Dodowa HDSS. Monthly under-five malaria mortality increased as rainfall lag0 and lag2 increased up 129.3mm and then decreased. For lag1, monthly under-five malaria mortality risk decreased as rainfall increased above 129.7mm and increased as rainfall decreased below 34.1mm. For rainfall lag3 three however, mortality risk decreased as rainfall dropped below 34.1mm and increased as rainfall rose above 129.7mm (Figure 58).

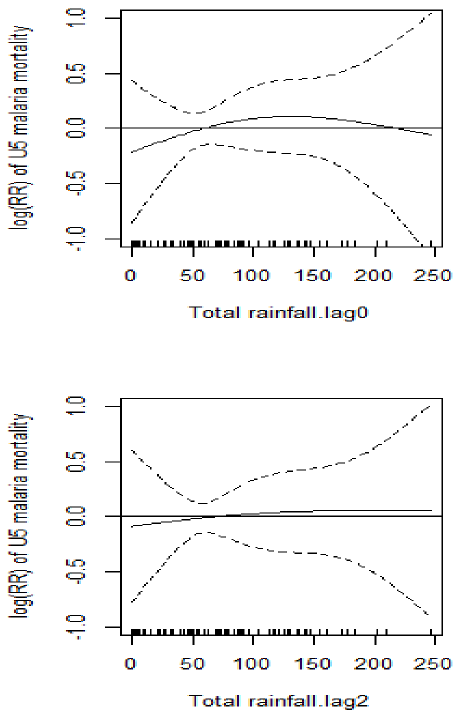

Figure 58: Plot of relationship between rainfall and under-five malaria mortality at the DHDSS site when rainfall lags were modeled separately.

With under-five malaria mortality at KHDSS, none of the rainfall lags strata was significant when modeled separately though for rainfall lag0 and lag3, under-five malaria mortality increased as rainfall increased while for lag1 and lag2, malaria mortality risk decreased (Figure 59).

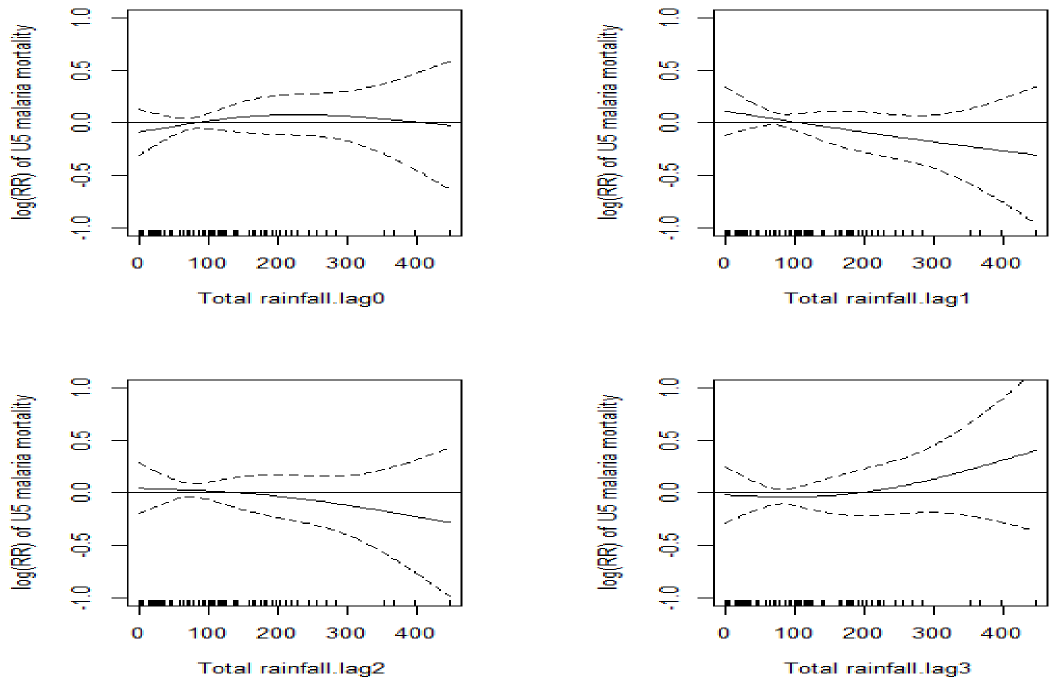

Figure 59: Plot of relationship between rainfall and under-five malaria mortality at the KHDSS

Plots for rainfall and under-five malaria mortality at the NHDS also suggest non-linear relationship between malaria mortality and rainfall (Figure 60).

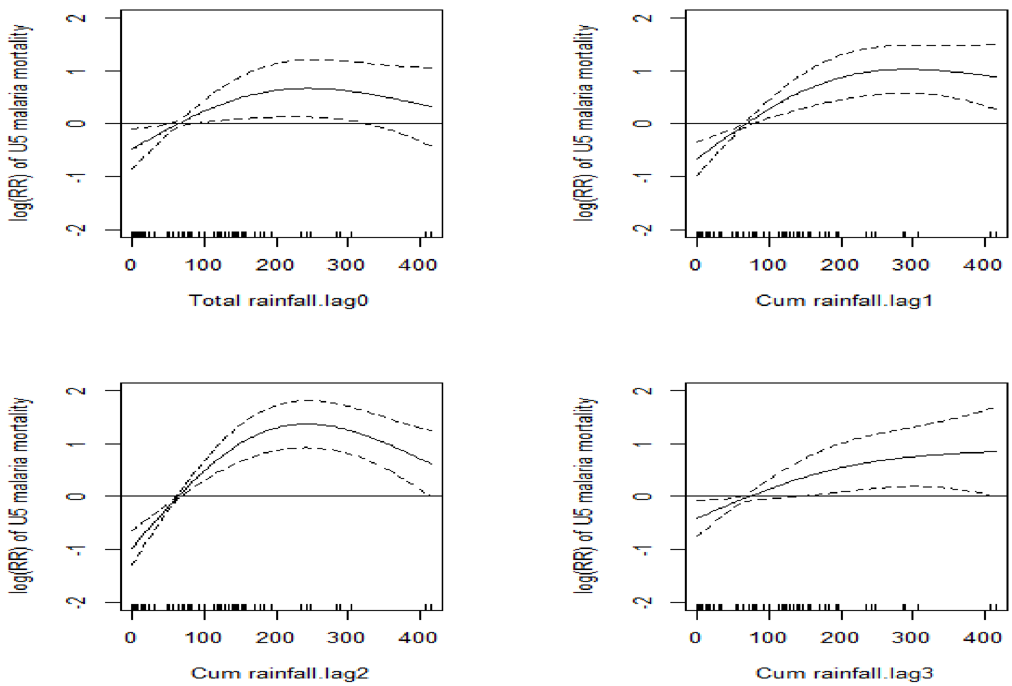

Figure 60: Plot of relationship between rainfall and under-five malaria mortality at the Navrongo HDSS site.

4.4.2.2 Quantification of the relationship between temperature and under-five malaria mortality at the HDSS sites

At the DHDSS, under-five malaria mortality was also associated with temperature lag1 with relative risk of 0.5111(95% CI, 0.2832, 0.9223) with mean temperatures below 27.6°C. This translated into a decrease of under-five monthly malaria mortality risk by 48.9%. With temperature lag0, under-five malaria mortality risk decreased by 23.9% with temperature below 27.6°C but this was not statistically significant (Table 10a).

Under-five malaria mortality at the Kintampo HDSS site was significantly associated with temperature lag2 and lag3. The relative risk with mean temperature lag2 above 27.0°C was 1.6876(95% CI, 1.0833, 2.6290), an increase in under-five malaria mortality by 68.76%. For the previous three months' temperature, under-five malaria mortality risk decreased by

31.27% with mean temperature above 27.0°C. With the temperature in the month of death, under-five malaria mortality risk increased with mean temperatures above 27.0°C or below 25.5°C (Table 10a).

Children Under-five years monthly malaria mortality risk was significantly associated with the mean temperature lag3 at NHDSS. Monthly under-five malaria mortality significantly increased by 57.6% with mean temperature lag3 below 27.4°C and by 76.6% with mean temperature above 30.7°C. For mean temperature lag0, the risk of monthly under-five malaria mortality decreased with mean temperature below 27.4°C and increased with mean temperature above 30.7°C but these associations were not statistically significant (Table 10b).

Table 10a : Estimation of the relationship between temperature, rainfall and malaria-specific mortality for under-five for Dodowa and Kintampo HDSS sites

	Crude Relative Risk^			**Adjusted Relative Risk~**		
Factor	**RR(95% CI)**	**% change**	**P value**	**RR(95% CI)**	**% change**	**P value**
Dodowa						
Temp lag 0						
<25th (27.6°C)	1.2390(0.9758,1.9862)	23.90	0.551	1.0618(0.5500, 2.0499)	6.18	0.859
>75th (29.5°C)	1.1482(0.8012,1.6455)	14.82	0.584	1.3059(0.4981, 3.4236)	30.59	0.589
Linear	1.0196(0.6625,1.569)	1.96	0.930	0.9720(0.6318, 1.4952)	-2.80	0.897
Temp lag 1						
<25th (27.6°C)	**0.5111(0.2832,0.9223)**	**-48.89**	**0.029**	0.2699(0.1307, 0.5574)	-73.01	0.001
>75th (29.5°C)	1.1173(0.4446,2.8081)	11.73	0.814	0.9170(0.4389, 1.9159)	-8.30	0.818
Linear	1.195(0.6107,2.3385)	19.5		1.1631(0.8169, 1.6561)	16.31	0.405
Rainfall lag 0						
<25th (34.1mm)	1.1033(0.5355,2.2733)	10.33	0.791	1.4904(0.7089, 3.1334)	49.04	0.297
>75th (129.mm)	1.3157(0.7720,2.2426)	31.57	0.317	1.4742(0.8565, 2.5373)	47.42	0.167
Linear	1.0012(0.9973,1.0052)	0.12	0.543	1.0002(0.9963, 1.0042)	0.02	0.909
Rainfall lag 1						
<25th (34.1mm)	**2.0515(1.0186,4.1318)**	**105.15**	**0.049**	2.5304(1.6253, 7.6684)	153.04	0.002
>75th (129.mm)	0.8519(0.4807,1.5098)	-14.81	0.585	0.8515(0.4833, 1.5003)	-14.85	0.580
Linear	0.9963(0.9921,1.0007)	-0.37	0.102	0.9968(0.9926, 1.0010)	-0.32	0.144
Kintampo						
Temp lag 0						
<25th (25.5°C)	1.2613(0.8247, 1.9290)	26.13	0.288	1.4289(0.9016, 2.2646)	42.89	0.134
>75th (27.0°C)	1.1058(0.6549, 1.8672)	10.58	0.708	1.0646(0.6357, 1.7829)	6.46	0.813
Linear	1.0795(0.8343, 1.3968)	7.95	0.563	1.0464(0.7860, 1.3931)	4.64	0.757
Temp lag2						
<25th (25.5°C)	0.9855(0.7032, 1.3812)	-1.45	0.933	0.9633(0.6597, 1.4065)	-3.67	0.847
>75th (27.0°C)	**1.6876(1.0833, 2.6290)**	**68.76**	**0.024**	1.4608(0.9019, 2.3661)	46.08	0.129
Linear	1.0928(0.8708, 1.3714)	9.28	0.447	1.0925(0.8653, 1.3795)	9.25	0.460
Temp lag3						
<25th (25.5°C)	1.0122(0.6647, 1.5413)	1.22	0.955	1.0684(0.6957, 1.6407)	6.84	0.764
>75th (27.0°C)	**0.6873(0.4914, 0.9615)**	**-31.27**	**0.032**	**0.7013(0.5015, 0.9806)**	**-29.87**	**0.043**
Linear	0.9480(0.7983, 1.1257)	-5.20	0.544	0.9493(0.7967, 1.1312)	-5.07	0.563
Rainfall						
Rainfall lag 0 mm						
<25th (22.8mm)	1.1747(0.7475,1.8461)	17.47	0.488	1.0646(0.6665, 1.7007)	6.46	0.794
>75th (177.5mm)	0.9133(0.6581,1.2673)	-8.67	0.589	0.9552(0.6668, 1.3683)	-4.48	0.803
Linear	1.0001(0.9987,1.0015)	0.01	0.893	1.0000(0.9985, 1.0015)	0.00	0.963
Rainfall lag 2						
<25th (22.8mm)	0.7357(0.4820,1.1231)	-26.43	0.160	0.7517(0.4839, 1.1678)	-24.83	0.209
>75th (177.5mm)	0.6670(0.4449,0.9999)	-33.30	0.054	0.6814(0.4425, 1.0494)	-31.86	0.087
Linear	0.9994(0.9977,1.0012)	-0.06	0.526	0.9995(0.9976, 1.0014)	-0.05	0.618

^: Estimates for temperature and rainfall modeled separately

~: Estimates for temperature and rainfall adjusted for each other (modeled together)

10b : Estimation of the relationship between temperature, rainfall and malaria-specific mortality for under-five for Navrongo HDSS site

	Crude Relative Risk^			Adjusted Relative Risk~		
Factor	**RR (95% CI)**	**% change**	**P value**	**RR (95% CI)**	**% change**	**P value**
Navrongo						
Temp lag 0 °C)						
<25th (27.4°C)	0.9186(0.6615,1.2756)	-8.14	0.614	0.9746(0.6514, 1.4583)	-2.54	0.901
>75th (30.6°C)	1.2951(0.5177,3.2400)	29.51	0.582	1.2734(0.5026, 3.2262)	27.34	0.612
Linear	1.1945(0.9811,1.4542)	19.45	0.082	1.2216(0.9267, 1.6105)	22.16	0.161
Temp lag 3 °C)						
<25th (27.4°C)	**1.5756(1.0188,2.4368)**	**57.56**	**0.045**	**1.6412(1.0344, 2.6041)**	**64.12**	**0.040**
>75th (30.6°C)	**1.7655(1.0188,2.9022)**	**76.55**	**0.029**	**2.0159(1.1237, 3.6165)**	**101.59**	**0.022**
Linear	1.2605(1.0272,1.5467)	26.05	0.030	1.2753(1.0063, 1.6163)	27.53	0.049
Rainfall						
Rainfall lag 0 mm						
>75th (147mm)	1.1344(0.7352,1.7504)	13.44	0.157	1.0622(0.6182, 1.8250)	6.22	0.828
Linear	1.0020(0.9994,1.0045)	0.20	0.135	1.0000(0.9969, 1.0031)	0.00	0.992
Rainfall lag 1 mm						
>75th (147mm)	1.3121(1.8550,2.0135)	31.21	0.219	1.2715(0.7644, 2.1150)	27.15	0.359
Linear	1.0022(0.9998,1.0045)	0.22	0.072	1.0000(0.9974, 1.0025)	0.00	0.977
Rainfall lag 2 mm						
>75th (147mm)	**1.4765(1.0099,2.1588)**	**47.65**	**0.049**	1.1968(0.8294, 1.7269)	19.68	0.341
Linear	**1.0028(1.0004,1.0052)**	**0.28**	**<0.027**	0.9996(0.9970, 1.0022)	-0.04	0.764

^: Estimates for temperature and rainfall modeled separately

~: Estimates for temperature and rainfall adjusted for each other (modeled together)

4.4.2.3 Quantification of the relationship between rainfall and under-five malaria mortality at the HDSS sites

Rainfall in the previous one month before occurrence of death was significantly associated with mortality for children under-five malaria mortality at DHDSS. Relative risks for under-five malaria mortality with previous one month's rainfall below 34.1mm was 2.0515(95% CI, 1.0186, 4.1318), an increase in mortality risk by 105.15%. For rainfall in the month of death, mortality risk increased by 31.57% with rainfall above 129.7 but this was not statistically significant (Table 10a).

For KHDSS rainfall in the previous two months before death was significantly associated with malaria mortality for under-five years when modeled separated was not significant when it was modeled in the presence of rainfall in the month of death. Malaria mortality risk decreased by 26.43% with the previous two months' rainfall below 22.8mm and by 33.3% with rainfall above 177.5mm (Table 10a).

Rainfall in the previous two months was significantly associated with under-five malaria mortality at NHDSS. Rainfall in previous one month was associated at the 10% significance level either when modeled separately or together. The relative risk with the previous two months' rainfall above 149.1mm was 1.4765 (95% CI, 1.0099, 2.1588), an increase of under-five malaria mortality risk by 47.7%. Linear estimates also indicated significant increase in mortality risk with rainfall (Table 10b).

4.4.2.4 Association between temperature and under-five malaria-specific mortality adjusted for the effect of rainfall and association between rainfall and under-five malaria-specific mortality adjusted for the effect of temperature at the HDSS sites

Temperature and rainfall in the previous one month before death were significantly associated with under-five malaria mortality when modeled together at DHDSS (Table 10a).

Under-five malaria mortality was associated with temperature in the previous three months and with rainfall in the previous two months at the 10% level for KHDSS, when temperature and rainfall were adjusted for each other (Table 10a).

Temperature in the previous three months was associated with under-five malaria mortality at NHDSS. Monthly under-five malaria mortality risk significantly increased with mean temperature below 27.4°C or above 30.7°C (Table 10b).

4.4.3.2 Quantification of the relationship between temperature, rainfall and malaria mortality in the elderly at the HDSS sites

None of the temperature lag strata was significantly associated with the risk of malaria mortality in the elderly (60+ years), at DHDSS (Table 11a). Monthly malaria mortality risk in the elderly at KHDSS was associated with previous one month's mean temperature at the 10% level. The risk of monthly mortality decreased with mean temperature below 27.4°C. Mean temperature in the previous three months was associated with malaria mortality at 10% with mean temperature below 27.4°C when modeled separately. It was however, not statistically significant when modeled in the presence of other lag strata (Table 11b). None of the rainfall lags was significantly associated with malaria mortality in the elderly at the HDSS sites.

None of the temperature or rainfall lags was significantly associated with monthly malaria mortality in the elderly (60+) in DHDSS (Table 11a). However, temperature in the previous three months was significantly associated with malaria mortality in the elderly (60+). For KHDSS and NHDSS, temperature in the previous three months and rainfall in the previous two months were associated with malaria mortality in the elderly at the 10% level of significance.

4.5.0 Clustering of all-cause mortality at Dodowa HDSS sites

Generally, spatial variation of mortality exists in the study area. Clustering of villages with both higher all-cause and malaria-specific mortality than the remaining areas were evident. Some of the villages or communities were identified as having high clustering of mortality in both under-fives and all-ages.

There were four statistically significant clusters of communities with higher all-cause mortality than the remaining communities in the Dodowa HDSS for the study period, 2006-20012 (Figure 61). The first cluster was in 2006 with a radius of 7.33km. This cluster was made up of 38 communities, 37 of which were from Ayikuma area council and one from Osuwem with a relative risk of 2.6 ($p<0.001$). The significant cluster identified between 2006 and 2007 had clustering of deaths in communities from Ningo area council. It had a radius of 0.25km with a relative risk of 2.57 ($p<0.001$). A significant cluster comprising of only one community in Prampram area council was identified between 2006 and 2008 with a relative risk of 3.1 ($p<0.001$). A cluster of 20 communities from Dawa area council was identified between 2009 and 2011 with a relative risk of 1.47($p<0.001$) and radius of 5.13km (Appendix H1).

For under-fives all-cause mortality, six clusters of higher mortality were identified (Figure 62). However, only the first cluster of 99 communities was statistically significant, and this was between 2009 and 2011. It had a relative risk of 1.7($p=0.002$) and radius of 14.93km. The communities forming this cluster comprised of 48 communities from Dawa, 41 from Ningo and 10 from Prampram (Appendix H2).

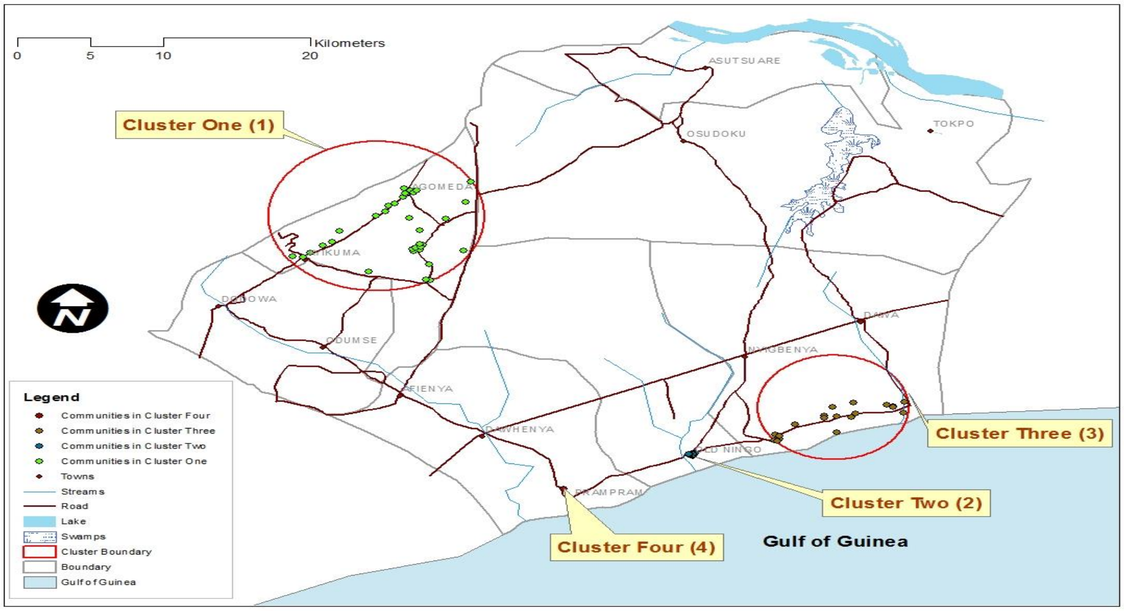

Figure 61: Clustering of all-cause mortality for all ages at Dodowa HDSS site

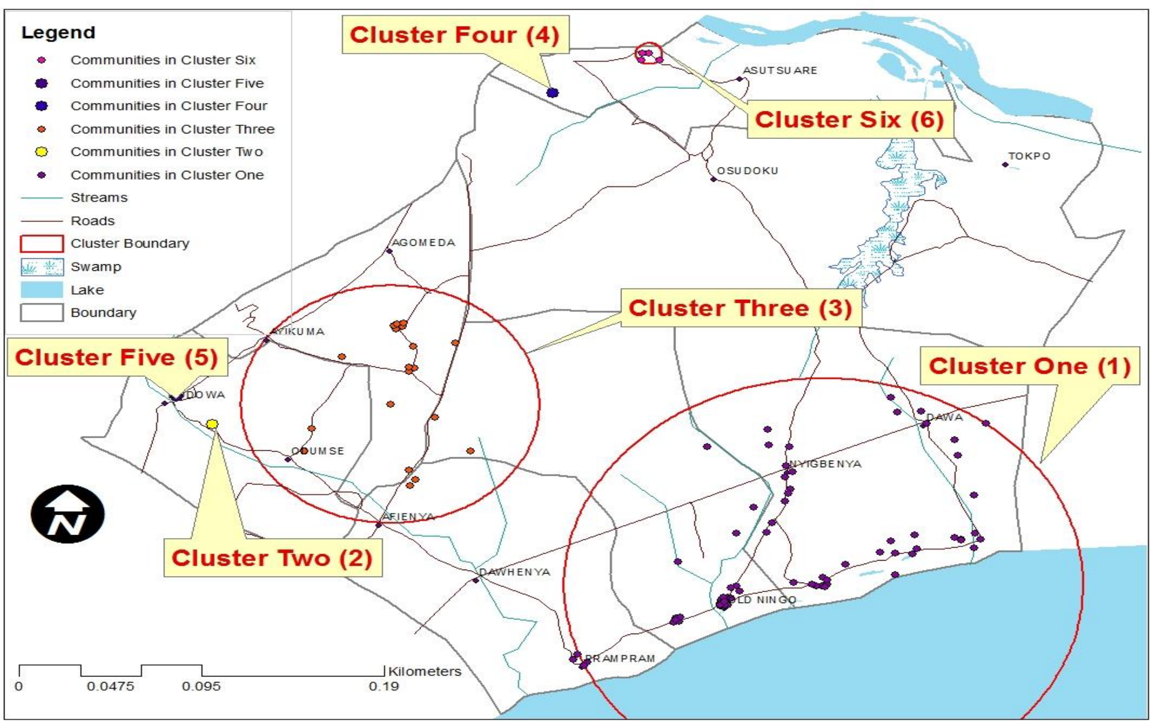

Figure 62: Clustering of all-cause mortality for under-fives at Dodowa HDSS site

4.5.1 Clustering of all-cause mortality at Kintampo HDSS site

Five clusters of communities with higher all-cause mortality than the remaining communities were observed for all ages in the KHDSS (Figure 63). The first two clusters were, however, the only clusters that were statistically significant. The first significant cluster was between 2007 and 2009 and comprised 17 villages. It had a relative risk of 1.6($p<0.001$) and radius of 18.41km. The second cluster was also made up of 17 villages observed in the period 2009-2011. It had a relative risk of 1.3($p=0.016$) and radius of 22.16km (Table Appendix H1).

For the under-five all-cause mortality, eight clusters of higher mortality were observed (Figure 64). However, only the first cluster was statistically significant with the clustered villages having significantly higher mortality rate than the remaining villages. It comprised 27 villages and was identified in 2006-2007. It had a relative risk of mortality of 2.1($p=0.010$) and a radius of 8.39km (Appendix H2).

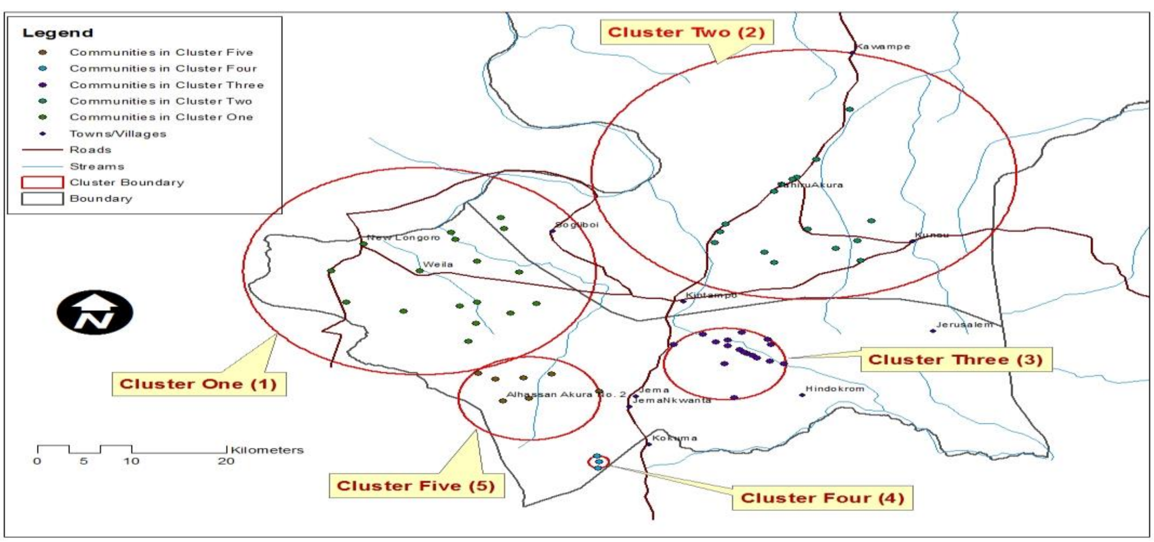

Figure 63: Clustering of all-cause mortality for all ages at Kintampo HDSS site

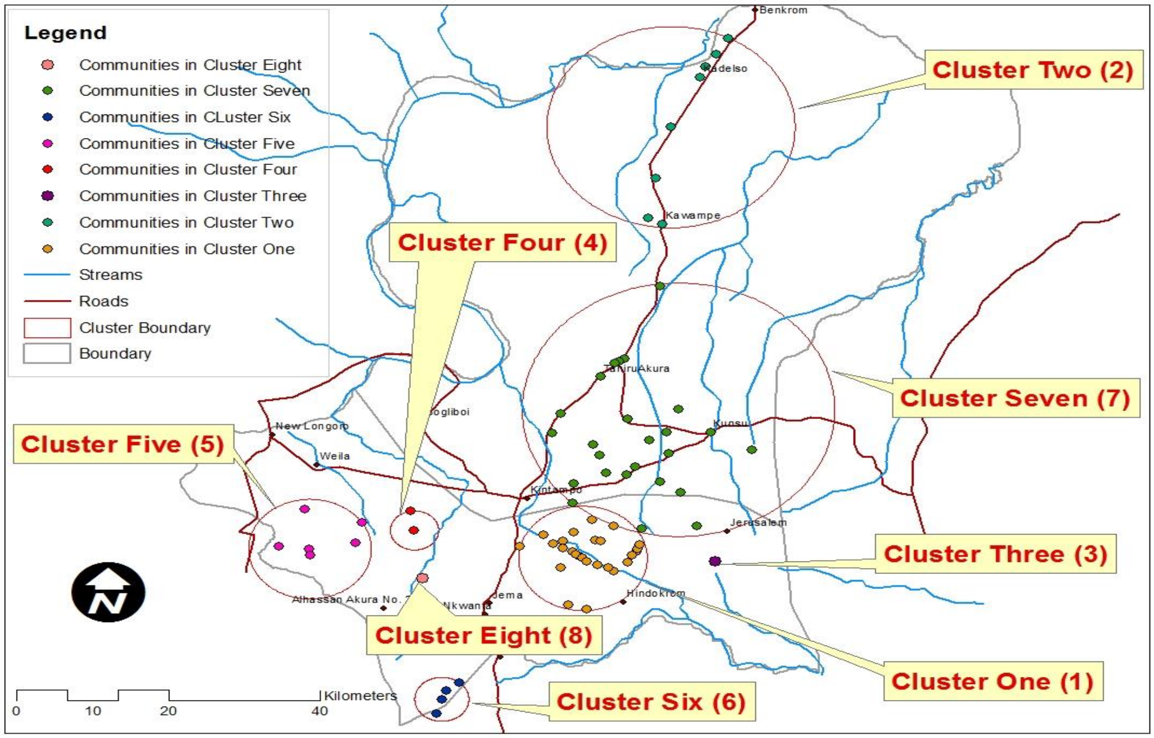

Figure 64: Clustering of all-cause mortality for under-fives at Kintampo HDSS site

4.5.2 Clustering of all-cause mortality at NHDSS site

Four clusters of villages with higher all-cause mortality for all ages than the remaining villages were also identified in the Navrongo HDSS (Figure 65). The first three of these clusters were statistically significant with mortality rates in the clustered villages being significantly higher than the surrounding villages. The first cluster in 2007-2008 comprised of 20 villages mostly from the East. It had a relative risk of 1.14 (p=0.004) with radius of 15.08km. The second cluster was made up of eight villages mostly in the West. The clustering was in 2008 with a relative risk of 1.36(p=0.006) and radius 15.59km. The last significant cluster, also in the West, comprised of five villages with a relative risk of 1.35(p=0.022) (Appendix H1).

With under-five all-cause mortality, five clusters of villages with higher mortality than the rest of the villages were identified (Figure 66) in the NHDSS. The first cluster however, was the only statistically significant cluster in which the villages had significantly higher under-five mortality than the rest of the villages. It comprised of 18 villages in 2006-2008 (Appendix H2). This cluster included villages from mostly the East, with few from the North and South. The relative risk was 1.37(p<0.001) and radius 15.1km. The second cluster with five villages most from the West had a significance of 10%. The relative risk is 2.0(0.082) with radius 4.44km.

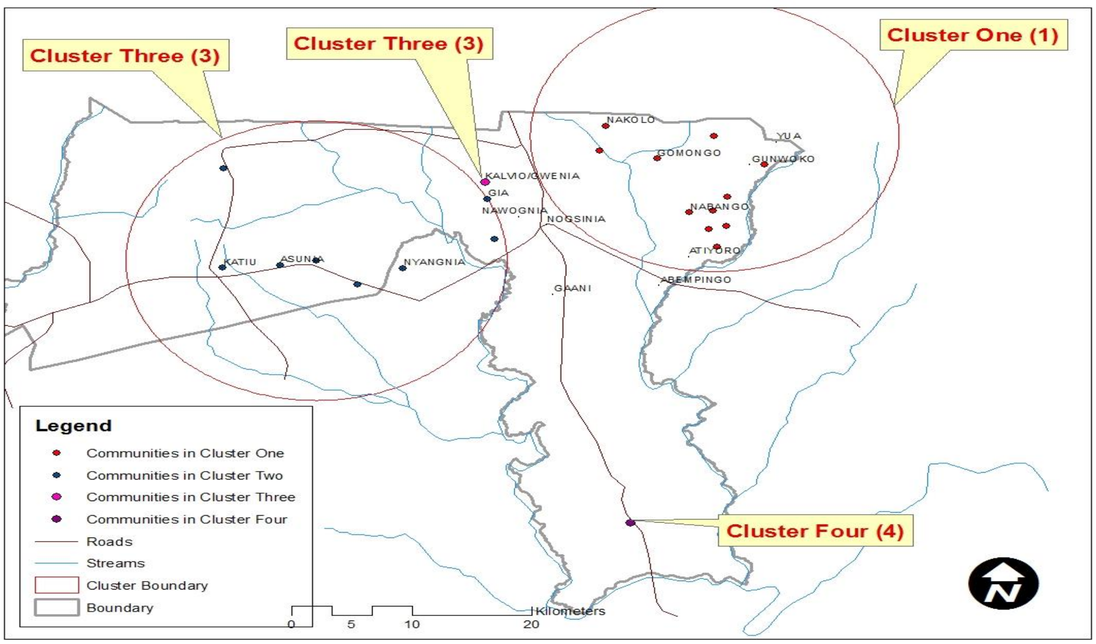

Figure 65: Clustering of all-cause mortality for all ages at Navrongo HDSS site

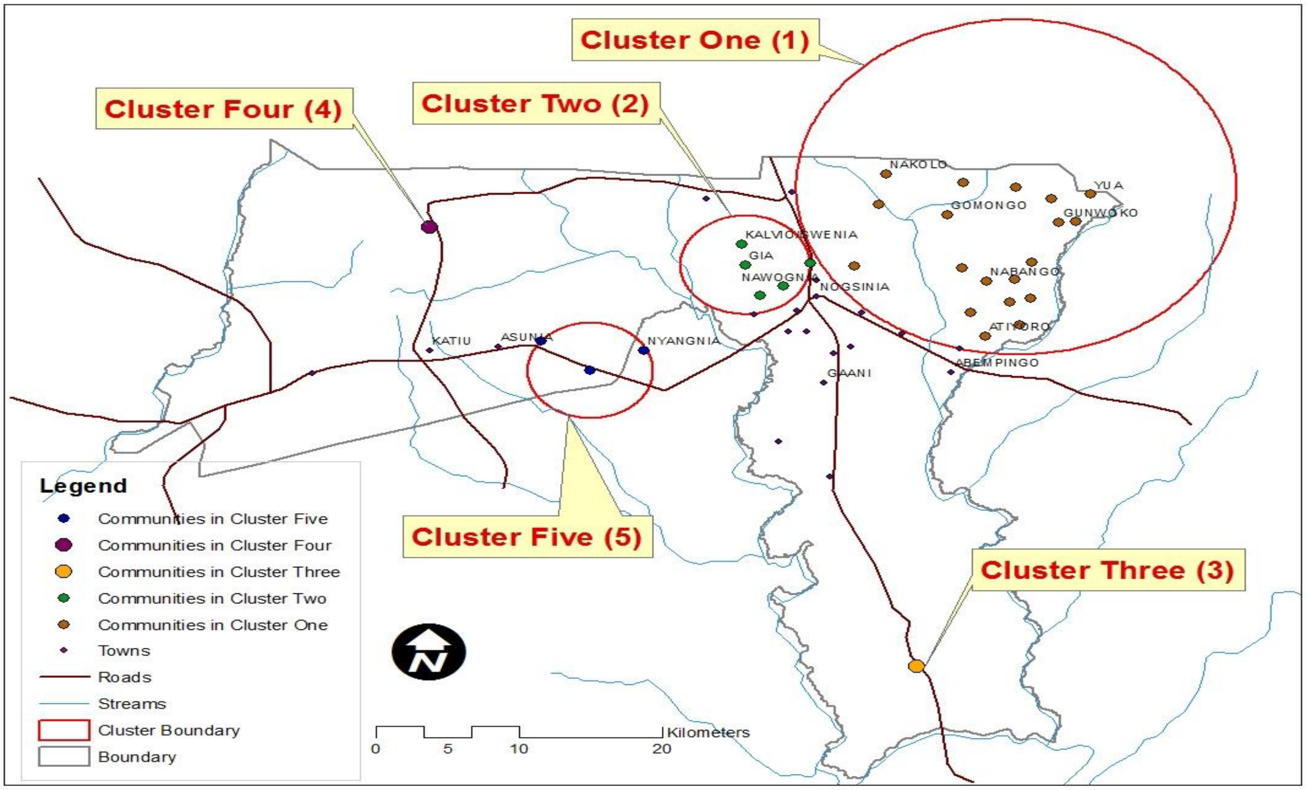

Figure 66: Clustering of all-cause mortality for under-fives at NHDSS site

4.5.3 Clustering of malaria-specific mortality at Dodowa HDSS site

With respect to malaria-specific mortality for all ages, six clusters of communities with higher malaria-specific mortality rates than the other villages were identified in Dodowa HDSS area (Figure 67). All these clusters were statistically significant with p<0.001. A cluster identified in 2006-2007 had four communities, three from Ayikuma and one from Dodowa area council with a relative risk of 7.0 and radius 1.3km. In 2008-2009, a cluster comprising three communities in Dodowa area council was identified with relative risk of 8.5 and a radius of 1.12km. The cluster identified in 2009 had five communities from Asutsuare with relative risk of 5.2. The year 2010 had two significant clusters. The first comprised 26 communities from Ayikuma with relative risk of 5.7 while the other had 21 communities, 11 from Asutsuare and 10 from Osuwem with a relative risk of 5.5. The cluster in 2010-2011 had the highest radius, 14.39km, and comprised a lot of communities. It had 103 communities, 47 from Dawa, 40 from Ningo and 16 from Prampram area councils with a relative risk of 1.68 (Appendix H3).

With under-five malaria mortality, seven clusters were observed in DHDSS and all of which were statistically significant with $p<0.001$(Figure 68). A cluster comprising 64 communities, 30 from Prampram, 20 from Ayikuma, eight (8) from Ningo and six (6) from Dawa area councils was identified in 2006. The relative risk was 5.0. Three significant clusters were identified in 2007. The first two comprised of one community each from Osudoku and Ayikuma area councils with relative risks of 114.2 and 73.1 respectively. The third significant cluster in 2007 comprised of communities from Dodowa area council with a relative risk of 13. Two communities from Asutsuare formed a significant cluster in 2009 with relative risk of 34.4. Another cluster with communities from Dodowa area council was in 2009-2010. It was made up of 12 communities with a relative risk of 13.4. A cluster in 2011 comprised of 13 communities from Asutsuare. The relative risk for this cluster was 10.1 with a radius of 4.2km (Appendix H4).

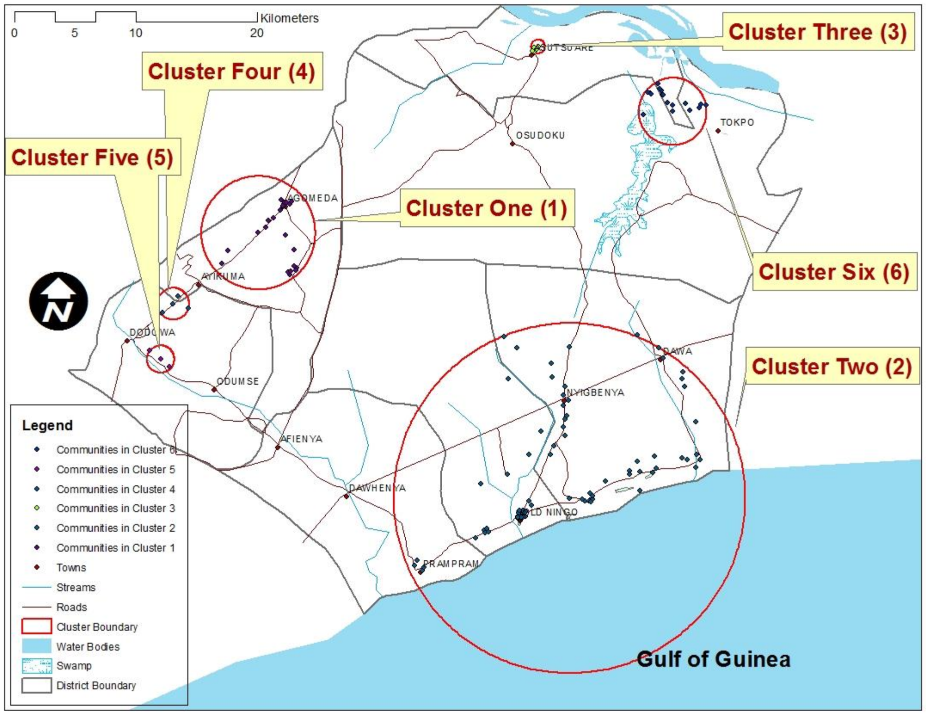

Figure 67: Clustering of malaria-specific mortality for all ages at Dodowa HDSS site

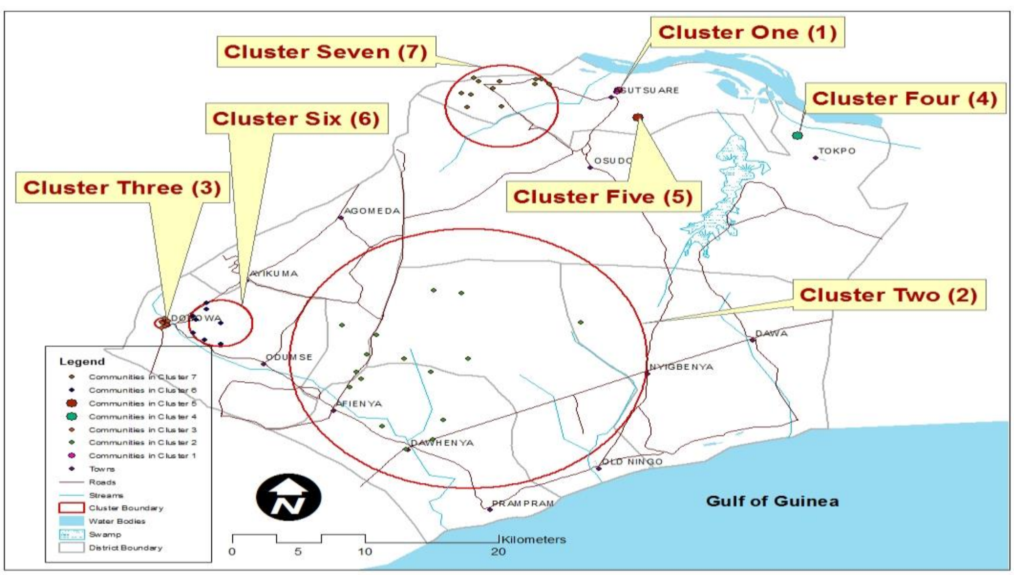

Figure 68: Clustering of under-five malaria-specific mortality at Dodowa HDSS site

4.5.4 Clustering of malaria-specific mortality at KHDSS

Seventeen clusters of higher mortality were observed for malaria-specific mortality in all ages (Figure 69) in the KHDSS. All these clusters had significantly higher mortality compared to the rest of the villages that were not included in the clusters with p<0.001(Appendix H3). Ten of the clusters comprised of one (1) village each with relative risks from 4 to 32.8. One cluster was made up of two villages with relative risk of 2.4 while two clusters comprised three villages each with relative risks of 3.7 and 3.0. The first cluster identified in 2006-2008 included five villages with a relative risk of 2.0. The other significant clusters comprised of 19 villages in 2007-2008, 25 villages and seven villages with relative risks of 2.1, 1.8 and 2.3 respectively.

Twelve clusters of under-five malaria specific mortality were identified at the Kintampo HDSS site (Figure 70). All these clusters were significant with p<0.001 (Appendix H4). As in the all ages, some of the clusters comprised of one village each. Six clusters had one village each with relative risk from 8.9 to 156. Two clusters had two communities each with relative risks of 5.2 and 4.6. Another two clusters comprised five communities each. The first of these clusters was in 2006-2007 with relative risk of 3.5 while the other was in 2010 with relative risk 2.3. Two clusters in 2009-2010 comprised of 18 and nine (9) communities with relative risks of 3.1 and 3.0 respectively. The first cluster identified in 2010-2011 with a relative risk of 3.0 comprised of 16 communities.

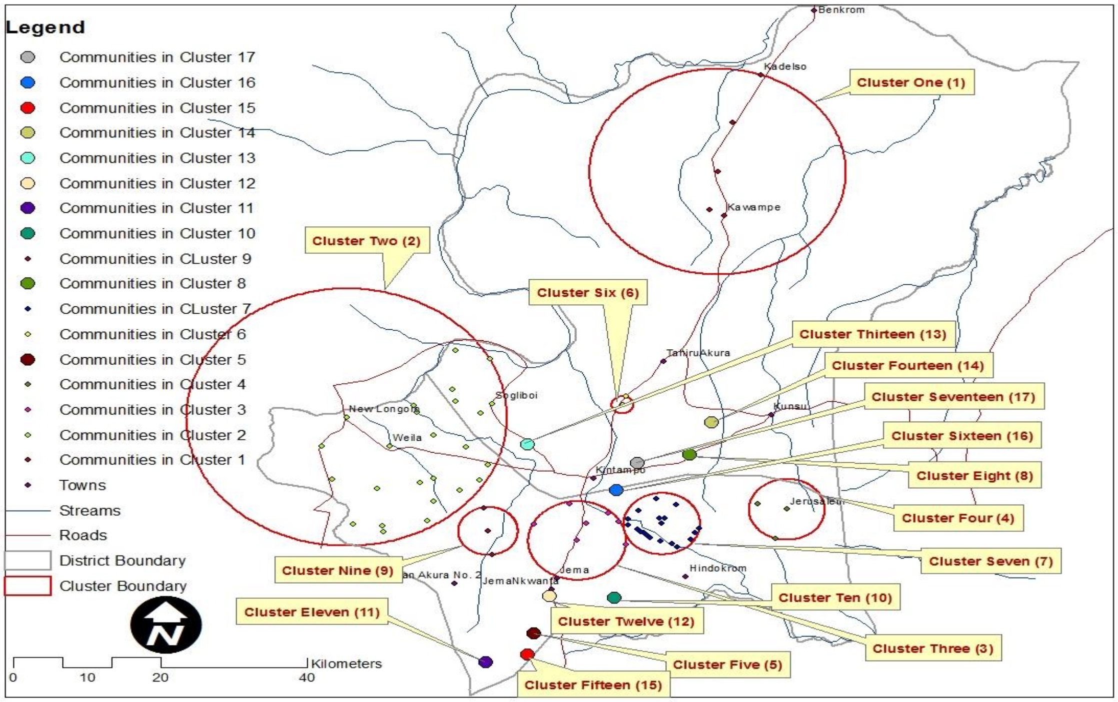

Figure 69: Clustering of malaria-specific mortality for all ages at Kintampo HDSS site

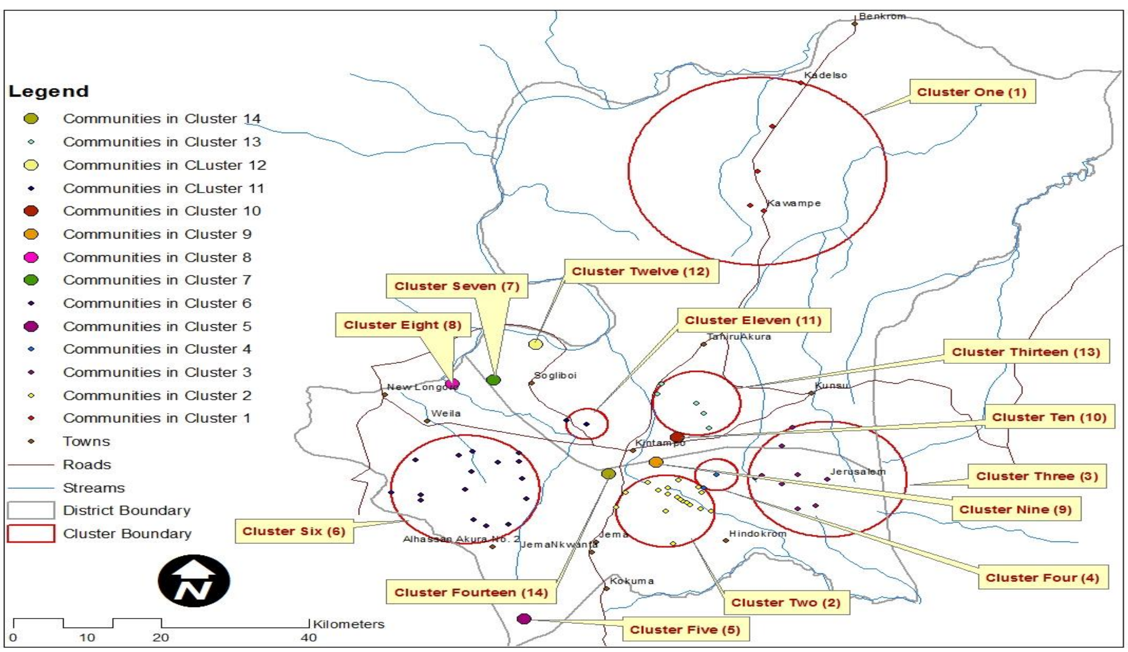

Figure 70: Clustering of under-fives malaria-specific mortality at Kintampo HDSS site

4.5.5 Clustering of malaria-specific mortality at Navrongo HDSS site

Four clusters of malaria-specific mortality for all ages were identified at the Navrongo HDSS site (Figure 71). All these clusters were significant with $p<0.001$ and each comprising a sizable number of communities (Table 14). The first cluster was identified in 2006-2008 with a relative risk of 2.4 and included 19 villages mostly from the East and then South. The second cluster made up of eight (8) villages was identified in 2008-2009 with a relative risk of 2.5 and mainly in the West. The third cluster with relative risk of 2.5 was in 2006 and comprised of six (6) villages from the North and West with only one from the Central. The last and smallest cluster with relative risk of 1.9 comprised of one (1) village the north and was in 2009-2010.

For the under-five malaria-specific mortality, three significant clusters were identified (Figure 72). The first cluster identified was in 2006-2007 with a relative risk of 3.0 and comprising of 10 villages from the East and South. The second cluster comprised of eight (8) villages mainly from the West and had a relative risk of 2.8. The last cluster identified was in 2006 with relative risk of 3.5 and included two (2) villages (Appendix H4).

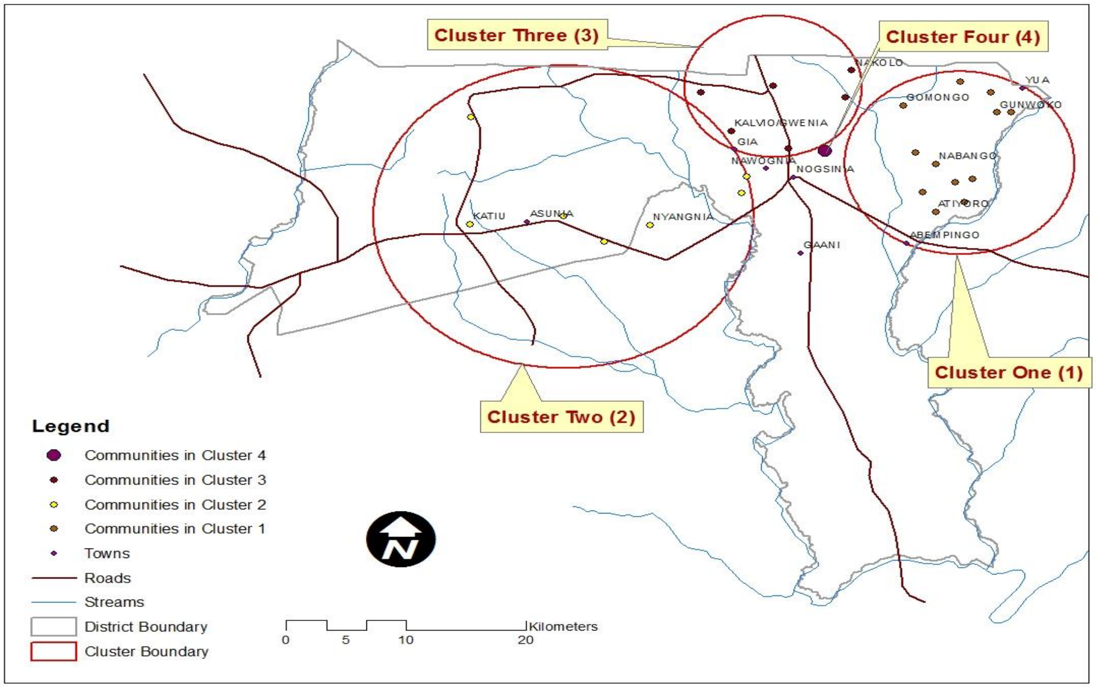

Figure 71: Clustering of malaria-specific mortality for all ages at Navrongo HDSS site

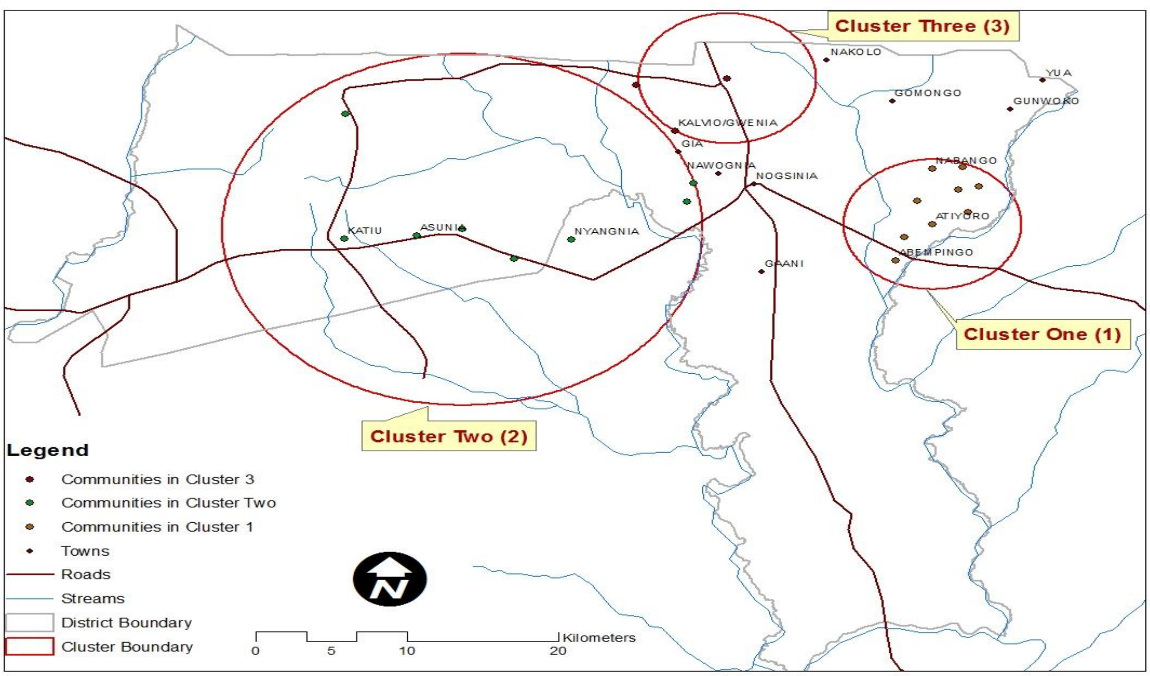

Figure 72: Clustering of under-fives malaria-specific mortality at Navrongo HDSS site

CHAPTER FIVE: DISCUSSION

5.0 Introduction

This study investigated the relationship between weather variables (temperature, rainfall) and mortality across three geographical zones in Ghana. It also investigated the spatiotemporal distribution of deaths across these zones. Results from the monthly analysis indicate that there is an association between the weather (temperature, rainfall) and mortality. The findings show a mixture of relationship (both linear and non-linear) and delayed effect between temperature, rainfall and mortality in the study areas. There was also evidence of clustering of mortality in each of the HDSS sites.

5.1.1 Seasonal variation and all-cause mortality

The plots of moving averages of monthly mortality rates and monthly rate ratios suggest seasonality of mortality at the HDSS sites. For all-cause mortality, the peak of overall mortality is in June at the Dodowa and Kintampo HDSS sites and in August at the Navrongo HDSS. Deaths from infectious diseases could have partly contributed to this phenomenon since this was in the rainy season(Drayna, McLellan, Simpson, Li, & Gorelick, 2010; Nichols, Lane, Asgari, Verlander, & Charlett, 2009). Rainy season is associated with vulnerability in various ways; rainy season provides a favourable breeding conditions for several disease causing vectors such houseflies which can transmit cholera and enteric fever(M.-J. Chen et al., 2012). The rainy season is also associated with bad roads hindering access to health facilities and is also the season for disasters such as floods; sources of drinking water may be contaminated around this period as observed by other studies (Akanda, Jutla, & Islam, 2009; Jutla et al., 2013); the rainy season also happens to be the lean season where there is less food, particularly in Navrongo HDSS and this can lead to nutritional problems and subsequently death (Rademacher-Schulz, Schraven, & Mahama, 2014). The peaks of mortality also coincided with the coldest months, especially at Dodowa and Navrongo HDSSs. The cold season is synonymous with respiratory tract infections (Eccles & Wilkinson, 2015) and this could trigger acute respiratory diseases and exacerbate genetically associated diseases such as haemoglobinopathies (e.g sickle cell disorders and asthma). Studies elsewhere have indicated that the peak season of mortality was the rainy season (Engelaer et al., 2014). This is, however, in contrast with a study in Burkina Faso that found that overall mortality was highest in the dry season instead of the rainy season (Kynast-Wolf, Hammer, Müller, Kouyaté, & Becher, 2006; Kynast-Wolf, Preuß, Sié, Kouyaté, & Becher, 2010). These findings are congruent with the results from Kintampo HDSS since apart from the month June, higher mortality rates are associated with months with low rainfall (December and January). This can partly be due to delayed or lag effect of rainfall for two to three months since two of the rainfall peaks in Kintampo HDSS were in September and October.

The seasonal pattern of mortality however, differs among the age groups. For instance, for under-five mortality, the mortality peak is observed in August at Dodowa HDSS, July at Kintampo HDSS and September at the Navrongo HDSS. This supports other findings that showed that seasonality of mortality varies by age (Ye et al., 2009). The differential in seasonal pattern among the age groups may be due to different exposures and vulnerability levels to the weather conditions. Children are more prone to infectious diseases such as malaria and diarrhoea, which are common in the rainy season and so could have partly been attributable to the deaths. Children are also vulnerable to the harsh conditions that come with rainfall such as poor shelter, hunger or malnutrition. The results also confirms the findings by Abdullah and colleagues which showed that mortality in children was highest in the rainy season (Abdullah et al., 2007). A study in Garu which is close to Navrongo HDSS in Ghana also observed that child mortality is higher in the rainy season and peaked in September (Engelaer et al., 2014).

5.1.2 Seasonality of malaria mortality

With malaria mortality for all ages, higher rates are observed between March and July, then in September with the peak mortality being observed in June, one month lag the peak of rainfall at Dodowa HDSS. High mortality rates in Kintampo HDSS were from April to October with peak in August. For the Navrongo HDSS, higher rates are observed from June to November with slightly highest peak in September. This corroborates the findings that malaria morbidity and mortality generally peaks in the rainy season (Engelaer et al., 2014; Ikeda et al., 2017). The differences observed in the peaks at the HDSS sites can be due to the weather conditions and transmission dynamics of malaria in the various locations. The findings from this study suggest that malaria mortality delays after peak of rainfall in Kintampo and Navrongo while that of Dodowa is immediate. This may be due to the fact that the intensity of rainfall at the Dodowa HDSS is less and so stagnant waters can gather immediately and provide conducive breeding grounds for malaria vectors. However, for Kintampo and Navrongo HDSS sites, the high intensity of rainfall during the peak season may be deleterious to proliferation of the malaria vector immediately. This may be because intense rainfall do not easily allow for the collection of stagnant waters that are necessary for vector proliferation but as the rainy season progresses with less intensity, it then allows for the collection of stagnant waters (Dieng et al., 2012; Paaijmans, Wandago, Githeko, & Takken, 2007).

It had also been observed that the *Anopheles gambiae s.l. Giles* is most prevalent in the DHDSS (MA Appawu et al., 2001; Quartey, 2016) and their population is said to increase at the onset of rains (Rumisha, Smith, Abdulla, Masanja, & Vounatsou, 2014). The vector *Anopheles funestus* is however, more abundant in KHDSS and NHDSS than the *Anopheles gambiae*. These two vectors have been shown to correlate with monthly rainfall patterns (Dery et al., 2010).

With malaria mortality in the under-five, high rates are from May to July then September with peaks in July and September at Dodowa HDSS. For Kintampo HDSS, under-five malaria mortality was high between April and October while at Navrongo HDSS it was June-November. The malaria deaths for all ages and under-fives were lowest during the dry months and this was the same for all the HDSS sites. This may be attributed to the fact that Entomological Inoculation Rates (EIR) and as such malaria incidence is higher in the rainy season and lower in the dry season (Abonuusum et al., 2011; Asare & Amekudzi, 2017; Dery et al., 2010; Kasasa et al., 2013) This corroborates with studies that have observed that malaria morbidity and mortality are higher in the rainy season and lower in the dry season (Engelaer et al., 2014; Owusu-Agyei et al., 2009).

5.2.1 Association between weather variables (temperature, rainfall) and all-cause mortality

The findings of this study reveal an association between weather variables (temperature, rainfall) and mortality. This is evident across all the sites.

Temperature in the previous one month before the occurrence of death, and temperature in the month of death are significantly associated with all-cause mortality. Overall mortality risk is insignificantly higher with hotter temperatures (above 29.5^{o}C for Dodowa, 30.6 ^{o}C for Navrongo) in the month of death. With temperature in the previous one month before death, mortality is significantly lower with hotter temperatures (above 29.5^{o}C for Dodowa, 30.6 ^{o}C for Navrongo) and insignificantly lower for Kintampo (above 27.0^{o}C). Mortality risks are however, non-significantly higher with relatively colder temperatures (below 27.6 ^{o}C for Dodowa, 27.4 ^{o}C for Navrongo, 25.5 ^{o}C for Kintampo). This association of the previous one month's mean temperature and mortality suggest delayed effect of temperature. The higher temperature may be protective of respiratory diseases such as asthma and non-communicable diseases such as haemoglobinopathies. Too high a temperature may also be deleterious to the development of disease vectors and some pathogens as these conditions could favour their competitors (Wu, Lu, Zhou, Chen, & Xu, 2016). A study to investigate the effect of cold weather on mortality reported that a decrease in temperature was associated with increased number of daily deaths (Analitis et al., 2008). This is however at variant with the results that mortality risk increased with temperature for all ages (Azongo et al., 2012). Azongo et al did analysis of daily mortality and temperature with data from 1995-2010 and found that mortality risk increased with temperature lag 0-1 and lag2-6 days. These temperature lag strata are within the month in which the death occurred. It concurs with the non-significant increase in mortality risk above 30.6 ^{o}C found in this study. Analysis of monthly weather and mortality data in Tanzania also found a significant reduction of mortality risk with temperature (Mrema et al., 2012). Callaly and colleagues showed in their study that mortality in the cold or winter may not be solely due to temperature but also as a result of co-morbidity, non-communicable diseases (NCDs) and severe illness since these are sensitive to drop in temperature (Callaly, Mikulich, & Silke, 2013). These results also confirm what has been found in other studies that colder temperature is associated with high mortality (Burkart et al., 2011; Gasparrini et al., 2015; Kynast-Wolf et al., 2010). The non-significant association found in Kintampo HDSS may partially be due to the fact that Kintampo HDSS site was the coldest. The highest mean temperature is 29 ^{o}C which implies that the range of temperature above the 27.0 ^{o}C (75th percentile) are all below 30 ^{o}C which is probably still within the range of temperatures with similar conditions for vector proliferation (Amek et al., 2012a; Kirby & Lindsay, 2009).

Monthly rainfall in this study is not significantly associated with all-cause mortality for all ages in Dodowa and Navrongo HDSS while in Kintampo HDSS, rainfall above 177.5mm in the month of death was significantly associated with higher mortality. Rainfall in the previous two months before death is associated with higher mortality risk at the 10% level of significance in Kintampo HDSS and in Dodowa HDSS, rainfall in the previous one month is associated with mortality at the 10% level. This may be due to the fact that rainfall is more intense at Kintampo. The high mortality with rainfall above 177.5 in Kintampo HDSS, may be due to some of the factors discussed above; intense rainfall is associated with bad roads hindering access to health facilities; flooding with its associated disasters; pollution of drinking water sources (Burkart et al., 2014b; Bush et al., 2014; Carlton et al., 2013; Patz, Vavrus, Uejio, & McLellan, 2008). It might also be a favourable condition for breeding of vectors (Díaz-Quijano & Waldman, 2012). The intense rainfall may also come with cold weather triggering conditions like asthma and acute respiratory diseases (Abe et al., 2009; Mourtzoukou & Falagas, 2007). The rainfall levels at the 75th percentiles at Dodowa and Navrongo may not have been as intense enough as to have a significant different effect on mortality above it. Though there is no significant association between rainfall and mortality at Dodowa and Navrongo, mortality risk increases by 1.0% with rainfall in the month of death below 34.1mm and by 1.9% with rainfall above 129.3mm in Dodowa. Also in Navrongo mortality risk increases insignificantly with rainfall in the month of death and previous one and two months before death.

When temperature and rainfall are adjusted for the effect of each other, mean temperature in the previous one month is still significantly associated with mortality in all ages at Dodowa and Navrongo HDSS sites. Mortality risk at Navrongo HDSS is, however, significantly higher with relatively lower mean temperatures (below 27.4°C) in the previous one month. Rainfall above 177.5mm in the month of death and the precious two months before death are significantly associated with higher mortality for all ages in the Kintampo HDSS. The association is stronger with relatively bigger effect size. This suggests that the risk of all-cause mortality for all ages is mostly affected by temperature in Dodowa and Navrongo and by rainfall in Kintampo. Kintampo is the coldest among the three HDSSs and is also the location with the heaviest rainfall.

5.2.2 Association between weather variables (temperature, rainfall) and under-five all-cause mortality

For children under five years, the effect of mean temperature in the month of death is stronger and higher mortality risks are associated with higher temperatures. This can be partially explained by the fact that under-fives are more vulnerable and experience immediate effect of temperature. Unlike adults who are partially immune and have built resistance, children under-five have very little immunity and so are quite susceptible and any small inoculum or dose can lead to sickness. Higher temperature leads to higher metabolic rate for children. For children with nutritional problems, this can impact negatively on their health and contribute to mortality. A study that investigated the relationship between extreme temperature and paediatric emergency admissions reported that high temperature had significant effect on several conditions including intestinal infectious, endocrine, nutritional and metabolic diseases (Xu et al., 2014). A study on ambient temperature and lung function in children with asthma revealed that high temperature was associated with low lung function of children with asthma (S. Li et al., 2014). A previous study in Navrongo HDSS observed that 1°C increased in daily mean temperature at lag days 2-6 and 7-13 above 30.7°C was significantly associated with increase in under-five mortality (Azongo et al., 2012). Analysis of Nouna HDSS data in Burkina Faso also reported that direct heat had a strong effect on under-five mortality in the study area (Diboulo et al., 2012)

Rainfall in this study is significantly associated with under-five mortality at the three HDSSs when it is modeled without adjusting for the effect of temperature. Under-five mortality risk is significantly higher with lower amount of rainfall (below 34.1mm) and non-significantly higher with rainfall above 129.3 in the previous one month before death at the Dodowa HDSS. Low rainfall (below 22.8mm) in the previous two months before death is significantly associated with lower under-five mortality risk at the Kintampo HDSS. For rainfall in the month of death, under-five mortality was associated at the 10% significant level. At the Navrongo HDSS, rainfall in the month of death, the previous one and two months before death are significantly associated with higher under-five mortality risk. The results in Navrongo seem to support a previous study in the area which observed that mortality was increasing with lagged days of rainfall (Azongo et al., 2012). This implies significant association could have been observed if the lagged days were extended.

A study in Tanzania on influence of weather on mortality reported that under-five mortality increased with rainfall and that under-five morality would increase by 72% with a rise of rainfall to 400mm (Mrema et al., 2012). Other studies have however, found no statistically significant association between rainfall and under-five mortality (Diboulo et al., 2012; Egondi et al., 2012).

While in DHDSS under-five mortality increased with rainfall below 34.1mm, under-five mortality risk decreased with rainfall below 22.8mm and increased with rainfall above 177.5mm though not significant in KHDSS.

When temperature and rainfall are adjusted for each other in the same model, mean temperature and rainfall are significantly associated with under-five mortality at the DHDSS. High mean temperature in the month of death is significantly associated with higher under-five mortality and low rainfall in the previous one month before death was associated with higher under-five mortality. In the KHDSS, rainfall in the month of death and the previous two months are associated with under-five mortality. For NHDSS, under-five mortality is significantly associated with temperature in the month of death and insignificantly increased with rainfall. This shows that for children under-five, mortality is affected by both rainfall and temperature. A study in India, using data from Vadu HDSS reported that under-five mortality risk increased by 66.5% with increase in temperature lag of 2-6 days and decreased by 29.3% with temperature lag 7-13 days (Ingole et al., 2012). A systematic review on the effect of season and health reported that heavy quantities of rainfall and rising temperatures are associated with excess mortality (Burkart et al., 2014a). The finding from this study is however, in contrast with what was reported by Mrema and colleagues when they analyzed monthly mortality and weather data. They observed that mortality increased with decreasing temperature and that under-five mortality would increase by 80.7% if monthly average temperature decreased from values (between 26°C and 27°C) to 24°C (Mrema et al., 2012).

5.2.3 Association between temperature, rainfall and all-cause mortality in the elderly (60+)

Temperature in the previous one month before death is associated with mortality in the elderly (60+ years) in DHDSS. With KHDSS, temperature in the month of death is associated with mortality in the elderly. Rainfall has no association with mortality in the elderly (60+ years) at the HDSSs. This can be because the aged are fragile and are easily prone to respiratory tract infections. Many of them also live with debilitating diseases that could easily be aggravated. Besides, they cannot withstand the effects of malaria and the other diseases and conditions associated with the temperature. The results from this study concur with findings from other studies that found no significant association between rainfall and mortality among the elderly (60+years) (Azongo et al., 2012; Egondi et al., 2012; Ingole et al., 2012; Mrema et al., 2012). The finding is, however, in variant with a study in Burkina Faso that found association between rainfall and mortality in the elderly. Rainfall lag 2-6 days was significantly associated with mortality among elderly (Diboulo et al., 2012). The findings from this study also corroborate studies that found association between temperature and mortality among the elderly. A metal-analysis and systematic review of the relationship between temperature and mortality among the elderly observed that both cold and hot temperature were associated with increased mortality among the elderly and the heat-related effects was higher (Yu et al., 2012) Yu et al also reported in their study that the effect of temperature was higher in the elderly (Yu, Vaneckova, Mengersen, Pan, & Tong, 2010).

5.2.4 Association between temperature, rainfall and mortality in the poorest and richest socioeconomic groups

Mortality in those in the poorest socioeconomic group in Dodowa and Navrongo HDSSs is associated with temperature in the previous one month before death while mortality in the richest socioeconomic group have no significant association with temperature. In the Kintampo HDSS, mortality in the poorest socioeconomic group is associated with mean temperature at the 10% significance level. This can be because people in the poorest socioeconomic group are more vulnerable to harsh weather conditions since they are less likely to be protected; have suitable housing infrastructure, protective clothing and not able to regulate variability of temperature (Ataguba, Akazili, & McIntyre, 2011; Kravchenko, Abernethy, Fawzy, & Lyerly, 2013; Wagstaff & Lindelow, 2011). They also lack quality health care due to limited resources (Asch et al., 2006; Peters et al., 2008).

Rainfall in the previous one month is associated with all-cause mortality in the poorest socioeconomic group at the 10% level of significance in the Dodowa HDSS. In the Kintampo HDSS, rainfall in the previous two months is significantly associated with mortality in the poorest socioeconomic group. All-cause mortality increases with rainfall above 177.5mm in Kintampo HDSS. However, at the Navrongo HDSS, rainfall in the month of death is significantly associated with mortality. For all-cause mortality in the richest socioeconomic group, rainfall is not associated with mortality at any of the HDSS sites. This can be explained as those in the poorest socioeconomic group are more prone to bad weather conditions because they do not have the resources for adaptive measures.

Temperature and rainfall are still associated with mortality among those in the poorest socioeconomic group when temperature and rainfall are adjusted for each other but not in the richest socioeconomic group. These finding are in confirmation with other studies. In a systematic review on the importance of social factors in health planning, Yardley and colleagues reported that, generally, the risk of mortality associated with temperature was higher in those in the lower socioeconomic group (Yardley, Sigal, & Kenny, 2011). A study to investigate the risk factors for direct heat related hospitalization during heatwave reported that those in the lower socioeconomic status had higher risk (Zhang, Nitschke, & Bi, 2013). The results from this study is, however, in contrast with findings from other studies that reported that they did not find significant association or effect modification by socioeconomic status on the effect of temperature on mortality (Gouveia, Hajat, & Armstrong, 2003; Yu et al., 2010)

5.3.1 Association between temperature, rainfall and malaria-specific mortality for all ages

Temperature in the previous one to three months before the occurrence of death is significantly associated with malaria mortality. Lower temperature (below 27.6 °C) in the previous one month before death is significantly associated with lower malaria mortality at the DHDSS. In Kintampo HDSS, temperature in the previous two months and three months before death are associated with mortality. Mortality risk was higher with temperature above 27.0°C in the previous two month while for temperature three months preceding, mortality risk decrease with mean temperature above 27.0°C. In NHDSS, lower temperature (below 27.4°C) in the previous three months before death is significantly associated with increased malaria mortality. This can be explained by the delay effect of temperature. A study in Kenyan reported that association between temperature and malaria mortality was higher between 9-12 weeks and 13-16 weeks temperature before death (M. O. Sewe, Ahlm, & Rocklöv, 2016). When rainfall and temperature are modeled together, temperature in the previous one month is associated with malaria mortality in all ages at the 10% level of significance in the DHDSS. In the KHDSS and NHDSS, temperature in the previous three months is significantly associated with malaria mortality. Rainfall in the month of death was associated with malaria mortality at the 10% level of significance in KHDSS.

Rainfall not being significantly associated with malaria mortality in NHDSS when adjusted can be due to the fact that there are sources of breeding of the malaria vector all year round. Dugouts and/or dams are at various locations. Production of the malaria vector is thus more driven by variability in the temperature than in rainfall. A recent study on malaria prevalence and transmission in DHDSS revealed that there is no marked difference in the prevalence of malaria in the wet and dry seasons with the dry season surprisingly having higher prevalence. The prevalence of malaria (parasite rate) in the district was 6.8% in the wet season and 7.1% in the dry seasons (Quartey, 2016). This could also explain the results in this study for DHDSS. Other studies, included a previous study in the study area around 1995 have however, reported malaria prevalence to be relatively higher in the wet season (Afari, Appawu, Dunyo, Baffoe-Wilmot, & Nkrumah, 1995; Dery et al., 2010; Owusu-Agyei et al., 2009). There have also been mixed findings about the relationship between malaria transmission and incidence.

5.3.2 Association between temperature, rainfall and under-five malaria-specific mortality

Low temperature (below 27.6°C) in the previous one month before death is significantly associated with low mortality at the DHDSS for children under-five. High mean temperature (27.0 °C) in the previous two months is associated with high under-five malaria mortality while that in the previous three months is associated with low mortality at the KHDSS. Both low temperature (below 27.4°C) and high temperature (above 30.6°C) in the previous three months are significantly associated with under-five malaria mortality in NHDSS. This also explains the delay effect of temperature on malaria mortality and concurs with the finding observed by (M. Sewe et al., 2015) in their study. Temperature lag 13-16 weeks was strongly associated with under-five malaria mortality. Byass and colleagues classified temperature and rainfall values into quartiles in their analysis and reported that high monthly mean temperature and monthly rainfall in one month preceding death significantly associated with malaria mortality (Byass et al., 2017).

Rainfall in the previous one month before death is associated with under-five malaria mortality in DHDSS. Under-five malaria mortality risk increases with rainfall below 34.1mm or rainfall above 129.3mm. Rainfall in the previous two months is also associated with under-five malaria mortality in KHDSS at the 10% level while at the NHDSS, rainfall in the previous three months is significantly associated with under-five malaria mortality risk. These results suggest delay effect of rainfall on malaria mortality. A study on modeling the relationship between precipitation and malaria incidence in children from a holoendemic area in Ghana indicated that rainfall predicted malaria incidence after a lag of 9 weeks (Krefis et al., 2011). This implies, deaths from malaria may also peak after a lag of 9 weeks, after two months. Similar findings were observed in Kenya where the researchers reported that under-five malaria mortality was associated with changes in rainfall up to 9-12 weeks (M. Sewe et al., 2015). Temperature and rainfall in the previous one month are both associated with malaria mortality in the DHDSS when the two were combined in the same model. Lower mean temperature is associated with low or decreased malaria mortality risk and lower rainfall with high mortality risk. Temperature lag3 is associated with under-five malaria mortality at the KHDSS while rainfall lag2 is associated at the 10% level of significance. Temperature lag3 is associated with under-five malaria mortality at the NHDSS site. These results show delay effect of temperature and rainfall on under-five malaria mortality risk and a biological mechanism underlying mosquito breeding and malaria incidence and mortality. A study in Kenya showed that the risk of under-five malaria and/or anaemia mortality increases with weekly mean temperature above 24°C 9-12 and 13-16 weeks after higher temperatures begins and with increasing amount of rainfall 9-12 weeks after rainfall increase (Sewe et al., 2015). The findings from this study also corroborates other studies in Ghana that investigated the relationship between rainfall and malaria incidence or malaria cases. The study on rainfall and malaria incidence observed that, depending on the village, malaria incidence lagged one week, two week or nine weeks behind weekly rainfall (Krefis et al., 2011). The study on monthly malaria cases and rainfall in Ejura and Winneba observed weak positive association at zero-month lag but a strong negative correlation between rainfall in the previous two months and malaria caseload (Klutse et al., 2014). A similar finding was reported by Arab and colleagues who modeled the effect of weather and climate on malaria distribution. The found that annual total rainfall and annual mean were negatively associated with malaria incidence (Arab et al., 2014).

5.4.1 Clustering of all-cause mortality at the HDSS Sites

Results from the clustering analysis indicate that there is clustering of mortality in the HDSS areas. A significant cluster of high under-five mortality in Dodowa HDSS is identified between 2009 and 2011 comprising 99 communities. One of the two clusters of high under-five mortality in 2005 is Ningo area council (Awini et al., 2010) which contributed about half (48) of the communities forming the significant cluster in this study. There was no significant cluster of high under-five mortality identified between 2006 and 2008 in the DHDSS. This concurs previous work from the area that reported that there was no significant cluster of high under-five mortality in 2006. However, there exist clustering of high under-five mortality after 2006. Other studies have also reported clustering of under-five mortality (Dedefo, Oljira, & Assefa, 2016; Kanjala, Alberts, Byass, & Burger, 2010; B. K. Sartorius & Sartorius, 2014).

However, for the overall mortality in this HDSS, four significant clusters of high mortality are identified with three of the clusters observed in 2006-2008. Ayikuma, Ningo, Dawa and Osuwem area councils are relatively deprived compared to other area councils in the DHDSS. A wealth index generated for the DHDSS area indicated that Dawa and Osuwem have most of their households in the poorest socioeconomic quintile while Ayikuma and Ningo are in the poorer quintile (Gyapong et al., 2013). For these area councils, access to health facility is relatively poor with bad road network. A high proportion of households in these area councils does not have adequate quality water source and toilet facilities. Studies have shown that socioeconomic status, remoteness of health facility, access to water and sanitation facilities are related to health outcomes (Bello & Joseph, 2014; Peter Byass, Fantahun, Emmelin, Molla, & Berhane, 2010; Dedefo et al., 2016; El Azar et al., 2009; Kanjala et al., 2010; Kolahi et al., 2010; Musenge et al., 2013; K. Sartorius et al., 2013).

For the Kintampo HDSS, the significant cluster of high under-five mortality identified in 2006-2007 comprised of 20 villages. For all ages, two significant high clusters of mortality comprising 17 villages each are observed in 2007-2009 and 2009-2011. Some of these villages are also included in the high clusters of under-five mortality. The villages in these clusters are among the deprived villages in the KHDSS. Most of them are scattered with poor access to health facilities. The road network is bad making it difficult for the inhabitants to access health facilities and other opportunities. Some of these villages were also identified in high mortality clusters in an earlier study (Nettey et al., 2010). A study in Burkina Faso also attributed clustering of mortality in the study area to distance to health facility (Schoeps, Gabrysch, Niamba, Sié, & Becher, 2011).

In NHDSS, the villages forming the significant cluster of under-five mortality between 2006 and 2008 in this study are the same villages that are consistently identified in the previous publication (Adjuik et al., 2010). Most of these villages are from the eastern part of the NHDSS area. The main attributable reason for the clustering of these villages between 1997 and 2006 is that these villages did not benefit from active intervention of the Community Health and Family Planning (CHFP) project at that time (Adjuik et al., 2010). This is alluded to by Binka and colleagues (Binka et al., 2007) who showed that the CHFP greatly reduced child mortality. This can still be one of the reasons for the high clusters of under-five mortality in the eastern part of the NHDSS compared to other parts. Though the CHFP project, now known as Community-based Health Planning and Services (CHPS) strategy was extended to the eastern part in 2004, its effect might have only been realized after four years. People from those areas that benefited from the CHFP project would have learnt the positive attributes of health seeking behavour that have been able to sustain the possible positive health outcome. The CHPS strategy has been proven to reduce under-five mortality (Awoonor-Williams, Sory, et al., 2013; Binka et al., 2007). Other factors can also be that, the eastern part of the NHDSS is among the most deprived. They have limited fertile land for farming and so food security is an issue and the road network is also poor. A recent study in Nouna also attributed the clustering of mortality observed to factors such as access to health facilities and good road network and malnutrition (Becher et al., 2016). Most of the areas identified as high clusters of mortality share similar cultural practices and taboos. The eastern part of the district is known for negative cultural practices, such as Female Genital Mutilation (FGM) and belief in “spirit child”. An unpublished report from a study conducted on FGM in the district showed that while the prevalence of the practice in the district was 23% that of the eastern part was 34%. It had also been reported that FGM is associated with higher caesarean section and stillbirths rates (A. Oduro et al., 2006). Spirit child is also said to have contributed to high childhood mortality risk in the district (Allotey & Reidpath, 2001; Denham, Adongo, Freydberg, & Hodgson, 2010). Other studies elsewhere have also reported the negative health effect of FGM. A study in six Africa countries reported that FGM was significantly associated with obstetric complications such as extended maternal hospital stay, stillbirth or early neonatal deaths, postpartum haemorrhage, caesarean section and infant resuscitation (Banks, Meirik, Farley, & Akande, 2006). Another study on the impact of FGM on the health of newly married women Egypt report that FGM had negative effect on the health of the women including dysmenorrhea, obstetric complications and distressed babies (Elnashar &

Abdelhady, 2007). This is reflected also in the overall mortality where the significant clusters of high mortality are concentrated in the east with few in the west and south.

There is no significant cluster of high mortality identified after 2008 for both overall and under-fives. This can be due to the fact that, after four years of the scale up of the CHPS, all areas now have relatively equal access to health care. The areas that were deprived of the CHO's are now able to benefit from their services and in effect change their health seeking behaviour. Several scientific studies conducted in the area might have also contributed to the non-significant clustering of high mortality observed in the later years (Aninanya et al., 2015; Awoonor-Williams, Bawah, et al., 2013; Baiden et al., 2007; Gomes et al., 2009; Wells Pence, Nyarko, Phillips, & Debpuur, 2007).

5.5.1 Clustering of malaria-specific mortality at the HDSS sites

More significant clusters of high mortality are identified for malaria deaths than that of the all-cause. For malaria deaths in the Dodowa (HDSS), many high clusters of mortality are identified and in almost all the area councils and through the years. Though for the all-cause mortality no significant cluster for under-five mortality is identified in 2006, a cluster of 64 communities from is identified for under-five malaria mortality.

More than 80% of the communities that made up the significant cluster of high under-five mortality are not part of the communities that formed the clusters of high under-five malaria mortality. This implies there are other major causes of under-five deaths in these communities other than malaria. These might be due to diarrhoea and other infectious causes since these communities to not have adequate quality water source and toilet facilities. These have been found to be associated with ill health (Borchardt et al., 2012; Gleason & Fagliano, 2017; Wallender et al., 2014). A survey carried out in 70 developing countries indicated that improved access to water and sanitation was associated with low risk of diarrhoea and mortality (Fink, Günther, & Hill, 2011).

However, four communities that are not identified with risk for all-cause under-five mortality have been included in the significant clusters of high under-five malaria mortality. These communities have or are close to water bodies which provide optimum breeding sites for mosquitoes. A study by Zhou et al, (2010) reported that malaria attack rate of people living near water bodies were higher than those who lived far from water bodies (Zhou et al., 2010).

Similarly, significant clusters of high malaria mortality for all ages are observed in all the area councils. A significant cluster of high malaria mortality for all ages with the highest number of communities and radius is observed in 2010-2011.

At the Kintampo HDSS, 12 significant clusters of high under-five malaria mortality are observed with six of them comprising one village each. Almost all communities identified for the all-cause under-five mortality are included in the significant cluster for malaria mortality. Ten of the clusters are however, made up of communities that never appeared in the all-cause mortality cluster. As observed in DHDSS, these communities have or are closer to water bodies compare to the others and so provide conducive breeding sites for mosquitoes (Zhou et al., 2010).

Similar patterns of mortality clustering is observed for malaria mortality for all ages in Kintampo HDSS except that more significant clusters (17) are observed here with 10 clusters comprising of one village each. Three of the clusters identified are also included in the significant clusters for all-cause mortality. Six of the clusters are made up of the same villages that had clustering for under-five malaria mortality. This suggests that generally, these villages have malaria mortality clustering.

However three significant cluster of high under-five malaria mortality are identified in Navrongo HDSS. The villages comprising these clusters are in the clusters for all-cause mortality. These clusters however, have fewer villages. There is s no cluster of high under-five malaria mortality after 2009. This can also be attributed to the scale up if CHPS. The communities members are then in touch with CHOs who give the health education and took care of their health needs.

For malaria deaths in all ages, four significant clusters are however identified in the NHDSS. As in the all-cause, the first significant cluster is made up of villages (17) from the eastern part. Besides the villages from the eastern part of NHDSS mention above, the villages constituting the high clusters of malaria mortality have concentration of dugouts compared to the others. Other villages besides those from the eastern part that are clustered are from the western and northern parts of the NHDSS which are either close to irrigation canals or have dams and/or dugouts. These irrigation canals, dams and dugouts provide sites for vector production especially breeding of mosquitoes and this can contribute to the relative higher malaria deaths. A study on malaria transmission dynamics in the NHDSS area reported that transmission was highest in the irrigated area with biting rate of 36.7 bite per man per night (B/M/N) compared to the lowland (B/M/N) and rocky highland (B/M/N) (Maxwell Appawu et al., 2004).

The findings from this study show that significant clusters of high mortality still exist especially in DHDSS and KHDSS. A recent study in Nouna HDSS also reported that clustering of mortality still existed in the area though it was not as strong as before (Becher et al., 2016). It is also evident that malaria mortality is more spatially distributed than all-cause mortality. This may be because of the transmission dynamics of malaria. Studies have confirmed that there is spatiotemporal heterogeneity in malaria transmission (Amek et al., 2012a; Kasasa et al., 2013).

5.6 Limitations

This study report some limitations that need to be considered when interpreting the results. Monthly data analysis is done instead of daily or weekly. This is because of excessive heaping of deaths around the 15th day and third week of every month. This could be due to the fact that field workers assigned 15th day of the month for those who actual dates were not known

In determining the malaria-specific deaths, verbal autopsy information were used which might have some limitation associated with recall bias. However, verbal autopsy was the most appropaite since most of the deaths occurred at home.

InterVA-4 method is used to extract the malaria deaths from verbal autopsy questionnaires. It is possible the method might have under-estimated or over-estimated malaria deaths at the sites since malaria diagnosis is difficult because its symptoms are non-specific. Verbal autopsy is, however, the most effective way of ascertaining cause of death in settings like Ghana where vital registration is inadequate and most of the deaths occur outside health facility. A few of the deaths did not have verbal autopsy done due to inability to find a relative or individual who was with or knew the deceased to interview and some had very limited information and so were classified as indeterminate. The InterVA-4 method has however, been shown to have high concordance with physician coding (Peter Byass et al., 2015). Also malaria deaths ascertained from this method compares well with Malaria Atlas projections (Streatfield, Khan, Bhuiya, Hanifi, et al., 2014).

The study was not able to account for other interventions in the HDSS sites in the analysis which probably would have explained differences in mortality especially the spatiotemporal distribution. Controlling for trend and season variables alone might not have capture the influence of unmeasured confounders such as air pollution.

The study is not also able to examine spatial heterogeneity of temperature, rainfall and mortality relationship because there is no weather data for the various villages.

CHAPTER SIX: SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

6.1 Summary of findings

This study used secondary data from Health and Demographic and surveillance System (HDSS) sites located in three geographical zones in Ghana (Dodowa (DHDSS), Kintampo (KHDSS) and Navrongo (NHDSS) to investigate the relationship between weather variability (temperature and rainfall) and all-cause and malaria-specific mortality. The study further determined the spatiotemporal distribution of all-cause and malaria-specific mortality in these areas. Monthly mortality data was generated from daily deaths extracted from the HDSSs. Data on temperature and rainfall from the study area were obtained from Ghana Meteorological Agency (GMA). Lagged variables of temperature and rainfall were generated to examine their delayed effect on mortality. Relative risks were estimated with monthly rainfall and mean temperature below the 25^{th} percentile or above the 75^{th} percentile with linear estimated calculated alongside. A Bayesian probability model for interpreting VA, InterVA-4 was used to determine malaria deaths for this analysis. The key findings from this study include:

1. That the risk of all-cause mortality in all ages decreased with higher mean temperatures and increased with lower mean temperatures in the previous one month before the occurrence of death in all HDSS sites. Whereas the associations in DHDSS and NHDSS were statistically significant that of KHDSS was not significant. Monthly rainfall was significantly associated with all-cause mortality for all ages in KHDSS. Rainfall above 177.5mm in the month of death and the preceding two months were significantly associated with increased risk of mortality.

2. In terms of sex-specific mortality, while in the NHDSS both male and female mortality decreased with higher mean temperatures in the previous one month, in the DHDSS and KHDSS, only male all-cause mortality decreased with mean temperatures in the previous one month.
3. For under-five all-cause mortality, the effect of temperature was stronger and immediate. Temperature in the month of death was significantly associated with increased risk of death in DHDSS. In NHDSS under-five all-cause mortality risk increased with mean temperature above 30.6^{0}C in the month of death. Rainfall alone was associated with under-five mortality in all the HDSS sites. However, when combined with temperature, the risk of under-five all-cause mortality increased with rainfall below 34.1mm in the previous one month before death in DHDSS and decreased with rainfall below 22.8mm in the month of death and previous two months before death in KHDSS.
4. There was delayed effect of temperature on malaria-specific mortality compared to all-cause mortality
5. With temperature and rainfall combined, higher mean temperatures in the previous three months was significantly associated with decreased malaria-specific mortality in KHDSS. Lower mean temperature in the previous three months was significantly associated with increased malaria-specific mortality in NHDSS while lower mean temperature in the previous one month associated with decreased malaria-specific mortality in DHDSS.

6. Higher mean temperature three months preceding was significantly associated with decrease risk of under-five malaria-specific mortality in KHDSS. Both high and low mean temperatures three months preceding were significantly associated with increased risk of under-five malaria-specific mortality in NHDSS while lower rainfall in the previous one month significantly associated with under-five malaria mortality in DHDSS.
7. Clustering of high all-cause and malaria-specific mortality or 'hot spot' of mortality around deprived communities in the three HDSS areas. DHDSS and KHDSS had more but smaller clusters of malaria-specific mortality identified. Significant clusters of high malaria mortality were identified in areas with or close to water bodies (dams, dugouts, streams)
8. There is seasonal variation of mortality at all three sites. Mortality was highest in the rainy season

6.2 Conclusions

The study concludes that higher temperature decreases the risk of all-cause mortality in all ages but increases the risk in children under-five. Higher rainfall increases the risk of all-cause mortality in all ages. However, among children under-five, lower rainfall increases risk of all-cause mortality in DHDSS and decreases the risk in KHDSS. For malaria-specific mortality, higher temperature decrease the risk of mortality in all ages but among children under-five, lower temperature decreases mortality in DHDSS but increase mortality in KHDSS. However, in NHDSS, both lower and higher temperatures increase under-five malaria mortality. Significant clusters of high mortality were identified around deprived communities and locations that were close to water bodies across the three HDSS sites.

6.3 Contributions to Knowledge

The study's contributions to knowledge are:

1. High and low temperatures contribute to increasing malaria mortality in children under-five
2. Rainfall in the month preceding death increases mortality risk
3. There is clustering of malaria specific mortality along deprived and communities close to water bodies.
4. The effect of temperature and rainfall on mortality vary across the three HDSS sites

6.4 Recommendations

The following recommendations are made based on the findings from this study:

Weather variability and mortality

Ghana Health Service

Weather variability (temperature, rainfall) is associated with mortality (all-cause and malaria-specific) risk in all the three geographical zones and by extension in Ghana. Health promotion efforts need to be focused on educating the people to use more appropriate adaptation measures to mitigate the health effects of changes in temperature and rainfall. However, it must be noted here that there are variations in the associations and so health managers and stakeholders need to adapt specific measures to increase the resilience of residents to any negative impact of weather variability.

District Health managers; to include in their health promotion messages the need for parents to protect their children during low and high temperatures

Ghana Education Service

Managers of pre-schools should educate and counsel parents to protect children during low and high temperatures

Disaster Management

Heavy rainfall in the month of death increases risk of all-cause mortality in all ages. This information can be used to inform disaster management programmes

Clusters of Mortality

Clusters of high mortality or 'hot spot' of mortality still exist in the HDSS area. The district and municipal health managers therefore need to put in more efforts in those villages and communities if mortality reduction and the SDGs are to be achieved.

DHMT focus on Dodowa

More attention should be on the communities in Ningo and Ayikuma area councils that have been appearing in the clusters of high mortality. Communities from Dodowa, Prampram, and Asutsuare and Osuwem had clusters of high malaria mortality and more efforts on malaria control need to be focus there.

DHMT focus on Navrongo

The results also revealed significant clustering of high mortality in Navrongo HDSS area, with the eastern parts contributing more villages to the mortality clustering. Some of the villages were consistently included in the significant clusters of high mortality. As a results it is recommended that health managers and other stakeholders in the district identify factors responsible for these high levels of mortality and appropriate intervention put in place. Specifically, health intervention activities should be intensified.

DHMT focus on KHDSS

District health managers in KHDSS need to strengthen their efforts to provide health care especially to villages that have been identified among cluster of high mortality and these targeted for the appropriate interventions. Malaria control efforts should be strengthened in the villages included in clusters of high malaria mortality.

DHMTs focus on all HDSS

It was observed from the results that communities where there were water bodies (dams, dugouts, and streams) had higher clusters of malaria mortality in all three HDSS sites. It is thus recommended that villages close to irrigation systems, dams and water bodies be educated and encouraged to protect themselves against malaria.

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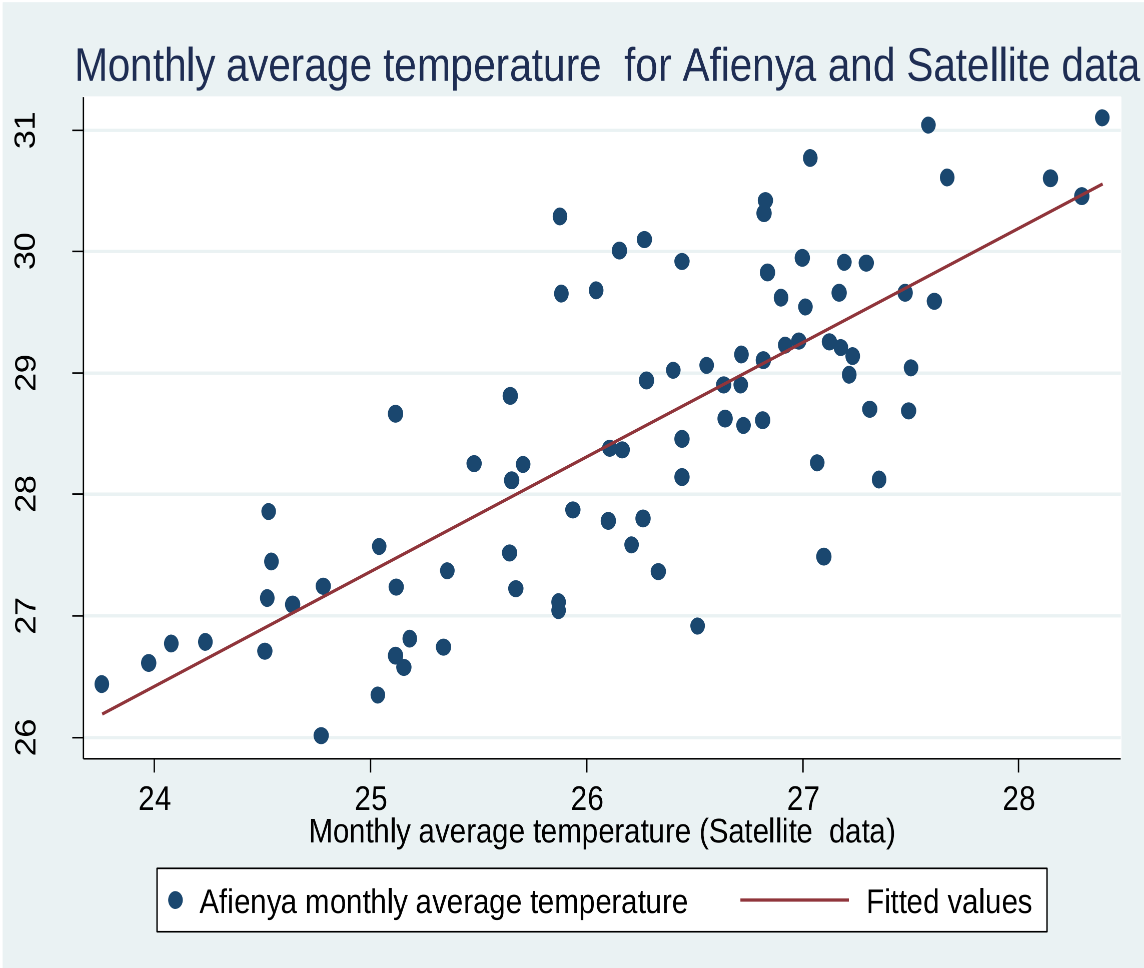
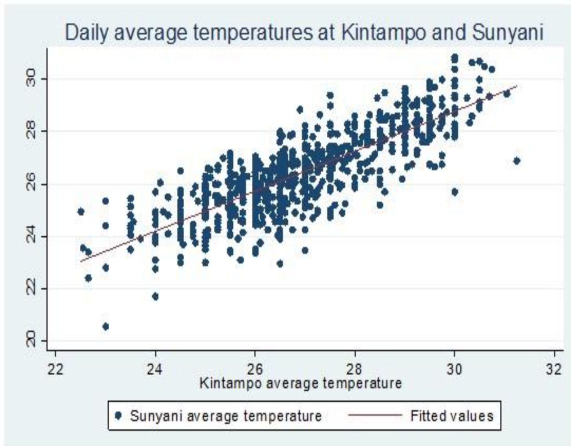
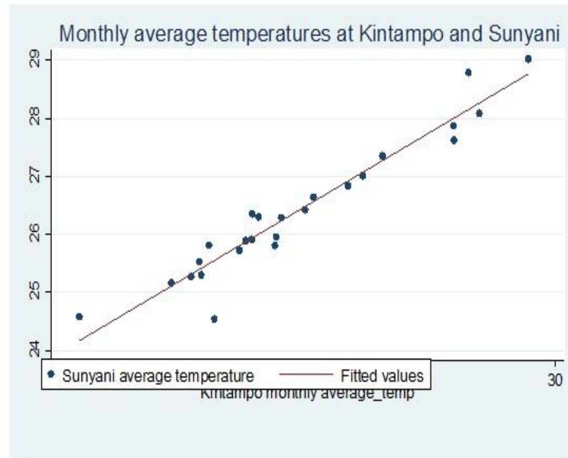
Appendix A: Correlations between weather variables in the HDSS sites



Appendix A1: Correlations between temperature from Dodowa HDSS GMet station and satellite data

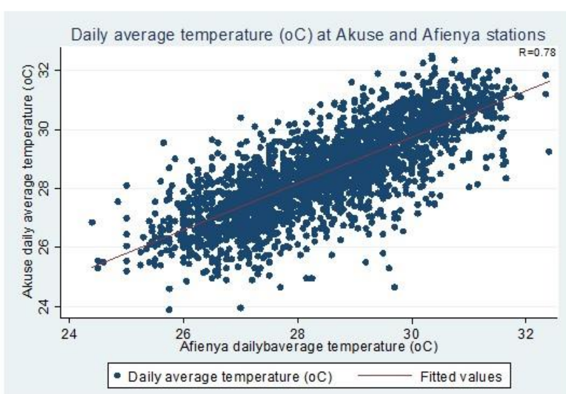


4a: Correlation of daily average temperature at Kintampo and Sunyani satellite stations

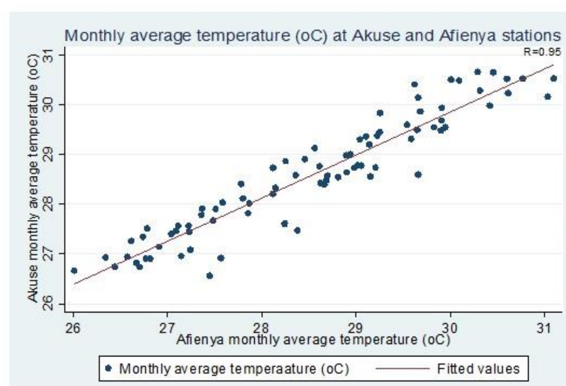


4b: Correlation of monthly average temperature at Kintampo and Sunyani satellite stations

Appendix A2: Correlations between temperature from Sunyani and Kintampo from GMet satellite stations



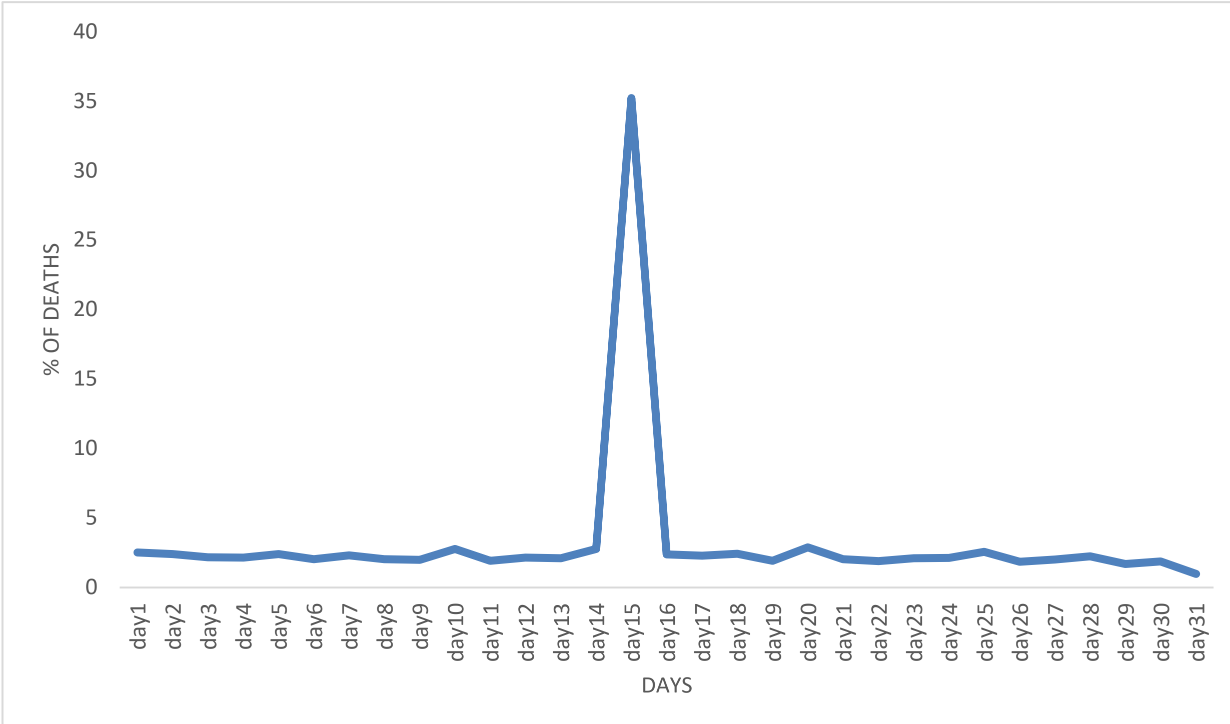
5a: Correlation of daily average temperatures from two satellite stations at Dodowa HDSS site



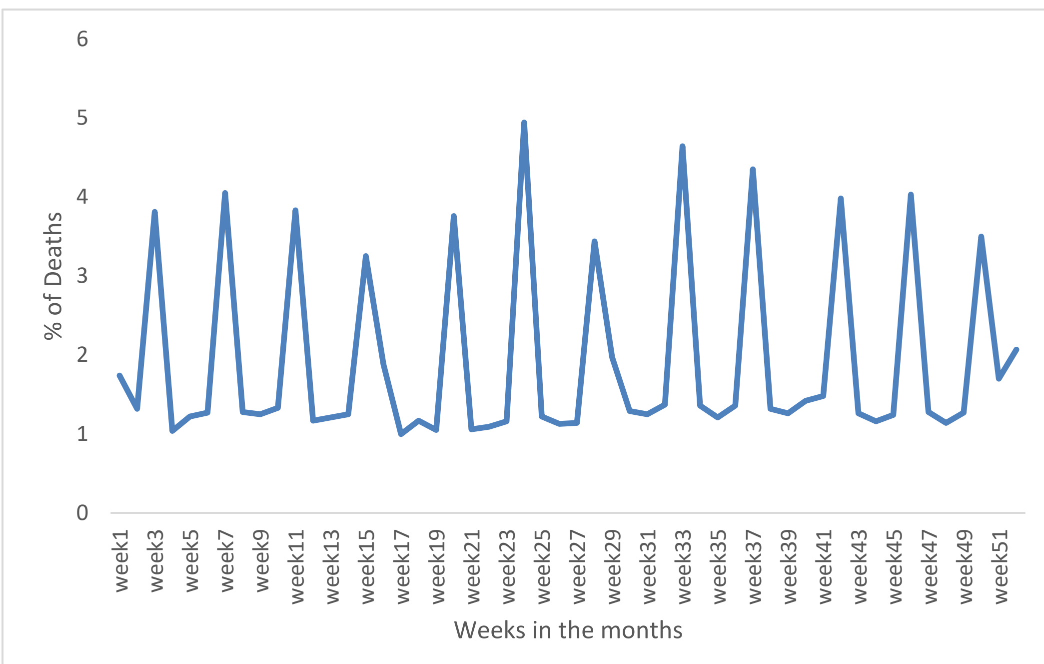
5b: Correlation of monthly average temperatures from two satellite stations at Dodowa HDSS site

Appendix A3: Correlations between temperature data from Afienya and Akuse from Gmet stations in DHDSS site

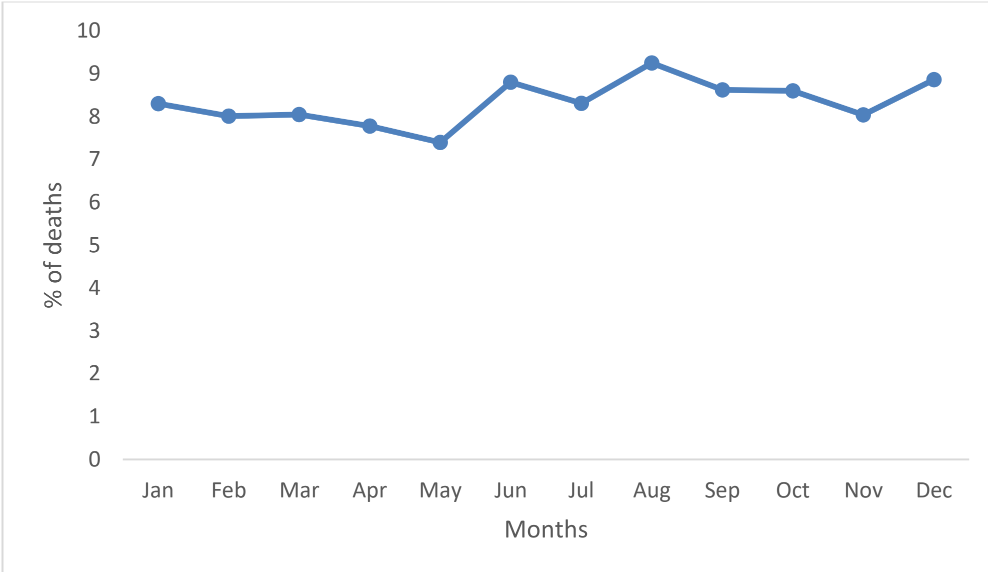
Appendix B: Distribution of deaths at the HDSS sites



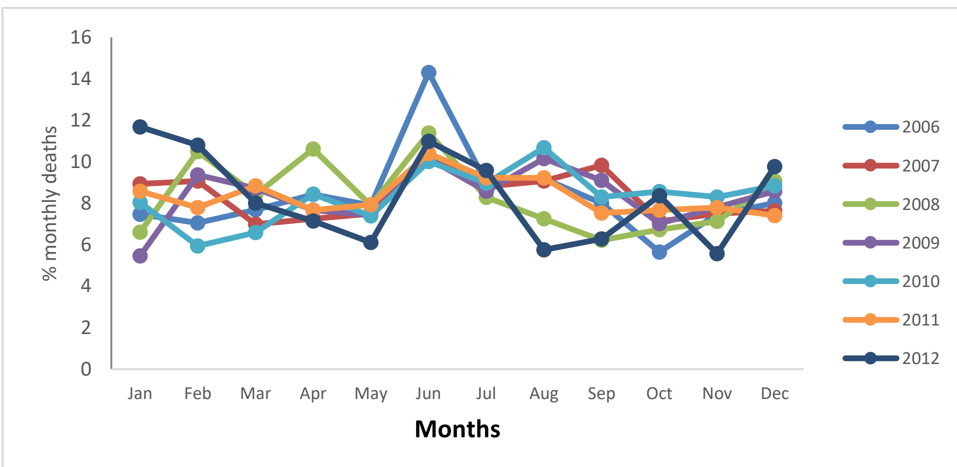
Appendix B1: Distribution of daily deaths at the three HDSS sites



Appendix B2: Distribution of weekly deaths at the three HDSS sites

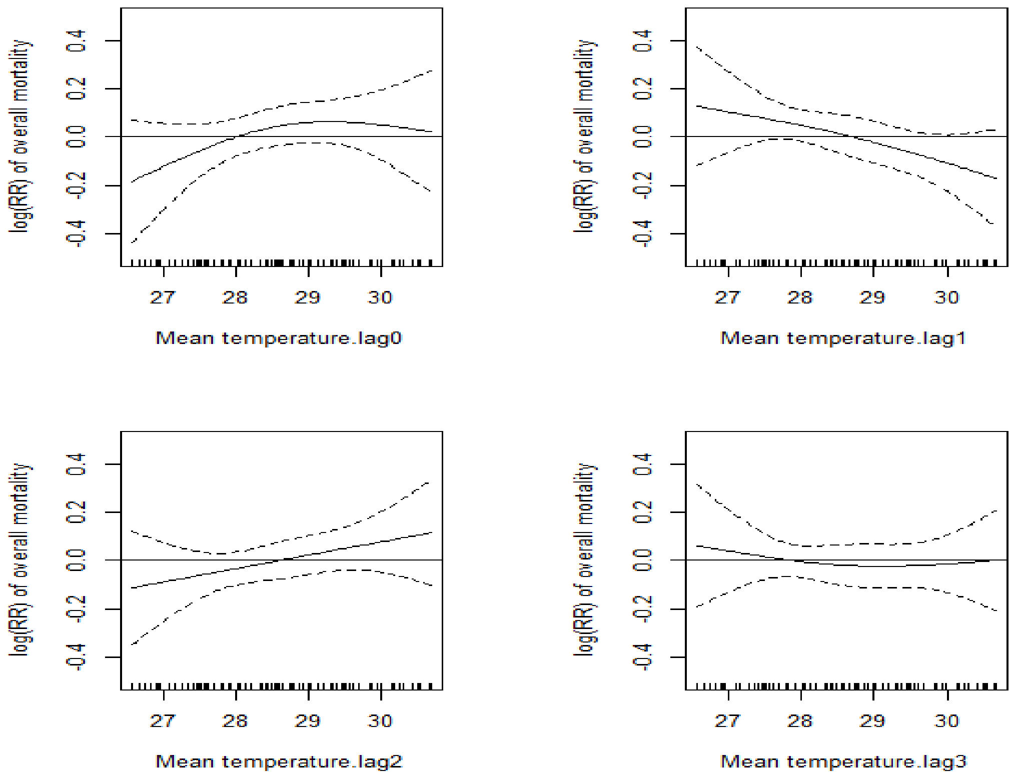


Appendix B3: Distribution of monthly deaths at the three HDSS sites

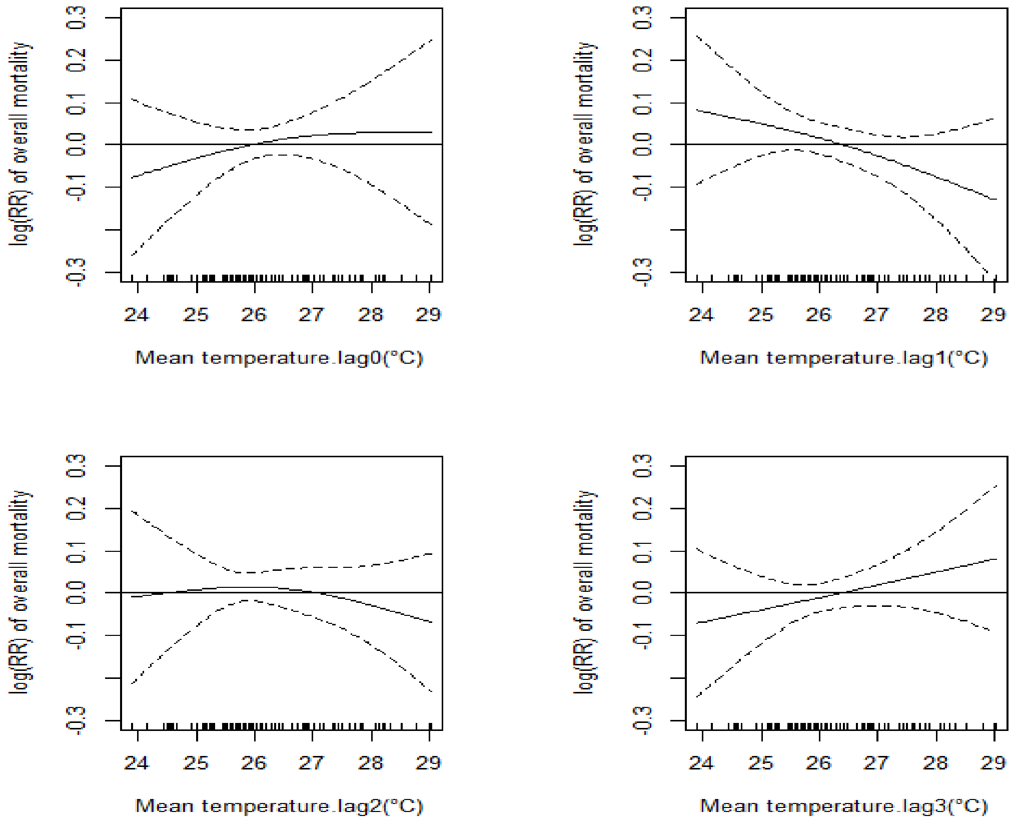


Appendix B4: Percentage distribution of monthly deaths by year at the Dodowa HDSS site

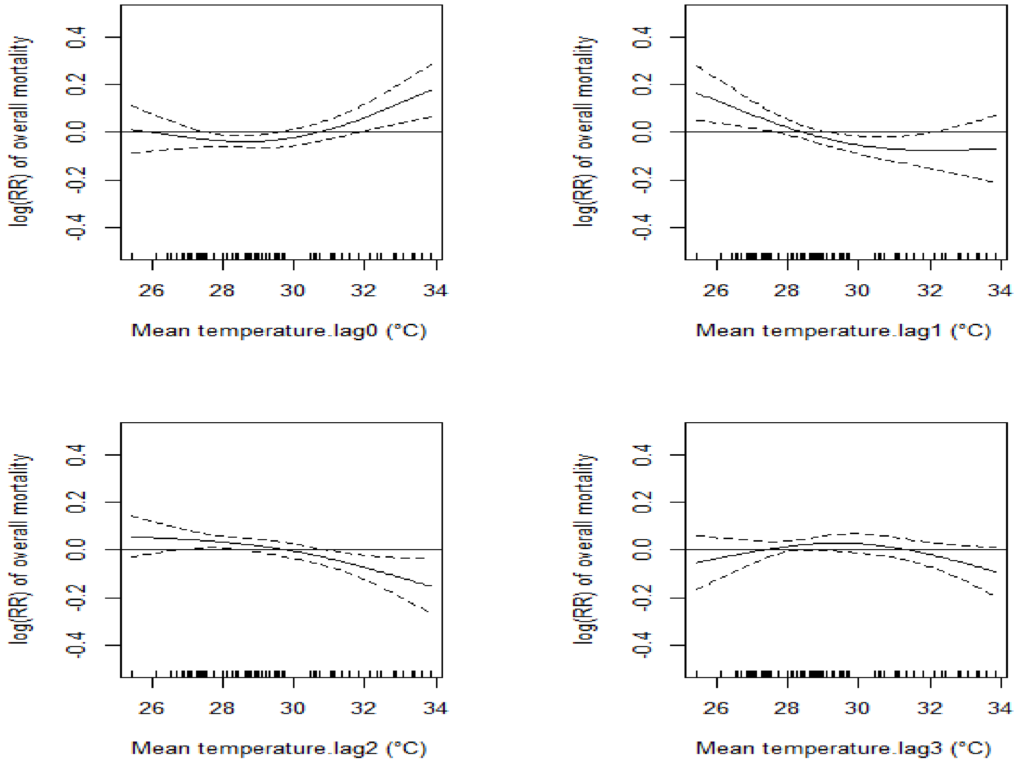
Appendix C: Smooth curves of separate rainfall lags and temperature lags for all-cause mortality in all ages



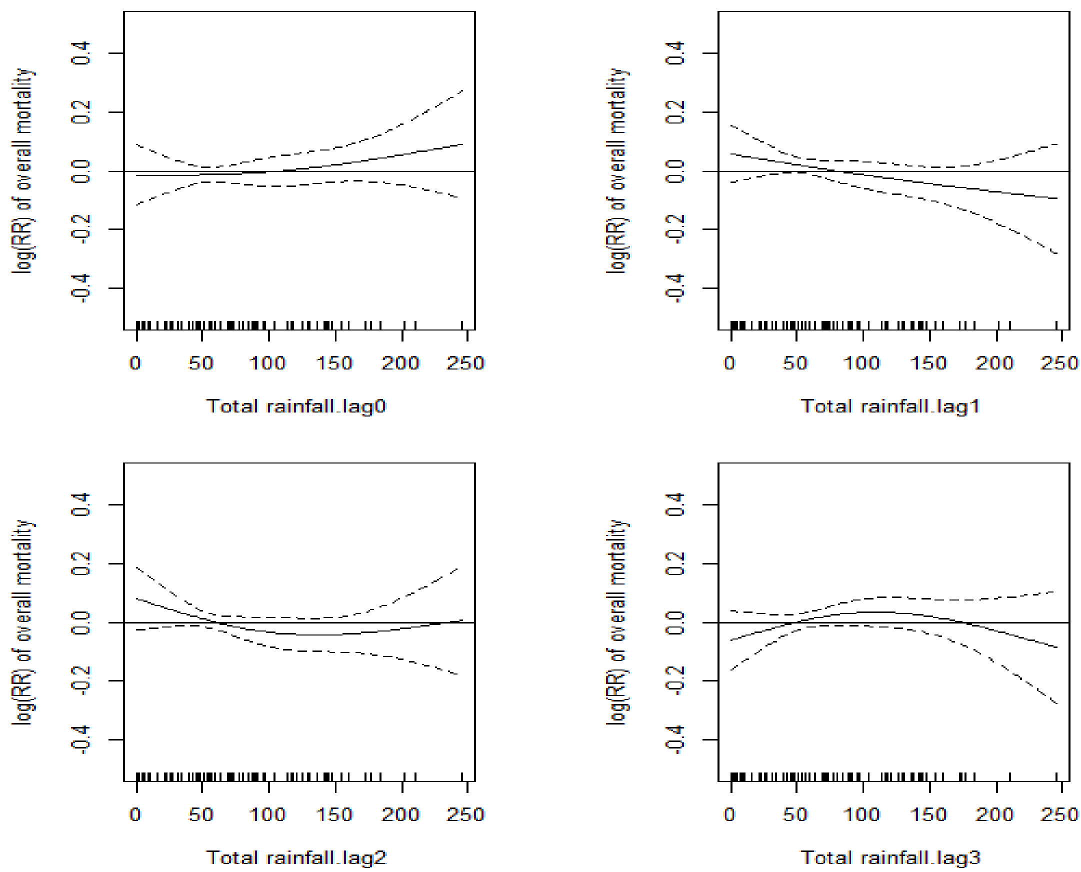
Appendix C1: Plot of relationship between mean temperature at lag0-3 and all-cause mortality for all ages at the Dodowa HDSS site when modeled separately.



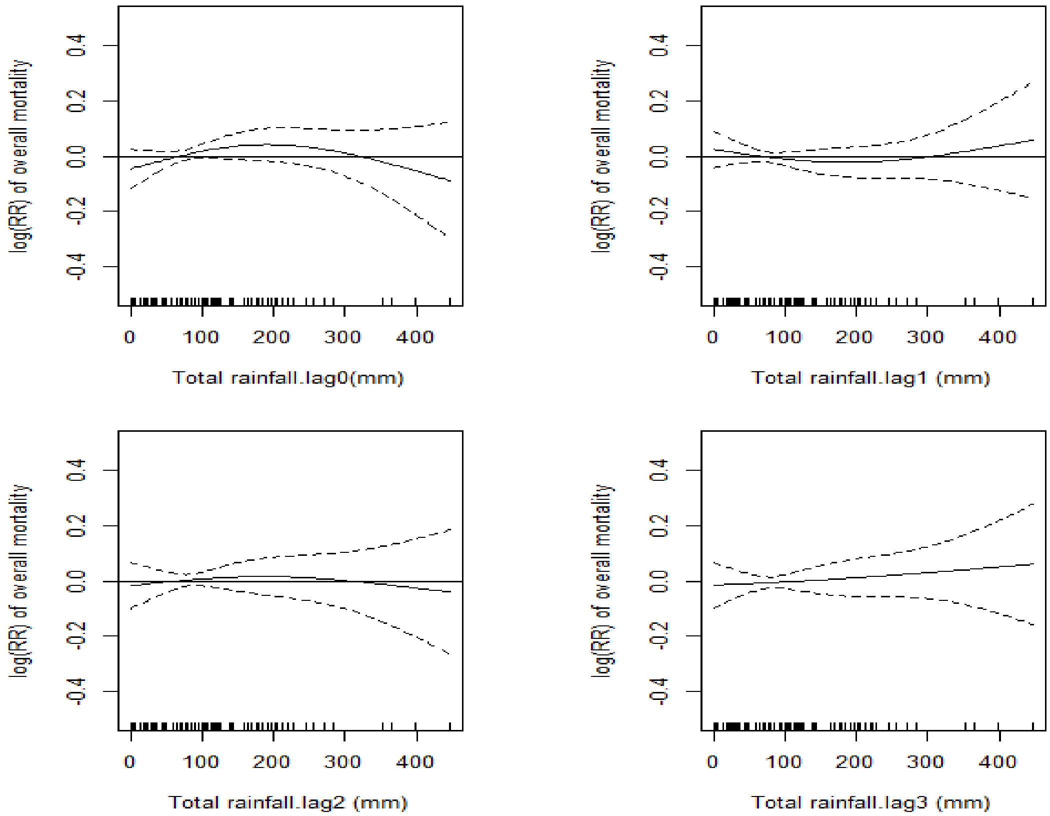
Appendix C2: Plot of relationship between mean temperature at lag0-3 and all-cause mortality for all ages at the Kintampo HDSS site when modeled separately.



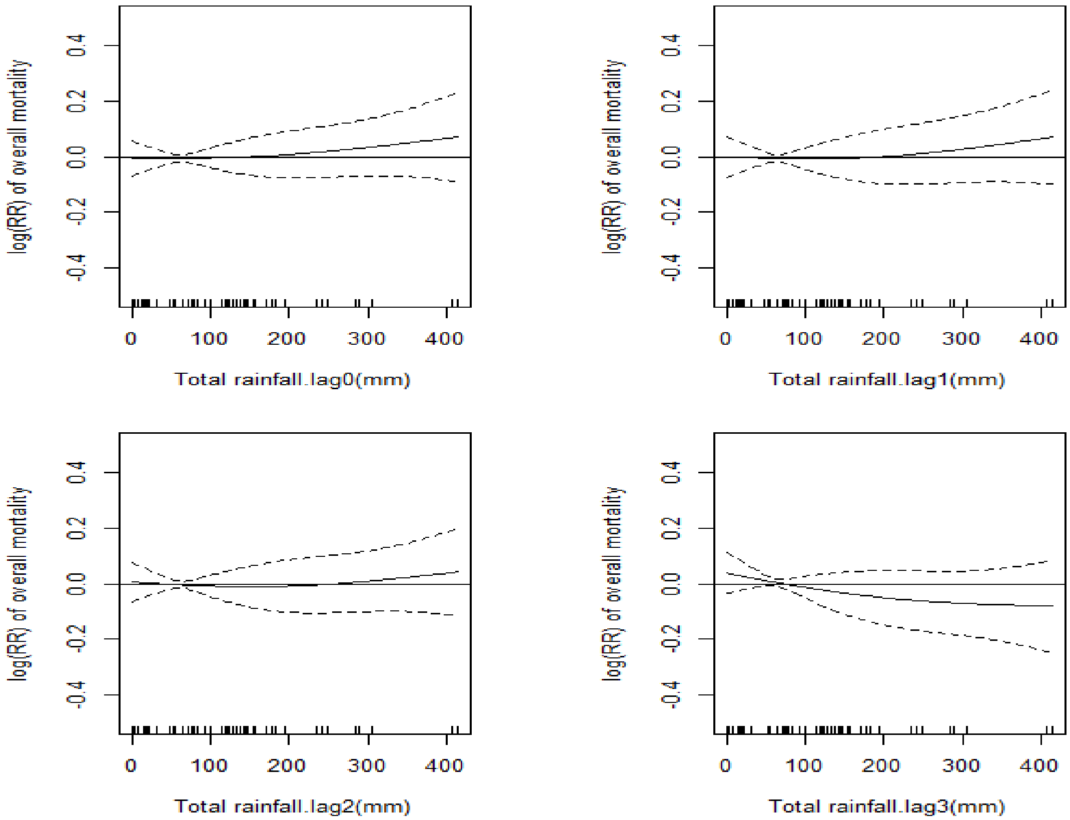
Appendix C3: Plot of relationship between mean temperature at lag0-3 and all-cause mortality for all ages at the Navrongo HDSS site when modeled separately.



Appendix C4: Plot of relationship between cumulative rainfall at lag0-lag3 and all-cause mortality for all ages at the Dodowa HDSS site when modeled separately.



Appendix C5: Plot of relationship between cumulative rainfall at lag0-lag3 and all-cause mortality for all ages at the Kintampo HDSS site when modeled separately.



Appendix C6: Plot of relationship between cumulative rainfall at lag0-lag3 and all-cause mortality for all ages at the Navrongo HDSS site when modeled separately.

Appendix D: Quantification of temperature, rainfall and all-cause mortality when each of the lags were modeled separately

Appendix D1: Association between temperature, rainfall and all-cause mortality in all ages in Dodowa HDSS (separate lags of temperature and rainfall)

Factor	PR(95% CI)	% change	P value
Mean Temperature			
Temp lag 0			
25%	0.9496(0.8151, 1.1063)	-5.04	0.509
75%	1.0943(0.9159, 1.3074)	9.43	0.325
Linear	1.0501(0.9501, 1.1607)	5.01	0.342
Temp lag1			
25%	1.0161(0.8843, 1.1675)	1.61	0.823
75%	0.7609(0.6538, 0.8854)	-23.91	<0.001
Linear	0.9277(0.8561, 1.0053)	-7.23	0.072
Temp lag2			
25%	1.0088(0.8643, 1.1776)	0.88	0.912
75%	1.0876(0.9222, 1.2827)	8.76	0.322
Linear	1.0576(0.9703, 1.1528)	5.76	0.207
Temp lag3			
25%	1.0714(0.9112, 1.2599)	7.14	0.407
75%	1.0274(0.8712, 1.2116)	2.74	0.749
Linear	0.9894(0.9115, 1.0739)	-1.06	0.799
Rainfall			
Rainfall lag 0			
25%	0.9832(0.9004, 1.0736)	-1.68	0.674
75%	1.0191(0.9131, 1.1375)	1.91	0.764
Linear	1.0004(0.9996, 1.0011)	0.04	0.335
Rainfall lag 1			
25%	1.0940(0.9909, 1.2078)	9.40	0.080
75%	0.9613(0.8804, 1.0496)	-3.87	0.382
Linear	0.9994(0.9986, 1.0001)	-0.06	0.112
Rainfall lag 2			
25%	1.0681(0.9581, 1.1909)	6.81	0.239
75%	1.0001(0.9140, 1.0942)	0.01	0.999
Linear	0.9996(0.9988, 1.0004)	-0.04	0.295
Rainfall lag 3			
25%	0.9177(0.8284, 1.0167)	-8.23	0.105
75%	0.9503(0.8707, 1.0372)	-4.97	0.258
Linear	1.0001(0.9993, 1.0009)	0.01	0.836

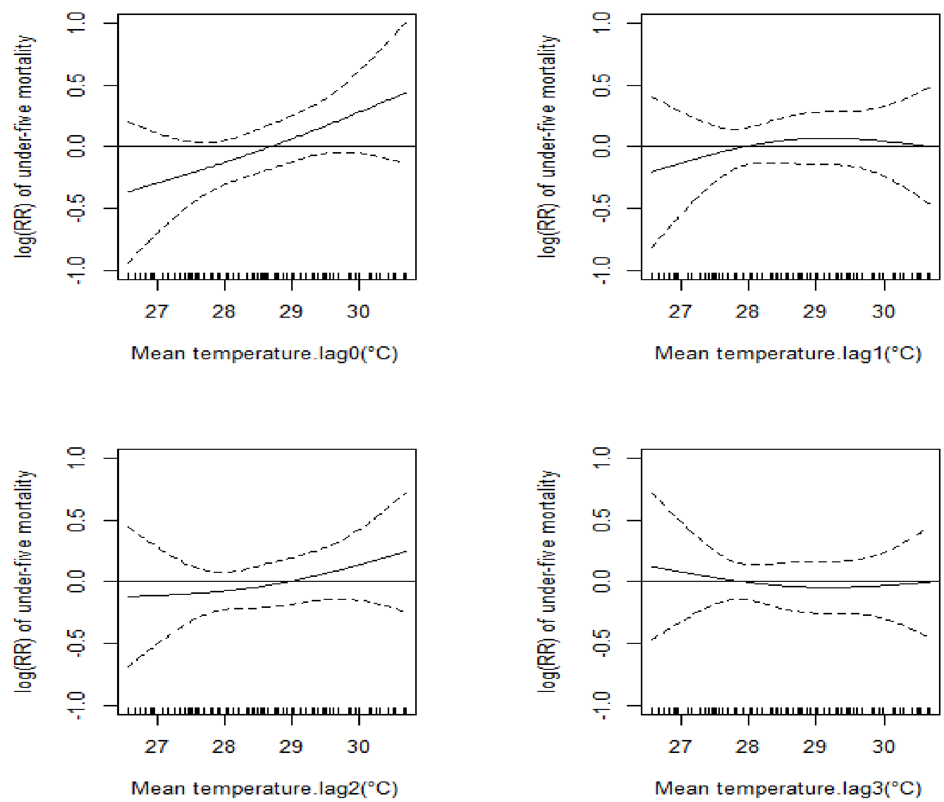
Appendix D2: Association between temperature, rainfall and all-cause mortality in all ages in Kintampo HDSS (separate lags of temperature and rainfall)

Factor	RR(95% CI)	% change	P value
Menn Temperature			
Temp lag 0			
<25%	0.9267(0.8379, 1.0249)	-7.33	0.144
>75%	1.0877(0.9540, 1.2401)	8.77	0.214
Linear	1.0223(0.9570, 1.0921)	2.23	0.514
Temp lag1			
<25%	1.0483(0.9426, 1.1658)	4.83	0.388
>75%	0.9018(0.8037, 1.0119)	-9.82	0.083
Linear	0.9596(0.9086, 1.0135)	-4.04	0.144
Temp lag2			
<25%	0.9492(0.8463, 1.0646)	-5.08	0.376
>75%	1.0494(0.9447, 1.1656)	4.94	0.372
Linear	0.9828(0.9312, 0.9312)	-1.72	0.529
Temp lag3			
<25%	1.0000(0.8980, 1.1135)	0.00	0.999
>75%	0.9790(0.8725, 1.0985)	-2.10	0.719
Linear	1.0303(0.9748, 1.0889)	3.03	0.295
Rainfall			
Rainfall lag 0			
<25%	0.9707(0.8661, 1.0879)	-2.93	0.611
>75%	1.0624(0.9792, 1.1528)	6.24	0.151
Linear	1.0001(0.9996, 1.0005)	0.01	0.745
Rainfall lag 1			
<25%	1.0569(0.9554, 1.1691)	5.69	0.287
>75%	0.9758(0.89631.0624,	-2.42	0.574
linear	1.0000(0.9996, 1.0004)	0.00	0.860
Rainfall lag 2			
<25%	1.0024(0.9036, 1.1119)	0.24	0.965
>75%	1.0235(0.9303, 1.1261)	2.35	0.635
linear	1.0000(0.9995, 1.0005)	0.00	0.993
Rainfall lag 3			
<25%	0.9532(0.8567, 1.0606)	-4.68	0.382
>75%	0.9837(0.8966, 1.0793)	-1.63	0.729
linear	1.0002(0.9997, 1.0006)	0.02	0.521

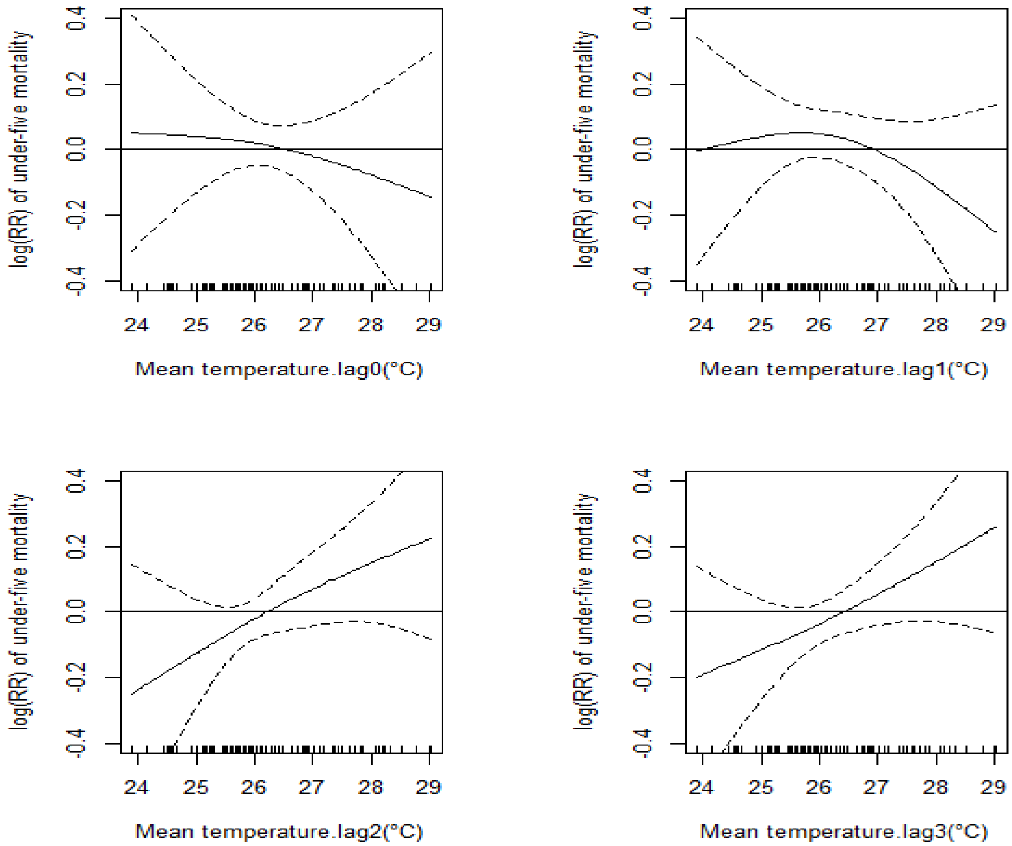
Appendix D3: Association between temperature, rainfall and all-cause mortality in all ages in Navrongo HDSS (separate lags of temperature and rainfall)

Factor	PR(95% CI)	% change	P value
Mean Temperature			
Temp lag 0			
25%	1.0073(0.9387, 1.0811)	0.73	0.840
75%	1.0818(0.9895, 1.1826)	8.18	0.084
Linear	1.0208(1.0003, 1.0417)	2.08	0.051
Temp lag1			
25%	1.1104(1.0350, 1.1913)	11.04	0.005
75%	0.9951(0.9040, 1.0954)	-0.49	0.920
Linear	0.9716(0.9463, 0.9977)	-2.84	0.037
Temp lag2			
25%	0.9949(0.9160, 1.0806)	-0.51	0.904
75%	1.0534(0.9361, 1.1853)	5.34	0.391
Linear	1.0255(0.9847, 1.0680)	2.55	0.229
Temp lag3			
25%	0.9866(0.9130, 1.0662)	-1.34	0.734
75%	0.9633(0.8893, 1.0434)	-3.67	0.362
Linear	0.9921(0.9745, 1.0101)	-0.79	0.391
Rainfall			
Rainfall lag 0	1.0002(0.9997, 1.0006)	0.02	0.427
Rainfall lag 1	1.0002(0.9997, 1.0007)	0.02	0.463
Rainfall lag 2	1.0001(0.9996, 1.0005)	0.01	0.679
Rainfall lag 3	0.9997(0.9992, 1.0002)	-0.03	0.265

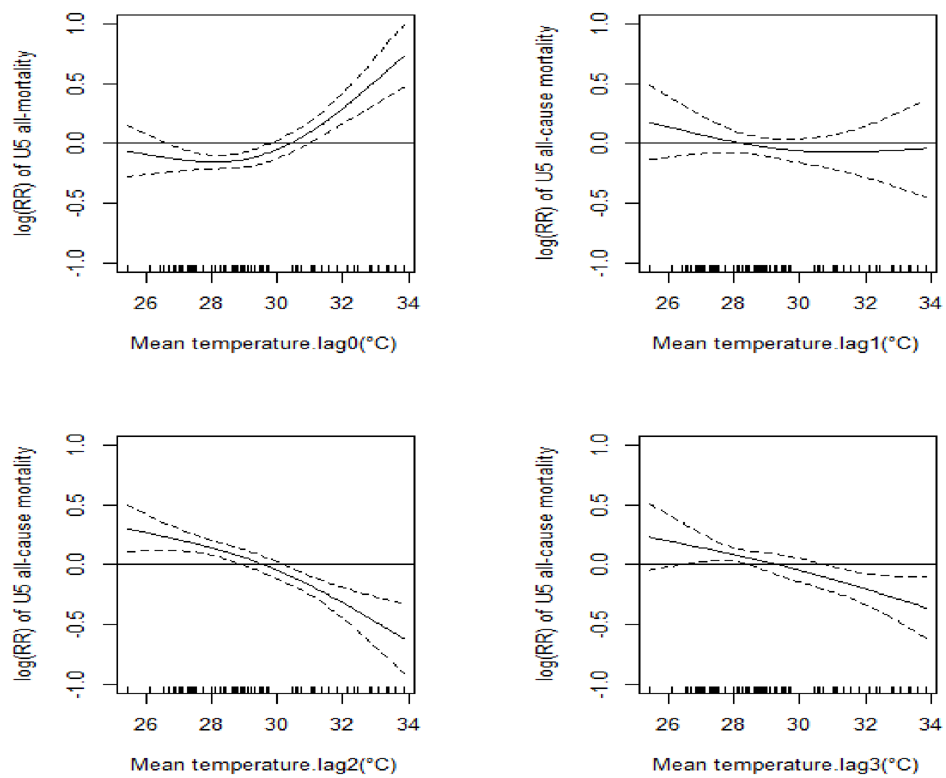
Appendix E: Smooth curves of separate rainfall lags and temperature lags for all-cause mortality in under-five years of age



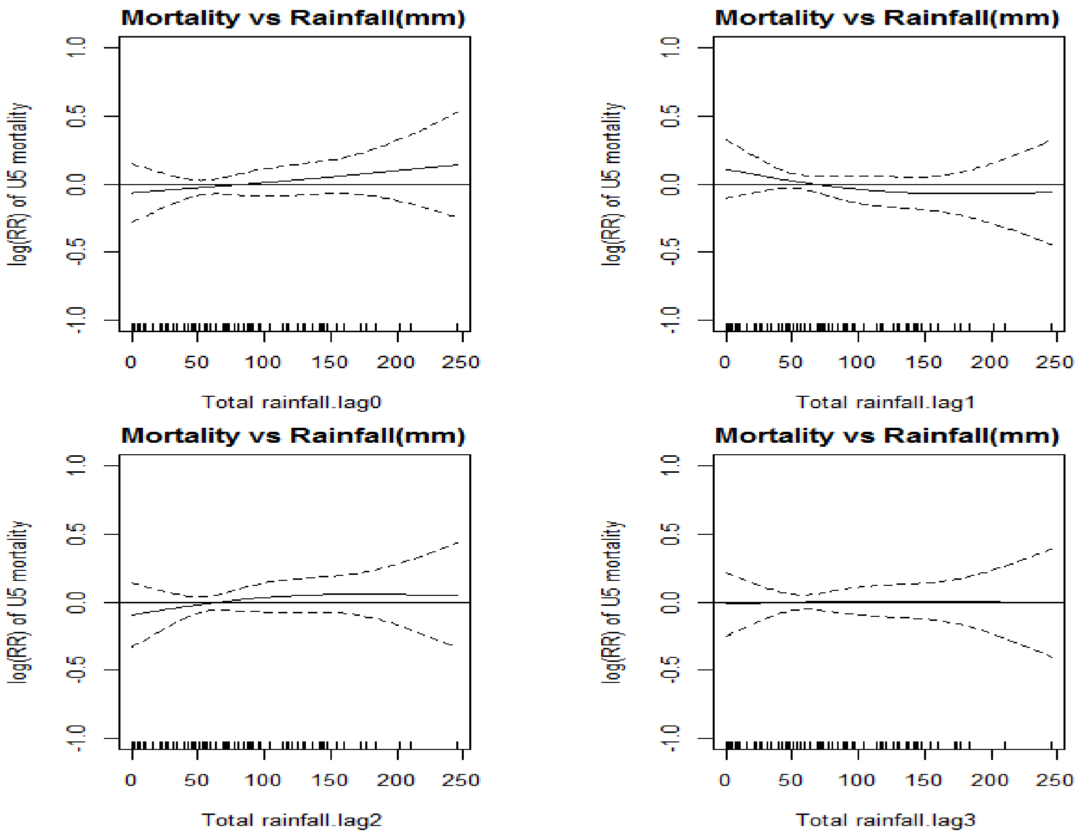
Appendix E1: Plot of relationship between mean temperature lag0–lag3 and under-five mortality at the Dodowa HDSS site when the lags were modeled separately.



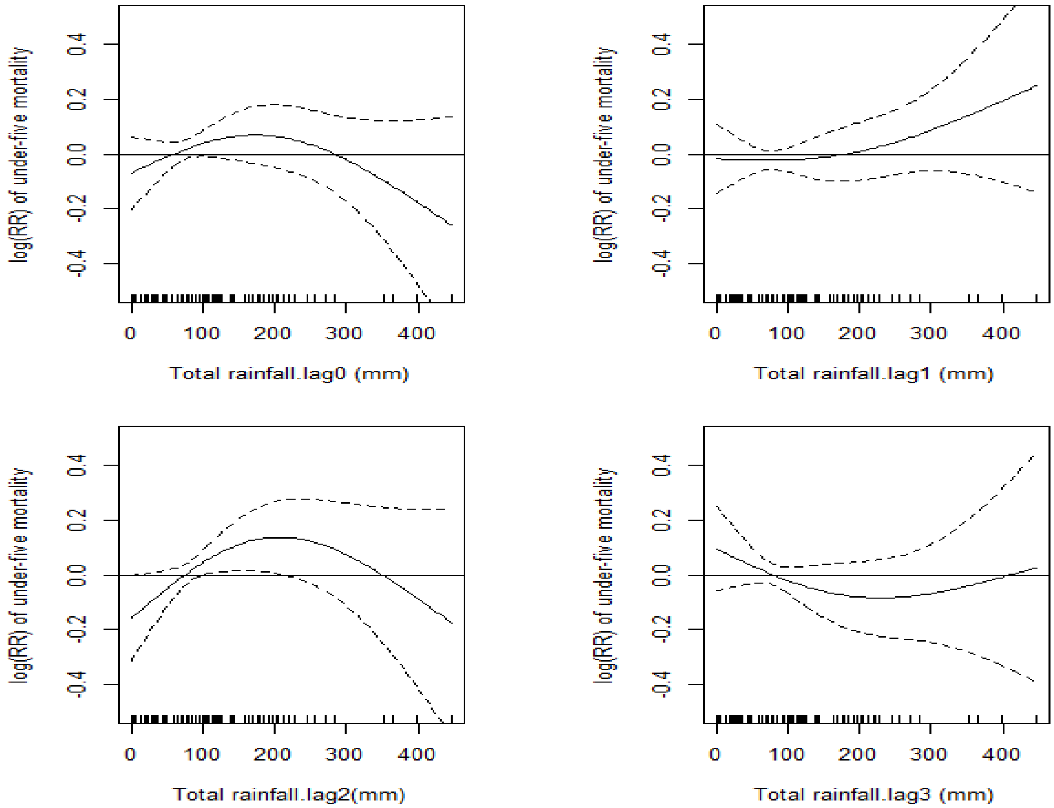
Appendix E2: Plot of relationship between temperature lag0–lag3 and under-five mortality at the Kintampo HDSS site when the lags were modeled separately.



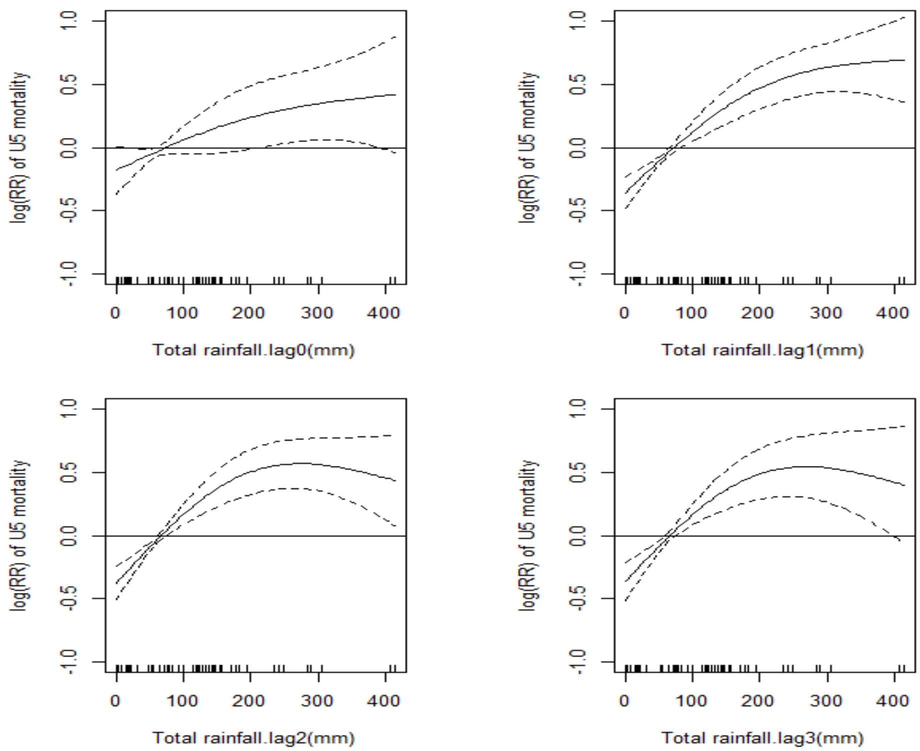
Appendix E3: Plot of relationship between temperature lag0–lag3 and under-five mortality at the Navrongo HDSS site when the lags were modeled separately.



Appendix E4: Plot of relationship between cumulative rainfall at lag0–lag3 and under-five mortality at the Dodowa HDSS site when the lags were modeled separately.



Appendix E5: Plot of relationship between cumulative rainfall at lag0–lag3 and under-five mortality at the Kintampo HDSS site when the lags were modeled separately.



Appendix E6: Plot of relationship between cumulative rainfall at lag0–lag3 and under-five mortality at the Navrongo HDSS site when the lags were modeled separately.

Appendix F: Quantification of the association between temperature, rainfall and under-five mortality in under-five in HDSS sites (separate lags of temperature and rainfall)

Appendix F1: Association between temperature, rainfall and under-five mortality in Dodowa HDSS (separate lags of temperature and rainfall)

Factor	PR(95% CI)	% change	P value
Mean Temperature			
Temp lag 0			
25%	1.0689(0.7585, 1.5063)	6.89	0.705
75%	0.8972(0.6059, 1.3284)	-10.28	0.590
Linear	1.2164(0.9707, 1.5242)	21.64	0.094
Temp lag1			
25%	0.9111(0.6375, 1.3020)	-8.89	0.611
75%	1.0872(0.7477, 1.5809)	8.72	0.663
Linear	1.0339(0.8519, 1.2547)	3.39	0.737
Temp lag2			
25%	1.0038(0.6981, 1.4434)	0.38	0.894
75%	1.1001(0.7682, 1.5752)	10.01	0.605
Linear	1.1004(0.9021, 1.3424)	10.04	0.349
Temp lag3			
25%	0.9949(0.6769, 1.4623)	-0.51	0.979
75%	1.0911(0.7641, 1.5580)	9.11	0.633
Linear	0.9795(0.8142, 1.1782)	-2.05	0.826
Rainfall			
Rainfall lag 0			
25%	0.9940(0.7761, 1.2730)	-0.60	0.962
75%	1.0648(0.8767, 1.2933)	6.48	0.529
Linear	1.0009(0.9992, 1.0025)	0.09	0.312
Rainfall lag 1			
25%	1.2599(1.0059, 1.5779)	25.99	0.049
75%	1.0399(0.8541, 1.2662)	3.99	0.698
Linear	0.9992(0.9975, 1.0009)	-0.08	0.350
Rainfall lag 2			
25%	0.9622(0.7469, 1.2395)	-3.78	0.766
75%	1.0750(0.8790, 1.3148)	7.50	0.484
Linear	1.0006(0.9989, 1.0024)	0.06	0.481
Rainfall lag 3			
25%	0.8898(0.6999, 1.1311)	-11.02	0.344
75%	0.9007(0.7387, 1.0983)	-9.93	0.305
Linear	1.0000(0.9982, 1.0018)	0.002	0.983

Appendix F2: Association between temperature, rainfall and under-five mortality in all ages in Kintampo HDSS (separate lags of temperature and rainfall)

Factor	RR(95% CI)	% change	P value
Mean Temperature			
Temp lag 0			
<25%	1.0217(0.8402, 1.2424)	2.17	0.830
>75%	1.0953(0.8466, 1.4170)	9.53	0.491
Linear	0.9652(0.8460, 1.1013)	-3.48	0.601
Temp lag1			
<25%	0.9038(0.7330, 1.1145)	-9.62	0.348
>75%	0.9644(0.7674, 1.2119)	-3.56	0.756
Linear	0.9544(0.8530, 1.0680)	-4.56	0.419
Temp lag2			
<25%	0.8247(0.6661, 1.0211)	-17.53	0.082
>75%	1.2110(0.9988, 1.4682)	21.10	0.056
Linear	1.0916(0.9838, 1.2113)	9.16	0.103
Temp lag3			
<25%	1.1213(0.9125, 1.3778)	12.13	0.280
>75%	0.9293(0.7546, 1.1445)	-7.07	0.493
Linear	1.0952(0.9852, 1.2175)	9.52	0.097
Rainfall			
Rainfall lag 0			
<25%	0.8764(0.7001, 1.0970))	-12.36	0.254
>75%	0.9897(0.8500, 1.1524)	-1.03	0.895
Linear	0.9999(0.9991, 1.0007)	-0.01	0.828
Rainfall lag 1			
<25%	1.1217(0.9210, 1.3661)	12.17	0.258
>75%	1.0892(0.9310, 1.2742)	8.92	0.290
linear	1.0004(0.9997, 1.0012)	0.04	0.272
Rainfall lag 2			
<25%	0.7567(0.6277, 0.9121)	-24.33	0.005
>75%	1.0832(0.9176, 1.2786)	8.32	0.349
linear	1.0003(0.9993, 1.0013)	0.03	0.550
Rainfall lag 3			
<25%	1.0850(0.8894, 1.3236)	8.50	0.424
>75%	0.8814(0.7401, 1.0498)	-11.86	0.162
linear	0.9997(0.9987, 1.0006)	-0.03	0.484

Appendix F3: Association between temperature, rainfall and under-five mortality in all ages in Navrongo HDSS (separate lags of temperature and rainfall)

Factor	PR(95% CI)	% change	P value
Mean Temperature			
Temp lag 0			
25%	1.0059(0.8641, 1.1710)	0.59	0.940
75%	1.6093(1.2911, 2.0059)	60.93	<0.001
Linear	1.0931(1.0419, 1.1468)	9.31	<0.001
Temp lag1			
25%	1.1608(0.9763, 1.3802)	16.08	0.096
75%	1.0109(0.7745, 1.3194)	1.09	0.937
Linear	0.9710(0.9027, 1.0445)	-2.90	0.432
Temp lag2			
25%	0.9140(0.7555, 1.1058)	-8.60	0.358
75%	1.0363(0.7702, 1.3944)	3.63	0.815
Linear	0.9627(0.8693, 1.0662)	-3.73	0.468
Temp lag3			
25%	1.0338(0.8523, 1.2539)	3.38	0.737
75%	1.1932(0.8991, 1.5836)	19.32	0.226
Linear	1.0122(0.9249,1.1077)	1.22	0.793
Rainfall			
Rainfall lag 0	1.0015(1.0002, 1.0027)	0.15	0.021
Rainfall lag 1	1.0027(1.0019, 1.0036)	0.27	<0.001
Rainfall lag 2	1.0022(1.0013, 1.0032)	0.22	<0.001
Rainfall lag 3	1.0021(1.0008, 1.0034)	0.21	0.002

Appendix G: Tables of villages with high mortality clustering in the HDSS sites

Appendix G1: Significant cluster of all-cause mortality for all ages at the three HDSS sites

Year	Location ID	Cases	Expected	Relative Risk	P-value
DHDSS					
2006	Ayikuma (37 communities), Osuwem (one community)	181	71.36	2.6	p<0.001
2006-2007	Ningo (15 communities)	78	30.71	2.57	p<0.001
2009-2011	Dawa (20 communities)	321	222.76	1.47	p<0.001
2006-2008	Prampram (1 community)	42	13.87	3.05	p<0.001
KHDSS					
2007-2009	Weila, Bug Nkwanta, Gombi, Nkwanta, Chara, New Longoro, Dwere, Sabule, Chingakrom, Ayorya, Nyabia, Sora, Mansra, Babiledor Konkonba, Old Longoro, Taningni, Mansie MA	324	225.13	1.46	p<0.001
2009-2011	Chiranda, Jato Akura, Mahama Akura,BawaAkura 2, Atta Akura, Tahiru Akura, Kaekae, Tadefufuo, Soronuase, Dawadawa, Wurikwae, Babator, Kwame Mensah,Kyia/Ali Kura/Nkwanta, Punpuano, Kyia/Bredi, Adumanoo	553	456.14	1.23	p=0.016
NHDSS					
2007-2008	Natugnia, Nyangoligo, Manyoro ,Gunwoko,Yua, Basengo, Gomongo, Bembisi, Mirigu, Longo, Nabango, Nakolo, Navio, Kurugu, Azeaduma, Azaasi, Kaasi/Akaamo, Pungu, Atiyoro, Nkwanta.	1447	1289.38	1.14	p0.004
2008	Kafania/Saboro, Asunia, Kanania, Nyangnia, Katiu, Kayoro, Bonia, Wuru	248	183.36	1.36	p0.006
2006-2008	Kalvio/Gwenia.	228.0	170.0	1.35	p0.022

Table G2: Significant clusters of under-five all-cause mortality at each HDSS site

Year	Location ID	Cases	Expected	Relative Risk	P-value
DHDSS					
2009-2012	Dawa (48 communities), Ningo (41 communities), Prampram(10 communities)	147	96.11	1.7	p=0.002
KHDSS					
2006-2007	Kofiekuma/Grunshieline, Mangoase/DagombaLine, Tankofo/Boabengfo, Bronikrom/Yefrifo, Awa, Yeboah, Nkurakan Isahaku, Drepo, Yepemso, Kofiekrom, Abena, Num, Bosomkai, Kwesi Addaikrom, Kwesi, Addaikrom Dantwi, OF, PF, AY, KB, AR, BC, YM, DU, DM, NZ	58	28.57	2.07	p=0.010
NHDSS					
2006-2008	Natugnia, Nyangoligo, Manyoro, Gunwoko, Yua, Basengo, Bembisi, Gomongo, Nabango, Nakolo, Navio, Kurugu, Azeaduma, Azaasi, Kaasi/Akaamo, Pungu, Atiyoro, Nkwanta.	455	357.62	1.37	p<0.001
2006	Gia, Kalvio/Gwenia, Wuru, Nawognia, Saboro.	41	20.59	2.02	p=0.082

Appendix G3: Significant cluster of malaria mortality for all ages at the three HDSS sites

Year	Location ID	Cases	Expected	Relative Risk	P-value
DHDSS					
2010	Ayikuma (26 communities)	15.96	2.8945	5.66	<0.001
2010-2011	Dawa (47 communities), Ningo (40 communities), Prampram (16 communities),	82.14	52.5442	1.68	p<0.001
2009	Asutsuare (five communities)	7.81	1.5239	5.19	p<0.001
2006-2007	Ayikuma (three communities), Dodowa (1 community)	5.60	0.869	7.01	p<0.001
2008-2009	Dodowa (three communities)	4.66	0.5550	8.47	p<0.001
2010	Asutsuare (11), Osuwem (10 communities)	6.42	1.1747	5.52	p<0.001
KHDSS					
2006-2008	Gulumpe, Kawampe Fulani, Portor, Kadelso	55.02	28.2147	2.03	p<0.001
2008-2010	New Longoro, Chingakrom, Weila, Dwere, Gomboi, Ayorya, Bug Nkwanta, Nkwanta, Mansra, Chara, Old Longoro, Sabule ,Nyabia,Gazienya, Gazienya, Sora, Kandige, Babukrom,Babiledor Konkonba,Sogliboi, Dakore, Mansie,Basabasa,Taningni,Busuama	40.66	23.0045	1.81	p<0.001
2009-2010	Nante, NanteZongo, Akruma, Pumpuatifi, Bawa Akura 1, Kwesi Addaikrom, Isahaku	16.75	7.3808	2.30	p<0.001
2008-2010	Jerusalem, Anokyekrom, Abom Basare	7.25	1.9695	3.71	p<0.001
2011	Pamdu	4.60	0.8616	5.37	p<0.001
2011	Babator Soronuase	12.85	5.4306	2.39	P<0.001
2007-2008	Yeboah, Yepemso,Drepo, Kofiekuma/Grunshieline, Tankofo/Boabengfo, Mangoase/DagombaLine, Awa, Bronikrom/Yefrifo, Yenkyikrom, Kofiekrom, Kwabia, Bosomkai, Oforikrom, Agyegyemakunu, Nkurakan, Abena, Num, Asuogya No 1, Dantwi, Attakrom	15.87	7.7237	2.08	p<0.001
2007-2008	Nyame Bekyere1	2.95	0.4597	6.44	p<0.001
2007-2008	Adiembra, Tanokrom, Tanokrom	6.60	2.1841	3.04	p<0.001
2007	Bredi2 /Junction	2.39	0.338	7.09	p<0.001
2010	Kyingabosom	0.96	0.0293	32.84	p<0.001
2011	Peposo	2.37	0.4784	4.97	p<0.001
2010-2012	Techira 1	2.94	0.7412	3.98	p<0.001
2012	Kwame Mensah	97	5.82	16.69	p<0.001
2006	Aworate2	0.74	0.0338	21.94	p<0.001
2010	Asante Akura	0.96	0.1473	6.52	p<0.001
2008	Moshie Akura	0.99	0.1819	5.45	p<0.001

Appendix G3B: Significant cluster of malaria mortality for all ages at NHDSS

NHDSS Year	Location ID	Cases	Expected	Relative Risk	P-value
2008-2009	Kafania/Saboro, Asunia, Kanania, Nyangnia, Katiu, Kayoro, Bona	31.75	13.1995	2.53	p<0.001
2006	Paga, Kalvio/Gwenia, Pindaa, Navio, Nakolo, Gia.	25.00	10.5891	2.45	p<0.001
2009-2010	Pungu	14.09	7.7267	1.85	P<0.001

Appendix G4: Significant clusters of under-five malaria mortality at the three HDSS sites

Year	Location ID	Cases	Expected	Relative Risk	P-value
DHDSS					
2009	Astsuare (two communities)	2.23	0.0671	34.41	p<0.001
2006	Ayikuma (20 communities), Dawa (six communities), Ningo (eight communities), Prampram (30 communities)	7.13	1.7535	4.98	P<0.001
2009-2010	Dodowa (nine communities)	2.72	0.2121	13.36	p<0.001
2007	Osuwem (one community)	2.72	0.2121	13.36	p<0.001
2007	Asutsuare (one community)	0.99	0.0138	73.06	p<0.001
2007	Dodowa (eight communities)	2.00	0.158	13.04	p<0.001
2011	Astsuare (13 comm)	1.89	0.192	10.12	p<0.001
KHDSS					
2006-2007	Gulumpe, Kawampe, Fulani, Kawampe, Portor ,Kadelso	22.68	6.9759	3.45	p<0.001
2009-2010	Isahaku, Bronikrom/Yefrifo, Yenkyikrom, Mangoase/Dagomba Line, Nkurakan, Kofiekuma, Grunshieline, Tankofo/Boabengfo, Kwesi Addaikrom, Abena Num,Awa, Pumpuatifi ,Bosomkai,Yeboah, Dumso 1,Kofiekrom,Drepo, Nante Zongo,Nante	0.12	0.0404	3.07	p<0.001
2009-2010	Jerusalem, Anokyekrom,Abom Basare, Apesika, Abom Kokonba, Nana Yaa, Akora Nkwanta, Akora, Asuogya No 2	10.45	3.5858	2.99	p<0.001
2007-2008	Kwabia, Yepemso	4.67	0.9116	5.19	p<0.001
2010	Kyingabosom				
2010-2011	Mansie, Sora,Boadi No2, Babukrom,Dakore,Chara, Babiledor Konkonba,Sabule,Boadi No1, Tanokrom, Adiembra,Nkwanta, Yaw Amoakrom, Babildor, Taningni, Gazienya	8.79	3.0421	2.95	p<0.001
2011-2012	Mansra	1.90	0.1214	15.75	p<0.001
2006-2008	Dwere	1.99	0.1996	10.04	p<0.001
2010	Asante akura	0.96	0.0584	16.49	p<0.001
2008	Moshie Akura	0.99	0.0788	12.6	p<0.001
2010 -2011	Techira2,Techira 1	1.89	0.4163	4.56	p<0.001
20211	Yaara	0.99	0.1035	9.60	p<0.001
NHDSS					
2006-2007	Atiyoro,Nkwanta,Azaasi,Kaasi/Akaamo, Azeaduma, Abempingo, Kurugy, Nabango, Longo, Doba	37.35	13.6635	2.98	p<0.001
2008-2009	Kafania/Saboro,Asunia,Kanania,Nyangnia, Katiu, Kayoro, Bonia,Wuru	26.60	10.2200	2.76	p<0.001
2006	Paga, Kalvio/Gwenia,	15.19	4.4917	3.51	p<0.001

Appendix H: Data extraction form for Health and Demographic Surveillance System (HDSS) data

Section A: Information on individual

1. Household id----------------------------------
2. Individual ID of household head-----------------------------
3. HDSS site name--
4. District name---
5. Community/cluster code -------------------------------

Household Roster

Individual Id	Sex 1. Male 2. Female	Date of birth	Start Event type	Start event date	End event type	End event date
1						
2						
3						
N						

Household assets

List of Household Assets	Number

Section C: Coordinates on Houses, compounds and other structures (GIS data)

1. Structure ID-------------------------------------
2. Structure name--
3. Structure Latitude --
4. Structure Longitude --

Data extraction form for Weather data

1. HDSS site name-------------------------
2. District name-------------------------------------
3. Weather station ID------------------------------
4. Date--
5. Minimum temperature-------------------------------------
6. Maximum temperature--------------------------------------
7. Total rainfall---