SPATIO- TEMPORAL EFFECT OF CLIMATE VARIABILITY ON THE OCCURRENCE OF MENINGITIS *(meningococci)* IN THE SUDANO-SAHELIAN AND GUINEA SAVANNA ZONES OF NIGERIA.

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ABSTRACT

Climatic alteration is likely to have an influence on the geographic array and seasonal activity of vector species, as well as disease transmission. In view of this, the study examines the spatio-temporal effect of climate variability on the occurrence of meningitis *(meningococci)* in the Sudano-Sahelian and Guinea Savanna zones of Nigeria. Four specific objectives are addressed by this research, these include: (i) to examine the Spatio-temporal trend of meningitis in the Sudano- Sahelian and Guinea Savanna zones of Nigeria between 2007 and 2019, (ii) to investigate whether there is a relationship between Climatic variables (Relative Humidity, Rainfall, Temperature and wind speed) and meningitis occurrence in the study area, (iii) to analyse the impact of the climatic variables on Meningitis occurrence in the study areas, and (iv) to attempt to generate a model for predicting CSM outbreak in the study areas using climatic variables. A twelve-year period was considered from 2007 to 2019 for twelve states; Sokoto, Katsina, Borno, Jigawa, in the Sudano-Sahelian region; Kaduna, Niger, Adamawa, and Abuja in the northern part of the Guinea Savanna and, Kogi, Enugu, Benue and Kwara state in the southern part of the Guinea Savanna. The climatic parameters in consideration are mean air temperature, maximum temperature, relative humidity, and rainfall and wind speed. Meningitis data was acquired weekly from Nigeria Centre for Disease Control (NCDC), bureau of statistics while weather parameters were sourced from daily satellite data set of the National Oceanic and Atmospheric Administration (NOAA), International Research Institute for Climate and Society (IRI). This daily data was aggregated into weekly data to suit the study. The data was analysed using linear trend analysis, Pearson correlation for relationship, multiple regression analysis and Generalized linear regression model. The linear trend results revealed a decline in Cerebro-Spinal Meningitis (CSM), wind speed, maximum and minimum temperature and an increase in relative humidity and rainfall. Generally, results reveal that the individual states and regions had various explanatory weather variables influencing CSM. Climatic variables such as relative humidity, rainfall amount, maximum air temperature, mean air temperature and wind speed have a great impact on the occurrence of meningitis over the study area. Rainfall and relative humidity are seen to have inverse relationship with meningitis occurrence in the study area. In the Sudano-Sahelian region, about 77% of the observed cases in meningitis prevalence was accounted for by climatic variables at a significant level of. 0.05. In the Northern Savanna zone, these climatic variables accounted for about 79% of meningitis cases in the region, at a significant level of at 0.05. The Southern Savanna had an R^2 value of 0.44 which implies that 44% of meningitis cases in Southern Savanna region were accounted for by climatic variables like relative humidity, rainfall amount, maximum temperatures, mean air temperatures and wind speed. Although the impact of these variables are low in the southern Guinea Savanna region, they are however significant at 0.05. Suffice it to add that climatic variables in Benue, Enugu and Kogi are not significant predictors of meningitis. For this reason, it can be established that climatic variables have no impact on meningitis outbreak. On modelling meningitis outbreak, different climatic variables are significant for the different zones in consideration. For northern Savanna, only three variable, mean air temperature, relative humidity and rainfall amount can be used to predict meningitis outbreak using the derived formula. In the Sudano-Sahelian region, rainfall amount and mean air temperature can be used to predict meningitis outbreak while in the Southern Savanna zone, only wind speed because it was the only variable that was statistically significant at 0.000. This study recommends that the model developed be used to forecast meningitis outbreak and also used to create a meningitis prevalence matrix based on behaviour of weather parameters.

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CHAPTER ONE

1.0 INTRODUCTION

1.1 Background to the Study

Climate is an essential component of the complex environment; it determines the distribution and abundance of insects and tick species, either directly or indirectly. It has direct and indirect effects on vector and parasite growth, as well as host plant and animal. Thus, climatic alteration is likely to have an influence on the geographic array and seasonal activity of vector species, as well as disease transmission (Adefale, 2016).

Akinsanaol *et al.* (2015) reiterated that every year, significant meningococcal meningitis (MCM) disease outbreaks hit West African countries in the Sudano-Sahelian band, affecting up lots of people, mostly children, in some of the world's poorest regions. The season commences in February and ends towards the end of May. This intensely puts forward a connection between meningitis and climate variability. Though, the mechanisms behind such trends have not yet been uncovered (Sultan *et al*., 2005).

The question is, how can the outbreak be prevented when it takes health practitioners unaware? Hence, this study seeks to predict future outbreaks of meningitis. As pointed out by Weisfelt *et al.* (2006), the aftermath of climate variability on the eco system is likely to affect population by creating favourable conditions for disease pathogens. The World Health Organization in 2014 gave an important information for understanding the potential impacts of climate change is the long lifetime of greenhouse gases in the atmosphere. Carbon dioxide can take more than 100 years to come to equilibrium once it is emitted.

Therefore, the Earth is committed to several decades of climate change after stabilization of greenhouse gas emissions is achieved, and sea level will continue to rise for more than 1,000 years as the ocean continue to warm because of the processes involved in stabilization, World Meteorological Organization (WMO, 2020). Nnadi *et al.* (2017) explained that Meningococcal disease caused by Neisseria meningitidis causes severe illness, and could lead to permanent disability or death if not swiftly detected and treated. The largest global burden of meningococcal disease is in sub-Saharan Africa, where annual epidemics caused mainly by N. meningitidis serogroup A were previously common. After the introduction of meningococcal "A" vaccine in 2013, meningitis caused by serogroup A declined.

Nevertheless, N. meningitidis serogroup C (NmC) has now emerged as a cause of large outbreaks. So, during December 2016–June 2017, the largest global epidemic of meningitis caused by NmC occurred in northern Nigeria, with 14,518 suspected cases and 1,166 deaths reported. An emergency operations centre coordinated rapid development and implementation of an emergency outbreak response plan, including administration of meningococcal serogroup C– containing vaccines to about two (2) million persons. Several logistical challenges were stumbled upon during the response, the outbreak was declared over in June 2017. The implications of these for public health practice is that National and regional evaluations of the outbreak response have outlined recommendations for improving meningitis outbreak prevention, timely detection, and response in Nigeria.

The question is, how can the outbreak be prevented when it takes health practitioners unaware? Hence this study. Implementation of these recommendations will be key to reducing future meningitis outbreaks. Expanding availability of multivalent vaccines that are effective against non-A serogroups of N. meningitidis might prevent future outbreaks in this region.

As pointed out by Weisfelt *et al*. (2006), the effects of climate variability on the eco system are likely to affect population by creating favourable conditions for disease pathogens. Abatzoglou and Williams (2016) also concurred that climate variability is essentially caused by natural and anthropogenic activities. Recently, there was a consensus that anthropogenic activities constituted a major cause in climatic variability for instance, human induced alterations of the natural world have contributed to the high increase in the rate of gaseous emissions into the atmosphere with the resultant effect as global warming. The World Health Organization (2017) estimated that about 150,000 deaths annually are attributed to climate variability and extreme weather events.

The World Meteorological Organization (WMO, 2017) stated that with a population close to about 300 million people, the meningitis belt of Africa which stretches from Senegal to Ethiopia is prone to severe and devastating effect of meningitis and that in 2009, over 8,000 cases of meningitis occurred in Nigeria in few weeks. For over 50 years, the influence of climatic factors such as relative humidity, dust and concentration of aerosol and migration on the dynamism of meningitis outbreak have been well appreciated but the precise factors still unknown. Having a better understanding of the climatic and environmental determinants of meningitis will aid easy identification of risks areas, measure and forecast a modification of the meningitis belt and also to adapt early intervention measures appropriately (WMO, 2017).

The climate in a particular location is defined as the 30-year average of weather variables, such as temperature and precipitation among others (Schneider, 2001). Climate scientists analyse data against this baseline. Weather is what we experience day-to-day while climate variability includes short-term fluctuations around the average weather, such as the El Nino Southern Oscillation (ENSO). Climate change operates over decades or longer and is projected using increasingly sophisticated earth system models (ESMs). It is important to understand that these models are based on scenarios or possible outcomes of how many people there will be in the world, where they will live, how wealthy they will be, etc. These scenarios project emissions of greenhouse gases. These emission concentrations are then input into the ESMs to project possible future climate. ESMs do not predict what will occur; they project how temperature and precipitation could change under different assumptions of greenhouse gas emissions.

Meningococcal meningitis is a bacterial form of meningitis, a serious infection of the meninges; the three membranes that line the skull and vertebrae canal and enclose the brain and spinal cord. It can cause severe brain damage and is fatal in 50% of cases if untreated. The bacteria are transmitted from person-to-person through droplets of respiratory or throat secretions from carriers. In the meningitis belt, dust winds, cold nights and upper respiratory tract infections combine to damage the back of one's throat, the upper pharynx, increasing the risk of meningococcal disease especially during dry season weather. There are 13 known sub types of meningococcal meningitis with types A, B, C, and W135 to be the main causes of epidemics in Africa. There are also four other types of meningitis worldwide beyond bacterial meningitis: viral, fungal, parasitic, and non-infectious meningitis (WMO, 2019).

Even with treatment, total death rate can exceed about 10%, and 10-20% of survivors' experience long term after-effects including brain damage and hearing loss (Greenwood, 2006). Meningitis can push a family into severe poverty which is especially significant in regions where annual per capital income ranges from $500 to $1,500 (WHO, 2017). Some meningitis cases are caused by a viral infection, but bacterial and fungal infections are other causes. Some cases of meningitis improve without treatment in a few weeks while others can be life-threatening and require urgent antibiotic treatment. It is therefore expedient to seek immediate medical care if there is a suspected case of meningitis because early treatment of bacterial meningitis can prevent serious complications. Early meningitis symptoms may mimic the flu (influenza). Symptoms may develop over several hours or over a few days.

Possible signs and symptoms in anyone older than the age of two (2) include: Sudden high fever, Stiff neck, Severe headache that seems different than normal, Headache with nausea or vomiting, Confusion or difficulty concentrating, Seizures, Sleepiness or difficulty waking, Sensitivity to light, No appetite or thirst and Skin rash (sometimes, such as in meningococcal meningitis). In the 2017/ 2018 outbreak, about ten (10) deaths resulted from stiff neck as recorded by Nigerian Centre for Disease Control (WHO, 2017). Signs in new-borns include: High fever, constant crying, Excessive sleepiness or irritability, Inactivity or sluggishness, poor feeding, a bulge in the soft spot on top of a baby's head (fontanel), stiffness in a baby's body and neck. Infants with meningitis may be difficult to comfort, and may even cry harder when held. Bacterial meningitis is serious, and can be fatal within days without prompt antibiotic treatment. Delayed treatment increases the risk of permanent brain damage or death, Centre for Disease Control (CDC, 2016).

The disease has existed in the Meningitis-belt region of Africa since the start of the 1900s. In past epidemics, the range of the attack rate has been 100 to 800 people per 100,000. However, communities can have attack rates as high as 1 in 100. During these epidemics, the very young ones are the most vulnerable according to the World Health Organization and the Meningitis Vaccine Project, those most vulnerable are below 30 years in age (Zûniga *et al*., 1992).

Africa’s meningitis belt includes part of twenty-six (26) countries from Senegal in the west to Ethiopia in the east. The burden of the disease is usually high with 7000- 180000 cases annually. There is a clear seasonal pattern of which this disease occurs in the first six (6) months of the year in the dry season with air borne dust and high temperatures being some risk factors. Meningitis poses a threat to public health in Africa as the epidemic appear irregularly every 5 to 12 years especially in the regions across Sub Saharan meningitis belt (Zhao *et al.*, 2018) Bacterial (meningococcal) meningitis is a devastating infectious disease with outbreaks occurring annually during the dry season in locations within the 'Meningitis Belt, a region in sub-Saharan Africa stretching from Ethiopia to Senegal. Meningococcal meningitis occurs from December to May in the Sahel with large epidemics every 5-10 years and attack rates of up to 1000 infections per 100,000 people. High temperatures coupled with low humidity may favour the carriage of disease as the meningococcal bacteria in the nose and throat are better able to cross the mucosal membranes into the blood stream. Similarly, respiratory diseases such as influenza and pneumonia might weaken the immune defences and add to the mucosa damage. Although the transmission dynamics are poorly understood, outbreaks regularly end with the onset of the rainy season and may begin anew with the following dry season (Dukić & Hayden *et al.* 2012).

Nigeria was struck hard in 1996 by Meningitis with about 109,580 cases and 11,717 deaths. In 2003, 4,130 cases and 401 deaths were recorded (Mohammed *et al*., 2017). In 2008, 562 deaths in 9,086 cases were recorded while about 333 deaths occurred in the country over a three-month period in twenty-two out of thirty-six states, (Mohammed *et al.,* 2017). About 217 local government areas were reported in 2009, Paul *et al*. (2019). In a study carried out by Gana *et al.* (2017), on the Outbreak of cerebrospinal Meningitis in Kebbi state, it was confirmed that a total of 1,992 suspected cases within 18 weeks that the outbreak lasted recorded fatality rate of 4.0%. Also, two thirds of the state were affected. This trend continued into 2017 as revealed by the Nigerian centre for disease control (NCDC, 2017) where about 1,447 cases were reported and 1,158 deaths recorded of which over 50 percent involved were children. According to de Oliveira *et al.* in 2017, for more than 60 years, it is known that meningitis epidemics in sub-Saharan Africa is partly related to climate and environmental conditions but factors other than climate, and a lack of data and knowledge have hindered the quantification of this relationship."

Meningitis remains a major health burden throughout Sahel Africa, especially in heavily populated northwest Nigeria with an annual incidence rate ranging from 18 to 200 per 100 000 people for 2000 to 2011 (WHO, 2000). Several studies have established that cases exhibit sensitivity to intra and inter annual climate variability, peaking during the hot and dry boreal spring months, raising concern that future climate change may increase the incidence of meningitis in the region (Abdussalam *et al.,* 2014). Bacterial meningitis is a bit more complex than viral meningitis. This can be seen in the study carried out by Christie *et al*. (2017) on "Impact of meningitis on intelligence and development: A systematic review and meta-analysis" where there was moderate evidence established between bacterial meningitis and performance IQ because the bacterial meningitis led to reduction in performance IQ compared to that of viral meningitis. Symptoms of meningitis mostly include headache and neck stiffness associated with fever, confusion or altered consciousness, vomiting, and an inability to tolerate light (photophobia) or loud noise (Phonophobia). Symptoms are often confused with the flu. Even when the disease is diagnosed early and adequate treatment is started, 5% to 10% of patients die, typically within 24 to 48 hours after the onset of symptoms, and many experience brain damage or hearing loss. A lumbar puncture is necessary to confirm the diagnosis followed by antibiotics to treat the disease as soon as possible. The average incubation period for bacterial meningitis is 4 days, but can range between 2 and 10 days. Children often exhibit only nonspecific symptoms such as irritability and drowsiness. If a rash is present, it may indicate a particular cause of meningitis, and meningitis caused by meningococcal bacteria may be accompanied by rash. (WHO, 2017). Meningitis is life threatening because of the inflammations proximity to the brain and spinal cord therefore the condition is classified as medical emergency. There are a few unique reasons for meningitis, including infections, microscopic organisms and growths. Be that as it may, huge outbreaks of the ailment are common the after effect of the microorganisms *Neisseria meningitidis*. Around 10 percent of individuals have these microbes in their throat with no negative impact. The microorganisms just turn into an issue when they contaminate the meninges which is the thin covering around the focal sensory system. Bacterial meningitis has a quick beginning that prompts death in approximately 1 out of 10 cases. Those that survive frequently experience the ill effects of mental disorders, deafness, or epilepsy.

The disease has a strong seasonality, evidenced by the fact that the rate of infection jumps up during the driest months of the year between January and May. In the rainy season, by contrast, the incidence drops by more than a factor of 100. In fact, rain has been described as the most effective vaccine for the disease. "The epidemics usually end when the first rain drops fall," said Lingani *et al.* (2015) and the strong seasonality could be due to changes in temperature, humidity and dust.

Models are simplified representations of complex, dynamic relationships. They aim to identify key processes for the association between climate change and health, to further insights into how changing weather patterns could affect the geographic range, seasonal length, and incidence of health outcomes. The goal of a “good” model is to provide insights into possible future changes in health outcomes with enough confidence for decision-makers to plan for possible interventions to avoid, prepare for, and effectively respond to the health risks of climate change. For example, several models suggest that a changing climate will provide an opportunity for various vector species to increase their geographic range in mountainous areas in the coming decades. Public health institutions and agencies can use that information to plan for where and when to alter current surveillance programs (World Health Organisation, 2019).

1.2 Statement of the Research Problem

Meningococcal disease outbreak occurs when multiple cases of the same serogroup (type) take place in a population over a short time period. These outbreaks can occur without spatial restriction, it could be in communities, schools, colleges, prisons, and other residents. Depending on the population size and specific circumstances, as a result, health officials may declare an outbreak after just two cases and this is mostly not the case because by the time these cases emerge, they have escalated and lives lost but being able to predict these cases keeps the people and health practitioners prepared.

Considering and acting on the association between weather and meningitis across regions, being able to predict number of cases of time of occurrence will help in making vaccines readily available and will save lives. It will help People residing in those areas know when exactly meningitis cases occur and what triggers it. Common perception is that meningitis epidemics occur in the dry season and end after the start of the rainy season, recently, meningitis outbreak has occurred in some southern cities like Enugu, this research will help reveal other factors responsible in addition to what is known. Being able to predict meningitis will aid improved awareness of early meningitis symptoms and vaccinations for people who travel seasonally.

The geographic distribution and epidemic potential differ according to the serogroup meningitis, (WHO, 2000). There are no reliable estimates of global meningococcal disease burden due to inadequate surveillance in several parts of the world. Most studies focused on Spatio-temporal variation of meningitis in one particular climatic zone of the country without considering possibilities of other climatic zones being high risk areas of meningitis outbreak which this study seeks to investigate. For instance, change in temperatures, low humidity, and rainfall patterns appear to influence spatial and seasonal distribution of the epidemic outbreak, hence the need to investigate the characteristics and influence of these climatic variables on meningitis outbreak with respect to space and time in various climatic zones of the country, namely, Sudano-Sahelian and Guinea Savanna. Also, mostly, meningitis outbreak takes health institutions and regulatory bodies in the country off guard hence inadequate preparation for the epidemic because of inability to predict its outbreak. Response to meningitis outbreak is most times too late. Threshold in CSM cases has to be monitored especially through reliance on surveillance, and sometimes there can be delays in reporting (Abatzoglou & Williams, 2016). Accurately modelling CSM outbreak will enable relevant health organizations to be proactive by making available vaccines before cases escalate and casualties are recorded.

In order to better anticipate future outbreaks, scientists from a variety of disciplines have come together as part of the Meningitis Environmental Risk Information Technologies (MERIT) initiative led by WHO in support of health ministries across the Sahel MERIT aim to create predictive models for the disease based on climate and environmental variables. Therefore, this research work aims at addressing the gap identified in previous studies. This study investigates the impact of climate on spatiotemporal variability in the occurrence and spread of meningitis in the Sudano-Sahelian and Guinea Savanna zones of Nigeria.

Two temperature categories were analysed, the maximum temperature and mean air temperature so as to ascertain which of the two have greater impact on CSM occurrence. This was when forecasting or drawing inference, it will be clear what variable is of impact than the other. This is because in most literatures, temperature is holistically referred to as just temperature without differentiating the variables.

1.3 Aim and Objectives

The aim of this research work was to investigate the Spatio-temporal association between climatic variability and the occurrence of meningitis *(meningococcal)* in the Sudano-Sahelian and Guinea Savanna zones of Nigeria.

1.4 Objectives.

The specific objectives were:

i, To examine the Spatio-temporal trend of meningitis in Sudano- Sahelian and Guinea Savanna zones of Nigeria between 2008 and 2019.

ii. To investigate whether there is a relationship between Climatic variables (Relative Humidity, Rainfall, Temperature and wind speed) and meningitis occurrence in the study areas.

iii. To attempt to generate a model for predicting CSM outbreak in the study areas using climatic variables. To analyze the impact of the climatic variables on Meningitis occurrence in the study areas.

iv. To attempt to generate a model for predicting CSM outbreak in the study areas using climatic variables.

1.5 Research Questions

i. What is the spatio-temporal trend for meningitis in the study area?

ii. Is there a relationship between climatic variables and meningitis cases?

iii. To what extent do Wind speed, Relative Humidity, Rainfall amount, maximum temperature and mean air temperature influence meningitis occurrence?

iv. How Can meningitis outbreak be predicted in the study area using climatic variables?

1.6 Hypotheses

1.6.1 Hypotheses One:

H_0 =There is no spatio-temporal trend in meningitis occurrence.

H_a=There is a spatio-temporal trend in meningitis occurrence.

1.6.2 Objective two:

$H_{o\,=}$ There is no relationship between Climatic variables and meningitis cases.

H_a = There is a relationship between Climatic variables and meningitis cases.

1.6.3 Objective three:

$H_{o\,=}$ The relationship between Climatic variables and meningitis cases is not statistically significant.

H_a = The relationship between Climatic variables and meningitis cases is statistically significant.

1.6.4 Objective four:

H_{o} = Meningitis outbreak cannot be predicted using climatic variables.

H_{a} =Meningitis outbreak can be predicted using climatic variables

1.7 Justification for the Study.

Representatives of the World Health Organization (WHO) have shown keen interest by putting meningitis high on the global agenda and coordinating progress in different areas. Its focus is on plummeting the epidemic meningitis from the meningitis belt and examining the potential for a more global agenda because of the threat it poses on the risk population. So, being able to predict meningitis outbreak will ease the ravaging effect of the risk population because it will help improve prompt response (Meningitis Research Foundation, 2019) because it will improve outbreak response and control of meningococcal epidemics in the meningitis belt as well as management of patients and survivors. It will also enhance disease surveillance in the meningitis belt. Furthermore, it will help promote development in the area of public health. Also, establishing the impact of climatic variables on meningitis occurrence will help create awareness on which variable to be on the lookout during surveillance. Determining the role of climate in the spread of certain diseases can assist health officials in "forecasting" epidemics. New research on meningitis incidence in sub-Saharan Africa pinpoints wind and dust conditions as predictors of the disease. The results of this study may help in developing vaccination strategies that aim to prevent meningitis outbreaks, such as the 1996-1997 epidemic that killed 25,000 people (Schweitzer *et al.,* 2018).

Pandya *et al.* (2015) in a study on using weather forecast to help manage meningitis in the West African Sahel revealed that given the impact of meningitis in the region, the correlation between meningitis cases and the average relative humidity, and the predictability of sub seasonal and meridional variations in humidity, its next step was to help public health decision makers use relative humidity predictions to inform their vaccination decisions. It stated that current global models routinely predict relative humidity up to 14 days in advance; coupled with the observed 2-week lag between relative humidity and meningitis cases, this means it is possible to make a meningitis prediction as much as a month ahead of time, enough lead time to influence a vaccination campaign (Collard *et al.,* 2013). Being able to give a medium range forecast on the outbreak of meningitis is one of the objectives of this research work. This will to a large extent reduce mortality rate due to meningitis.

1.8 Scope of the Study

The research focused on investigating the impact of climate on spatio-temporal variability in the occurrence and spread of meningitis *(meningococci)* in the Sudano-Sahelian and Guinea Savanna climatic zones of Nigeria. To achieve this, twelve states where picked randomly across the study area to give a balanced representation of results. The states considered were Sokoto, Katsina, Jigawa, Borno, Niger, Kaduna, Abuja, Adamawa, Benue, Kwara, Enugu and Kogi. Four states in the Sudano-Sahelian region (Sokoto, Katsina, Jigawa and Borno). The Guinea Savanna was divided into two regions; the Northern Guinea Savanna (Kaduna, Niger, Adamawa and Abuja) and Southern Guinea Savanna (Kwara, Benue, Enugu and Kogi state). The period under consideration was from 2008 to 2019. Making a total of twelve years. Due to time constraints, the entire country was not captured.

1.9 Study Area

1.9.1 Nigeria

Nigeria lies between longitudes 2°E and 15°E and latitudes 4°N and 14°N. The Sudano-Sahelian climate is the predominant type in Northern Nigeria with rainy season lasting for only three months (June to September) the rest of the year is hot and dry having temperatures as high as 40^0C. On the other hand, the Guinea Savanna extends down to about latitude 7^0N, with a rainy season lasting from April to November, relatively high and uniform temperatures, and high humidity (Abubakar, 2009). The study area lies between latitude 6^0N to 14^0N.

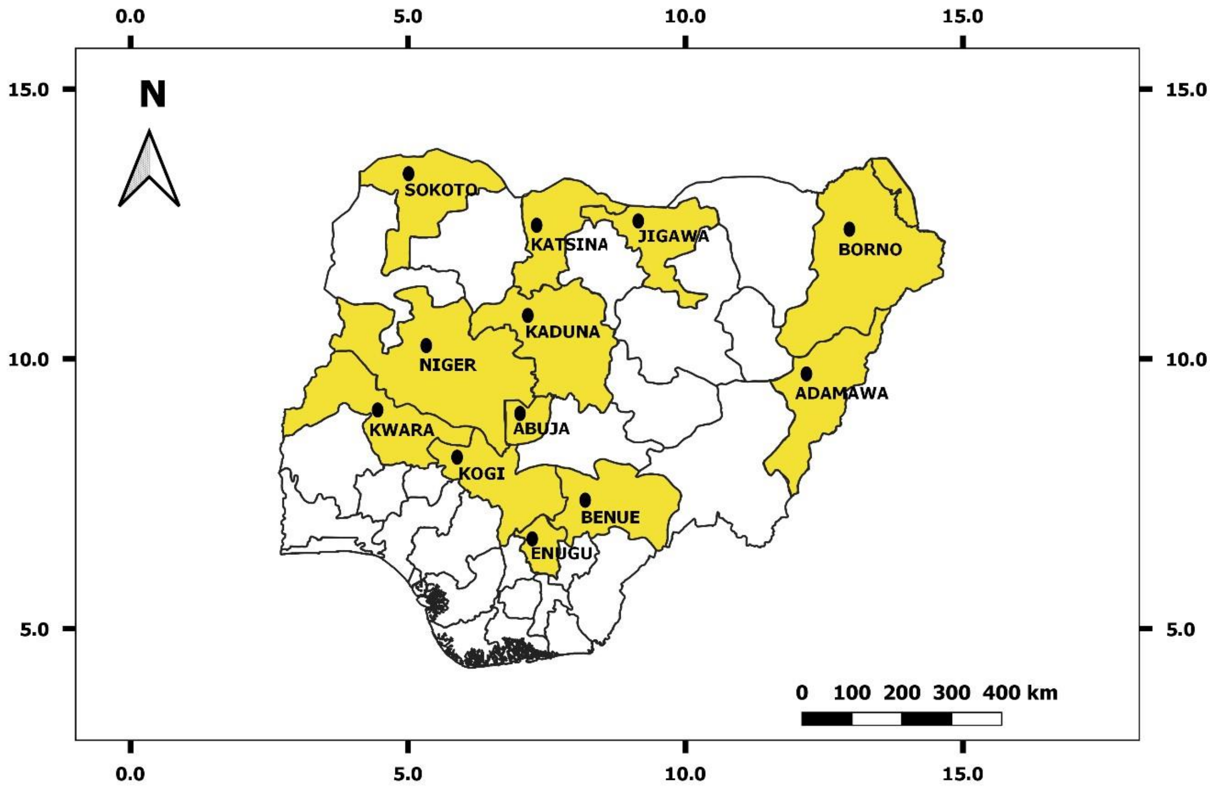

Figure 1.1: Nigeria showing study area.
Source: Author (2018)

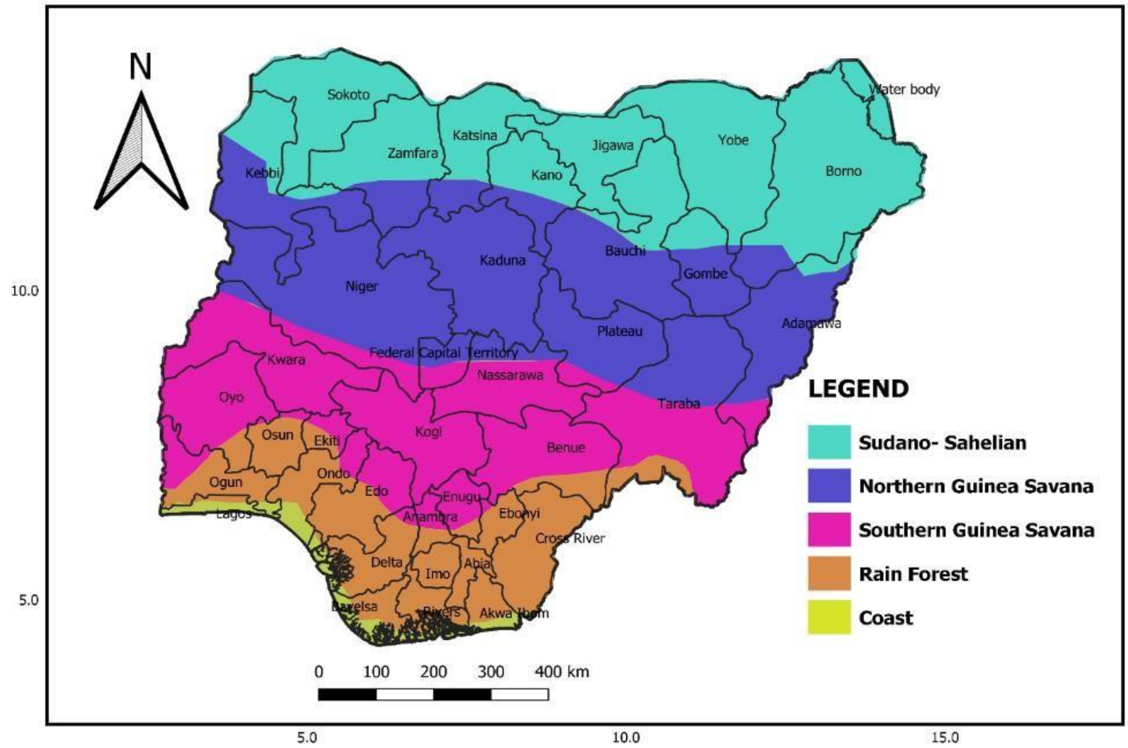

Figure 1.2: The Climatic Zones of Nigeria.

Source: Author (2018)

1.9.2 Climate

The climate of Nigeria has been experiencing change and variability over the first few years and this has generated considerable concern due to ever increasing impact of these changes on socio economic activities. Temperature across the country is relatively high with a very narrow variation in seasonal and diurnal ranges (22-36^{0}C). There are two basic seasons; wet season which lasts from April to October; and the dry season which lasts from November till March. The dry season commences with harmattan, a dry chilly spell that lasts till February and is associated with lower temperatures, a dusty and hazy atmosphere brought about by the North-Easterly winds blowing from the Arabian Peninsula across the Sahara; the second half of the dry season, February - March, is the hottest period of the year when temperatures range from 33 to 38 degrees centigrade on the average. The extremes of the wet season are felt on the south eastern coast where annual rainfall might reach a high of 330cm; while the extremes of the dry season, in aridity and high temperatures, are felt in the northern part of the country (Abubakar, 2009).

1.9.3 Vegetation

In line with the rainfall distribution, a wetter south and a drier northern half, there are two broad vegetation types: Forests and Savanna. There are three variants of each, running as near parallel bands east to west across the country. Forests Savanna Saline water swamp Guinea Savanna Fresh water swamp, Sudan Savanna, Sahel Savanna and the evergreen Rainforest. There is also the mountain vegetation of the isolated high plateau regions on the far eastern extremes of the country (Jos, Mambilla and Obudu). The Savanna, especially Guinea and Sudan, are the major grains, grasses, tubers, vegetable and cotton growing regions. The Tropical evergreen rain forest belt bears timber production and forest development, production of cassava; and plantation growing of fruit trees - citrus, oil palm, cocoa, and rubber, among others (Ogungbenro and Morakinyo, 2014).

1.9.4 Sudano-Sahelian Region

In Africa, the Sudano-Sahelian climatic zone is the zone of transition between the Sahara to the north and the Savanna to the south. Stretches across the south-central latitudes of Northern Africa between the Atlantic Ocean and the Red Sea. North of the zone of the Guinea Savanna the amount of precipitation decreases to 500-1000 mm and the dry period lasts more than six-seven months, and a zone of Sudanese Savanna a with a dense but low grass cover is located. Areas which have rainfall under 500 mm produces Sudan Savanna type of vegetation. The topography of this region is mainly flat; most of the region lies between 200 and 400 meters (660 and 1,310 ft.) of elevation. The main characteristic of Sahel Savanna is desert vegetation. The annual precipitation is poor, and the wet season lasts three to four months, while the other months may remain absolutely dry.

The region generally receives annual rainfall of about 100 mm and 600 mm so the vegetation of this zone is rare and the present grasses are extremely short. The relative humidity is usually low often between 10% and 25% during the dry season and between 25% and 75% during the rainy season. The least humid places have a relative humidity under 35%. The Sahel is characterized by intense heat, with an unvarying temperature. During the hottest period, the average high temperatures are generally between 36 and 42°C often for more than three months, while the average low temperatures are around 25 to 31°C. During the not so hot period, average high temperatures are between 27 and 33°C while the average low temperatures are between 15 and 21°C. Everywhere in the Sahel, the average mean temperature is over 18°C due to the tropical climate.

1.9.5 Guinea Savanna

Almost half of the territory of Nigeria is occupied by a moist, so-called Guinean high grass Savanna. It is the largest of all vegetation belts in Nigeria. Average annual precipitation is about 1000-1400 mm. The Guinea Savanna is subdivided into Northern Guinea Savanna, Southern Guinea Savanna and the Derived Savanna (Abubakar, 2009). There are tall trees, few scattered ones. Grasses are green during rainy season and turn brown in the dry season, the grass reaches a great height, in which not only a man, but also a large animal can hide. Parts of Kaduna, Kwara, Benue, Kogi, Abuja, Niger, Enugu, Ondo, Osun, and parts of Oyo are in this vegetation zone

CHAPTER TWO

2.0 LITERATURE REVIEW

2.1 Meningitis and Climate

An epidemic can easily spread rapidly among a large number of people in a community within a short period of time. Some infectious diseases, including influenza, hand, foot and mouth disease, dengue and meningitis, are temporally limited by variations in the meteorological factors, such as sunshine, temperature, humidity, rainfall, atmospheric pressure, wind speed and so on. Hence, it is crucial to predict the behaviour of outbreak of these infectious diseases based on meteorological factors. The need to review various epidemic models related to meteorological factors become expedient.

Yang *et al.* (2004) discussed two kinds of epidemic models: deterministic models and stochastic models. The deterministic models include switched SIR model, seasonal SIR model, periodic SEIR system and seasonal SEIQR model. The stochastic models involve multiple regression models, auto-regressive moving average model, autoregressive distributed lag model, time series Poisson regression models and generalized additive models. Furthermore, they introduced the latest applications of these models, respectively. In conclusion, these deterministic models and stochastic models can successfully predict the diseases outbreak using meteorological factors, and they all are now widely used in the field. However, few meteorological factors are used in these models. With the development of Meteorological Science, large amounts of Meteorological factor data will be obtained. More key Meteorological factors causing an epidemic will be identified. Therefore, in the future, more key meteorological factors will be considered in models and they will further improve the accuracy of the forecast, (Liu *et al.,* 2017).

Bacterial meningitis causes a high burden of disease in the African meningitis belt, with regular seasonal hyper endemicity and sporadic short, but intense, localized epidemics during the late dry season. Chowdhury *et al.* (2018) taking Bangladesh as a case study revealed that being one of the world's most vulnerable countries for climate change, the observational study examined the association of temperature, humidity and rainfall with six common climate-sensitive infectious diseases in adults, diseases like malaria, diarrheal disease, enteric fever, encephalitis, pneumonia and bacterial meningitis in the north-eastern part of Bangladesh. Subjects admitted to the adult medicine ward of a tertiary referral hospital in Sylhet, Bangladesh from 2008 to 2012 with a diagnosis of one of the six chosen climate sensitive infectious diseases were enrolled in the study. For the study, Climate-related data were collected from the Bangladesh Meteorological Institute. Afterwards, disease incidence was analysed against mean temperature, humidity and average rainfall for the Sylhet region. Statistical significance was determined using Mann-Whitney test, Chi-square test and ANOVA testing. In the study, 5,033 patients were enrolled (58% male, 42% female in the ratio 1.3:1). All six diseases showed highly significant *(P = 0.01)* rises in incidence between the study years 2008 (540 cases) and 2012 (1330 cases), compared with no significant rise in overall all-cause hospital admissions in the same period (P = 0.19).

The highest number of malaria (135), diarrhoea (266) and pneumonia (371) cases occurred during the rainy season. On the other hand, the maximum number of enteric fever (408), encephalitis (183) and meningitis (151) cases occurred during autumn, which follows the rainy season. A positive (P= 0.01) correlation was observed between increased temperature and the incidence of malaria, enteric fever and diarrhoea. For meningitis, pneumonia and encephalitis, a negative correlation was gotten. Higher humidity correlated (P = 0.01) with a higher number of cases of malaria and diarrhoea, but inversely correlated with meningitis and encephalitis. Higher incidences of encephalitis and meningitis occurred while there was low rainfall. Incidences of diarrhoea, malaria and enteric fever, increased with rainfall, and then gradually decreased. The outcomes support a relationship between weather patterns and disease incidence, and provide essential baseline data for future large prospective studies (Chowdhury *et al.,* 2018).

Meningococcal disease is of major public health concern in Sub-Saharan Africa as it is responsible for the occurrence of epidemic Meningitis in the 'African Meningitis belt' an area which comprise of 26 countries extending from Senegal in the West to Ethiopia in the East with an estimated population of about 500 million. For more than a century, this region has experienced large serogroup 'A' epidemics every 7-10 years, with annual rates as high as 1,000 per 100,000 populations. The onset of cases in the sub-Saharan region typically begins during the dry season, possibly related to drying and damage to the nasopharyngeal mucosa, and subsides with the rainy season, and may re-emerge the following dry season. In Nigeria, the belt covers all 19 northern States including the Federal Capital Territory, Abuja (Abdulkadir, 2014). Meningitis outbreak has been an extensive public health threat in some parts of Africa as the extended belt of Sub-Sahara Africa stretching from Senegal in the west to Ethiopia in the East, that is about twenty-six (26) countries has the highest rate of the disease. Nigeria Centre for Disease Control, (NCDC, 2017).

The indexed cases of meningitis were reported in week 50 of 2016 and within a short time not less than 4,255 suspected cases were reported with 455 deaths with case fatality rate (CFR) of 10.7% from 128 Local Government Areas (LGAs). Within that short while five States reached epidemic proportion. These States were Zamfara, Sokoto, Kebbi, Katsina and Niger States (Gana *et al.*, 2017). However, the Red Cross (2018) chose to launch its Disaster Relief and Emergency Fund (DREF) operation in the most affected states in the north-western States which include Sokoto, Zamfara and Katsina. As at July 2017, a total 14,518 cased reported and 1,166 deaths recorded with case fatality rate of 8% (Abdulkadir, 2014).

A study was undertaken in the Obuasi Municipality of Ghana to evaluate the effects of climatic factors on the outbreak of Cerebrospinal Meningitis by Trumah *et al.* (2015), the task provided a validated climatic pattern and served as reference point to health administrators on CSM emergency preparedness which could lead to the prevention of fatalities as measures would be put in place to address an occurrence. Secondly, Environmentalists on the environmental factors that cause CSM outbreak. Also to benefit from the study were health consultants for sensitization and creations of awareness of the causes of CSM as well as stakeholders for planning and implementation of outbreak preparedness methods and strategy.

Time series data on rainfall, temperature, and relative humidity was obtained from Ghana Meteorological Agency in Accra and AngloGold Ashanti, Obuasi. The rainfall and temperature values were taken from 1980 to 2011 while that of relative humidity was from 1987 to 2011 due to the unavailability of data. Data on the reported case of CSM was obtained from Ghana Health Service. The data was analysed using Cluster and correlation analysis. It was found that correlation analysis indicated that the reported cases of CSM in Obuasi are positively and significantly related to temperature. Nonetheless, from the cluster analysis, there were no reported cases of CSM in other towns in the same cluster as Obuasi. In conclusion, it can be stated that climatic factors serve as catalyst for the occurrence of CSM. Without the complex interplay amongst these factors and the virus or bacterial CSM will not break out as the bacteria causing bacteria meningitis are commonly found in the nose and throat but not harmful. (Adeyemo, 2012).

In Korhogo which is northern Côte d'Ivoire, precisely in, the decade 2000-2010 it was marked by major climate variability, including relatively low rainfall in 2002-2003, followed by a severe drought in 2004 and this led to the drying of the dam holding the drinking water for the city of Korhogo in 2005. 2006 was characterized by a gradual recovery in rainfall; in 2007, heavy rains caused flooding in Korhogo and its surroundings. The objective of the study was to examine the indirect effects of this climate variability on population health particularly as it relates to cerebrospinal meningitis. Historical clinical data about meningitis from 2005 to 2010 and meteorological data from 2004 to 2010 for the Korhogo health district were collected and analysed. The yearly changes in the incidence of meningococcal meningitis during the period 2005-2010 was marked by an epidemic year; 2006, following two years of extreme drought; 2004 and 2005. The months of intense drought (January, February, March and April) were up the season when cerebrospinal meningitis occurred most often; the most cases were recorded in February and March. Analysis of epidemiologic and meteorological data during the epidemic year in 2006 showed a significant negative correlation between the incidence of CSM and relative humidity ($r=-0.61$, $p<0.05$) and a significant positive correlation with temperature ($r=0.66$, $p<0.05$). These correlations do not fully explain the occurrence of epidemic meningitis, but they however do point to indicators to be considered for setting up an early warning system for cerebrospinal meningitis (N'Krumah *et al.*, 2014).

Nakazawa and Matsueda (2017), over Burkina Faso, four meteorological variables namely, north easterly surface wind (WS), relative humidity (RH), rainfall (Rain) and temperature (T2m)) and one of four dust products (dust surface mass concentration or aerosol optical depth, D1–D4) were used, a differential equation for meningitis incidence (N) was applied to the multivariate log-linear regression analysis to get each contribution from the variables (WS, RH, Rain, T2m and one of four dust products) to meningitis incidence.

The climatological data show that dust and temperature were synchronized with meningitis incidence, but the meningitis incidence reached a peak several months after the north easterly wind became maximum and the relative humidity was minimum during the no-rain period. That is, meningitis incidence increases when the north easterly wind prevailed under dry and no-rain conditions and decreases when the south westerly wind prevailed under wet and rain conditions, and it has a peak under dusty and hot conditions. After performing all possible combinations of the regression analysis (but choosing only one dust dataset for each combination) using models with one to five parameters, the time derivative of the weekly meningitis incidence from 2006 to 2014 was estimated and compared with that observed.

The more parameters that were included, the higher the correlation coefficients between the estimated and observed tendency. However, the north easterly wind had a major contribution to the rate of change of the number of cases. The highest correlation coefficient was for the models with all four meteorological variables plus the dust surface mass concentration data. Even in one- or two-parameter models, a maximum correlation co-efficient of 0.666 is obtained for the WS model, and the WS + RH model gives a maximum of 0.754, which showed some forecast skill using surface wind and relative humidity data. Although the modelled derivative underestimated the outbreaks in 2006 and 2007, it correctly simulated the timing of the zero crossing of the weekly rate of change of N. Thus, this approach may be useful to identify the timing of the peak season of meningitis in Burkina Faso.

Molesworth and Noah (2002), in a study also opined that Meningococcal meningitis is a major public health problem in Africa. The study explored the potential for climate/environmental models to predict the probability of occurrence of meningitis epidemics. To achieve this, time series of meningitis cases by month and district were obtained for Burkina Faso, Niger, Mali and Togo. Environmental information (19891999) for the continent [soil and land-cover type, aerosol index, vegetation greenness (NDVI), cold cloud duration (CCD) and rainfall] was used to develop models to predict the incidence of meningitis. Meningitis incidence, dust, rainfall, NDVI and CCD were analysed as anomalies (mean minus observed value).

The models were developed using univariate and stepwise multi-variate linear regression. The result revealed that anomalies in annual meningitis incidence at district level were related to monthly climate anomalies. Significant relationships were found for both estimates of rainfall and dust in the pre-, post- and epidemic season. While present in all land cover classes these relationships were strongest in Savanna areas. Based on the study, predicting epidemics of meningitis could be feasible. To fully develop this potential, one requires a better understanding of the epidemiological and environmental phenomena underpinning epidemics and how satellite derived climate proxies reflect conditions on the ground and more extensive epidemiological and environmental datasets. Climate forecasting tools capable of predicting climate variables 3-6 months in advance of an epidemic would increase the lead-time available for control strategies. The increased capacity for data processing; the recent improvements in meningitis surveillance in preparation for the distribution of the impending conjugate vaccines and the development of other early warning systems for epidemic diseases in Africa, favours the creation of these models which this study seeks to unravel.

Jackou-Boulama *et al.* (2005), in a study to evaluate the relationship between the recorded rainfall and reported incidence of meningococcal meningitis in Niger from 1996 to 2002. A total of 58 277 cases of meningococcal meningitis were reported in Niger during the study period. The mean annual incidence was 82.2 per 10(5) inhabitants. Two epidemic years occurred during the study period, i.e., 1996 with 183 cases per 105 inhabitants and 2000 with 140 cases per 10(5). Meningitis incidence increased during the dry season and decreased at the beginning of the rainy season. The correlation coefficient between rainfall and incidence of meningococcal meningitis showed a statistically significant negative correlation (r = -0.27; p = 0.01). Since 2002, Neisseria meningitidis sero-group A was predominant but strains of Neisseria meningitidis sero-group W135 as found in specimens collected. Occurrences of meningococcal meningitis epidemics were found to be multi-factorial. They concluded that the Multivariate analysis of all factors would allow implementation of preventive measures earlier than the epidemic prediction strategy based on threshold rates proposed by the World Health Organization.

2.2 Climate Variability

Abdulkadir (2014), on the effect of climate variability in occurrence of meningitis in Minna, Niger state, Nigeria stated that variability in weather and climate has been shown to have an impact on infectious disease outbreak and spread. The occurrence of meningitis has become a seasonal phenomenon as shown in the study. It went further to show that children under the age of ten (10) had the highest record of meningitis occurrence with about sixty-eight (68) cases, children within ages eleven (11) and twenty (20) recorded about thirty (30) cases. While ages twenty-one (21) and above had about twenty-four (24) cases. This implies that children below ten (10) years are more vulnerable to the disease, hence the need to be able to predict the disease so as save the vulnerable group for early intervention because they are the leaders of tomorrow. The study also established positive relationship between meningitis occurrence and maximum temperature and rainfall. This means that increase in annual rainfall and maximum temperature over Niger state would correspond to an increase in meningitis occurrence, implying a direct relationship between occurrence of the disease and these two climatic variables. This study suggests that keen attention should be paid to climatic factors in relation to meningitis.

As pointed out by Abdussalam *et al.* (2014), Northwest Nigeria is a region with a high risk of meningitis. In this study, the influence of climate on monthly meningitis incidence was examined where monthly counts of clinically diagnosed hospital reported cases of meningitis were collected from three hospitals in northwest Nigeria for a 22-year period spanning 1990-2011. Generalized additive models and generalized linear models were fitted to aggregated monthly meningitis counts.

Descriptive variables included monthly time series of maximum and minimum temperature, humidity, rainfall, wind speed, sunshine, and dustiness from weather stations nearest to the hospitals, and the number of cases in the previous month. The effects of other unobserved seasonally varying climatic and non-climatic risk factors that may be related to the disease were collectively accounted for as a flexible monthly varying smooth function of time in the generalized additive models, s (t). Results revealed that the most important explanatory climatic variables are the monthly means of daily maximum temperature, relative humidity, and sunshine with no lag; and dustiness with a 1-month lag. Accounting for *s (t)* in the generalized additive models explains more of the monthly variability of meningitis compared to those generalized linear models that do not account for the unobserved factors that s (t) represents. The skill score statistics of a model version with all explanatory variables lagged by 1 month. This suggested that there was potential to predict meningitis cases in northwest Nigeria up to a month in advance to help decision makers. In addition to this, this study seeks to predict the number of meningitis cases in the study area.

Pandya *et al.* (2015) reiterated that understanding and acting on the association between weather and meningitis in the Sahel could help develop vaccine distribution which will save lives. In the Sahel region, it is believed that those living there know that meningitis epidemics occur in the dry season and end after the start of the rainy season. However, Integrating and analysing newly available epidemiological and meteorological data quantified this relationship because it showed that that the risk of meningitis epidemics scaled from a background level of 2% to a maximum risk of 25% during the dry season. According to the study, the data also suggested that, of all meteorological variables, relative humidity had the strongest correlation to cases of meningitis. Weather alongside an intricate set of environmental, social, and economic drivers, and a complementary investigation of local and regional knowledge, attitudes, and practices suggested several additional interventions to manage meningitis.

These include improved awareness of early meningitis symptoms and vaccinations for farmworkers who migrate seasonally. Furthermore, it was revealed that an economic survey showed that the cost of a single case of meningitis is three times the average annual household income, highlighting the need for improved vaccination strategy. By means of these insights, meteorologists and public health workers developed a tool to guide vaccination decisions. Iterative development allowed a multinational team of public health officials to use the tool while guiding its refinement and directed research toward maximum practical use. That meant focusing on predicting areas where high humidity would naturally end epidemics so vaccines could be moved elsewhere. Using afore mentioned tool and approach could prevent an estimated 24,000 cases of meningitis over a three-year period.

Pandya *et al*. (2015), in a project produced several original results that clarified and quantified the long-observed relationship between relative humidity and meningitis, it revealed and documented knowledge, attitudes, and practices related to meningitis in rural Ghana; and provided one of the first estimates of the household costs of meningitis. It also produced operational results, including a rule of thumb that public health decision makers can use in allocating vaccine which is if the average relative humidity exceeds 40% in a district for a few weeks, the epidemic will end naturally with no vaccine and a decision-informing tool that leverages existing forecasts to predict future average relative humidity. The question is will this be applicable in Nigeria, or will it be different?

Persistent humidity ends the epidemics even without using vaccine. In April, 2009, over Kano, meningitis epidemic ended after relative humidity crossed 40%. Also on D'jamena and Gaya in Niger, when average relative humidity rose above 40%, attack cases fell (Broman and Rajagopalan *et al.,* 2014). It was also revealed that mean air temperature and north easterly winds also improved the outbreak but less than relative humidity. In addition, the probability of an epidemic decreased significantly for relative humidity above 40%. In summary, they suggested that humidity can be used to predict the end of the epidemic with 2 – 4 weeks lead time. The 2009 and 2010 West African meningitis outbreak is an epidemic of bacterial meningitis which has been occurring in Burkina Faso, Mali, Niger and Nigeria. Since January 2009, an annual risk in the African meningitis with a total of 13, 516 people have been infected and 931 have died. Nigeria has been the most severely affected with over half of the total cases and deaths occurring in the nation. The WHO reported that about 1,100 have died and there were 25,000 suspected cases (WHO, 2017). Epidemics of meningitis occur frequently in sub-Saharan Africa during the dry season. RAL scientists have developed a prototype Earth-gauging system that integrates weather and health data to manage meningitis across the African Sahel. This decision-support system integrates two- to 14-day weather forecasts and epidemiological data to provide actionable information that can be used to contain the spread of meningitis epidemics. Particularly, the system is being used to inform officials from the World Health Organization about the spatial variability of meningitis risk, so that scarce vaccine can be distributed to the regions of highest risk for meningitis. Local-scale work is being performed through partnerships in Ghana to better understand the disease burden and to verify the decision-support system. It is the worst outbreak in the African region since 1996, and a third of the world's emergency vaccine stockpile for the bacterial form has been consumed. West Africa is struck by an annual meningitis epidemic, usually affecting between 25,000 and 200,000 inhabitants. However, the current epidemic has been the deadliest outbreak since 1996. That year meningitis infected over 100,000 people and killed about 10,000 during a three-month period according to Delaunay (2016).

Dukić *et al.* (2012) presented the analysis of monthly reported meningitis counts in Navrongo, Ghana, from 1998-2008. In the study, generalized additive modelling approach was employed to assess the link between number of reported meningitis cases and a set of weather variables like relative humidity, rain, wind, sunshine, maximum and minimum temperature. The association was adjusted for air quality (dust, carbon monoxide), as well as varying degrees of unobserved time-varying confounding processes that co-vary with both the disease incidence and weather

Also, Loh *et al.* (2013), while styding how temperature triggers immune evasion by Neisseria meningitidis noted that Neisseria meningitidis has several strategies to evade complement-mediated killing, and these add to its ability to cause septicaemic disease and meningitis. However, the meningococcus is primarily a commensal of the human nasopharynx, and it is unclear why the bacterium has evolved exquisite mechanisms to avoid host immunity. Here it was demonstrated that mechanisms of meningococcal immune evasion and resistance against complement increase in response to an increase in ambient temperature.

Up to 400 vaccination teams of five people each immunized thousands of people every day. In total, about 2.8 million people were vaccinated in Zinder, Maradi and Dosso regions in Niger and about 4.5m people in Katsina, Jigawa, Bauchi Kebbi, Sokoto, Niger, Zamfara, Kaduna, and Gombe States in Nigeria. Vaccination campaigns continued at some sites in Nigeria for a total of 255,000 people (Medical News Today, 2012).

Umaru *et al.* (2015), used monthly maximum and minimum temperature records and reported cases of Meningitis and Measles in Zaria, Kaduna State for 10 years (1999-2008) to determine the influence of temperature on the outbreak of these two diseases. The results show that the reported cases of Meningitis and Measles are highest between March and April when the temperatures are also high. Results of the correlation analysis indicate that the reported cases of these two diseases have positive and significant relationship with temperature. Regression analyses show that about 78.4 and 84.5% of the variations in the occurrence of Meningitis and Measles respectively are accounted for by variations in temperature. The study revealed that the cases of Meningitis and Measles would increase by 6 and 19 persons, respectively for every 1°C increase in temperature. It was found out that the traditional architectural setting of Zaria city also aggravates the effect of temperature in that part of Zaria.

Cheesbrough *et al.* (1995), stated that areas that are humid throughout the year have low disease rates. His study agreed with that of Abdussalam (2014), where it was observed that the epidemics largely occurred in areas with rainfall amount of about 200 to 1100mm; this is the semi-arid zone, south of the Sahara. However, Abdulkadir (2014) in a study carried out in Minna on the relationship between meningitis occurrence and temperature, came to the conclusion that there was an increase in meningitis cases with increase in rainfall. To detect the effect of climatic variation, there is the need monitoring of data for environmental and disease related variables covering long time series. Meningococcal meningitis is a bacterial form of meningitis, a serious infection of the thin lining that surrounds the brain and spinal cord. It is associated with high fatality (up to 50% when untreated) and high frequency (more than 10%) early antibiotic treatment is the most important measure to save lives and reduce complications.

Factors that affect human heath are complex and one of which is climate, this is because of climatic variability. Its impact to a large extent poses threat to mankind (Intergovernmental Panel on Climate Change, 2014) noted that given the complexity of factors that influence human health, assessing health impacts related to climate variability poses a serious challenge. Also, climatic variability has negative impact in this century. Although if there is good medical care and high quality public health systems, it may lessen climate impact on health, however, climate variability may directly affect human health through increasing temperatures. Extreme weather events can be very destructive to human health and the extent to which climate variability can affect the severity of these events cannot be overemphasized. Climate variability may increase the risk of some climate sensitive disease (Intergovernmental Panel on Climate Change, 2014). Cerebrospinal Meningitis (CSM) is one of the infectious diseases likely to be affected by climate change. Although there are a few studies on the climate change-CSM nexus, none has considered perceptions of community members. However, understanding public perception in relation to a phenomenon is very significant for the design of effective communication and mitigation strategies as well as coping and adaptation strategies (Codjoe and Nabie, 2014). The World Health Organization emphasized that climate change is a significant and emerging threat to public health, especially in lower income populations and tropical/subtropical countries. However, people in Asia and Africa were the least likely to perceive global warming as a threat. In Vietnam, little research has been conducted concerning the perceptions of effects of climate change on human health. (Tuyet *et al.*, 2020).

A particularly severe epidemic of meningococcal meningitis (cerebrospinal meningitis, CSM) occurred in Nigeria between January and June 1996. There were 109,580 recorded cases and 11,717 deaths, giving a case fatality rate of 10.7% overall (WHO, 2017). This is the most serious epidemic of CSM ever recorded in Nigeria, and may be the largest in Africa this century. It took over 3 months and the combined efforts of a National Task Force set up by the Federal Ministry of Health, the WHO, UNICEF, UNDP, Médecins Sans Frontières, the International Red Cross and several other non-governmental organizations to bring the epidemic under control. The main control measures centred on active treatment of infected persons, mass vaccination and health education. The exact number of persons treated cannot be ascertained, but there were treatment centres in almost every Local Government Area in the affected States. A study of 1577 patients admitted at the Infectious Diseases Hospital, Kano, showed that 84% of those infected were aged less than 20 years and that, for the first time, infants aged less than two months were affected. Despite intervention, the case fatality rate of 9.1% among this group of patients was similar to the nationwide figure of 10.7%. Long-acting oily chloramphenicol proved highly effective in the treatment of patients, and its routine use in epidemic CSM is recommended. Over 13 million persons were vaccinated in the course of the epidemic. For the first time, cases of CSM were reported from States south of the 'African meningitis belt', suggesting an extension of the belt. The severity of this epidemic yet again underscores the need for a clear policy regarding control measures aimed at forestalling future epidemics. The availability of the recently developed polysaccharide-protein conjugate vaccine should facilitate a decision on mass vaccination for the prevention of epidemic CSM in Africa (Mohammed *et al*., 2017).

In 2017, as reiterated by Inter Health, in Nigeria, the Northern region lies within the African meningitis belt and has experienced some systematic epidemics of Meningococcal meningitis. It revealed that between 26/01/15 and 05/03/15, the Nigeria Centre for Disease Control (NCDC) of the Federal Ministry of Health notified the World Health Organization (WHO) of about 652 suspected cases to 1,380 with 83 deaths, these cases it said were reported in 10 local government area of Kebbi and Sokoto States. It is believed that dust which is common in the dry season aids increase in respiratory infection and helps spread the disease because bacterium attaches itself to dust particles and since the weather condition in the Northern region of Nigeria is dry and dusty during harmattan, which favours the spread of the epidemics.

It went further to state that in the 22nd week of the Cerebrospinal Meningitis (CSM) outbreak in 2017, about four additional Local Government Areas (LGAs) were affected, making a total of affected LGAs to 226. At the time, a total of 14,005 suspected cases were identified from 23 States and the Federal Capital Territory. Out of 901 samples that were sent for laboratory testing, 423 (46.9%) were confirmed positive for *Neisseria meningitidis*. 73% (309) of tested samples showed the causative organism to be *Neisseria meningitidis* serogroup C. The number of deaths recorded was about 1,114 giving a case fatality rate (CFR) of 8% (WHO, 2017)

2.3 Predicting Meningitis Occurrence

Parenti *et al.* (2014), said Meningitis prediction is a relatively new field, and researchers are perfecting their efforts in the Sahel region of Africa, which extends from Senegal to Ethiopia. This area, which is south of the Sahara Desert, has the greatest incidence of the disease. For reasons that are not entirely clear, outbreaks of bacterial meningitis appear to favour the dry, dusty conditions common from November to April across this semiarid region, known as the African meningitis belt.

Colombini *et al.* (2009), during the Meningitis Environmental Risk Information Technologies (MERIT) disclosed that many human diseases are climate-sensitive such as malaria and meningitis among others with climate acting as an important driver of spatial and seasonal patterns, year-to-year variations (including epidemics), and longer-term trends, as a result, the need to critically look at the impact of climatic risks factors on Meningitis occurrence cannot be overemphasized.

Although climate is only one of the many drivers of both infectious and non-infectious disease, public health policy makers and practitioners are increasingly concerned about the potential impact of climate change on the health of populations thus it is pertinent to be able to predict meningitis outbreak in the study area which will help health care providers prepare in advance to combat the menace the disease might pose, this is because vaccine are only made available when cases of meningitis are reported not before the outbreak as no concrete study on the outbreak prediction yet. In recent times, NCDC (2017) reported meningitis cases in Calabar placing it under high surveillance thereby making it expedient to investigate its occurrence as far as the Guinea Savanna region.

Furthermore, it was revealed by Abatzoglou & Williams (2016) that the amount of dust is particularly high in the Sahelian region due to the harmattan resulting from strong wind that come in from the northeast because the Harmattan picks up dust as it blows over desert regions like the Bodélé Depression, a dried-up lake bed in central Chad that is the largest dust source on Earth. The resulting dust storms are so thick that they can block out sunlight for several days. Dust may influence the spread of meningitis in a number of ways. The most common proposed mechanism is that dust particles can irritate a person's throat, making it more vulnerable to infection. Dust storms also force people to stay indoors, where they may transmit the disease more easily to each other (Guibourdenche *et al.,* 1994).

Pérez (2014), investigated the role of dust in meningitis outbreak by using observations from the ground and from satellites to construct a model that could compute the level of near-surface dust at different times during the study period (1996-2006). Along with these dust estimates, they compiled a list of climate variables, such as temperature, winds and humidity. They then compared their climate and dust variables to the meningitis incidence during the peak season (January to May) so as to see which variable had the most significant association with the disease. They found that the associations were stronger when including cases in the early months (prior to January). These "early cases" gives an indication of how susceptible a certain population may be to the disease.

Paireau *et al.* (2016), reiterterated that Bacterial meningitis is caused mainly by Neisseria meningitidis, Haemophilus influenzae, and Streptococcus pneumonia which inflicts a substantial burden of disease worldwide. Yet, the temporal dynamics of this disease are poorly characterised and many questions remain about the ecology of the disease. In the study, they aimed to comprehensively assess seasonal trends in bacterial meningitis on a global scale. Hence, they developed the first bacterial meningitis global database by compiling monthly incidence data as reported by country-level surveillance systems. Using country-level wavelet analysis, it was identified whether a 12-month periodic component (annual seasonality) was detected in time-series that had at least 5 years of data with at least 40 cases reported per year. The mean timing of disease activity was estimated by computing the centre of gravity of the distribution of cases and investigated whether synchrony exists between the three pathogens responsible for most cases of bacterial meningitis. They used country-level data from 66 countries, including from 47 countries outside the meningitis belt in sub-Saharan Africa. The finding was a detection of persistent seasonality in 49 (96%) of the 51 time-series from 38 countries eligible for inclusion in the wavelet analyses. The mean timing of disease activity had a latitudinal trend, with bacterial meningitis seasons peaking during the winter months in countries in both the northern and southern hemispheres. The three pathogens shared similar seasonality, but time-shifts differed slightly by country. On that note, it can be said that the study provided a key insight into the seasonal dynamics of bacterial meningitis and add to knowledge about the global epidemiology of meningitis and the host, environment, and pathogen characteristics driving these patterns. Comprehensive understanding of global seasonal trends in meningitis could be used to design more effective prevention and control strategies.

The incidence of meningococcal disease varies seasonally in both tropical and temperate countries. This association is most apparent in sub-Saharan Africa, where almost all epidemics start in the dry season and abate during the rains. Meningococcal carriage rates do not vary with season either in Africa or in temperate countries, suggesting that seasonal factors have little influence on the frequency of meningococcal transmission. It is suggested that changes in the ratio of clinical to subclinical cases of infection are more important than changes in the frequency of transmission in producing seasonal variations in the incidence of meningococcal disease. Some evidence to support this hypothesis was obtained during an epidemic of group A meningococcal disease in northern Nigeria in 1977-79 (Greenwood *et al.,* 1987).

At the national level, some researchers found that one of the best forecasting model was one that combined early cases and the average east-to-west wind strength in November and December. A similar model based on surface dust concentration performed equally well. However, forecasting meningitis outbreak has been a challenge at least over Nigeria and Africa at large. Pérez (2014), imagines these climate predictors could become part of the national health programs in the Sahel region. For example, if the early-season wind and dust levels are strong and the population is susceptible, then health officials might be able to plan ahead. "This could give more lead time for distributing vaccines to vulnerable districts," Pérez (2014) said. He believes some pilot studies would be the first step in sizing up how effective such a strategy would be. "If the models here can be validated, we'll have an additional tool to anticipate the next epidemic" (William, 2015) It was also reiterated that Bacterial meningitis, which is caused mainly by Neisseria meningitidis, Haemophilus *influenzae*, and *Streptococcus pneumoniae*, inflicts a substantial burden of disease worldwide. Yet, the temporal dynamics of this disease are poorly characterised and many questions remain about the ecology of the disease. So they aimed at comprehensively assessing seasonal trends in bacterial meningitis on a global scale. This was done by developing the first bacterial meningitis global database by compiling monthly incidence data as reported by country-level surveillance systems. Using country-level wavelet analysis, they identified whether a 12-month periodic component which is annual seasonality was detected in time-series that had at least 5 years of data with at least 40 cases reported per year. The mean timing of disease activity was estimated by computing the centre of gravity of the distribution of cases and investigated whether synchrony exists between the three pathogens responsible for most cases of bacterial meningitis.

Their findings after using country-level data from 66 countries, including from 47 countries outside the meningitis belt in sub-Saharan Africa was that a persistent seasonality was detected in 49 (96%) of the 51 time-series from 38 countries eligible for inclusion in the wavelet analyses. The mean timing of disease activity had a latitudinal trend, with bacterial meningitis seasons peaking during the winter months in countries in both the northern and southern hemispheres. The three pathogens shared similar seasonality, but time-shifts differed slightly by country. It can be interpreted that their findings provide key insight into the seasonal dynamics of bacterial meningitis and also adds to knowledge about the global epidemiology of meningitis and the host, environment, and pathogen characteristics driving these patterns. They suggested that comprehensive understanding of global seasonal trends in meningitis could be used to design more effective prevention and control strategies and to improve ability to predict epidemic.

Another study from the School of Public Health Minnesota, USA shows that bacterial meningitis cases vary by season and peak during the winter months around the world. Bacterial meningitis, which is highly fatal and caused by common bacterial infections like streptococcus, has an estimated 1.2 million cases annually. Interest in the seasonality of meningitis outbreaks stems from the previously observed annual dry season outbreaks of the disease occurring in the sub-Saharan area of Africa known as the “Meningitis Belt.” The analysis of the seasonal dynamics of meningitis across diverse geographic settings is the first step towards understanding what factors drive these trends,” The researchers believe their findings provide key insight into the global epidemiology of meningitis and can be used to develop hypotheses about the host, environment, and pathogen characteristics that may be driving these patterns. It was also argued that Comprehensive understanding of global seasonal trends in meningitis could be used to design more effective prevention and control strategies(Paireau *et al.,* 2016).

2.4 Causative Organism of Meningitis

According to Delaunay (2016), the most common organisms isolated from the respiratory tract and their significance Site of detection Organism Significance Nasal cavity *Staphylococcus aureus* -colonization of the nasal cavity occurs in about 30% of children and adults -this sometimes leads to impetigo in the nasal cavity, but otherwise is a benign condition, increases the risk of indwelling venous catheter or wound infections with *Staphylococcus aureus* a patient with colonization but no infection may require isolation if the organism is methicillin-resistant Oropharynx/ Group A *streptococcus* present in up to 20% of children, the bacteria that cause meningitis depends on the age of the patient, so, infants are commonly affected *by Streptococcus Pneumonia, Listeria, E. coli* and *Hemophilus influenza* but Meningococcus *(Neisseria meningitidis)* is the commonest causative organism in adolescents and middle aged individuals, while among elderly, *Streptococcus pneumonia* is the most common causative bacterial organism causing meningitis. Mycobacterium are also a causative of meningitis. Organisms that cause meningitis includes bacteria, fungi or viruses. Meningococcal meningitis, caused by *Neisseria meningitidis* bacteria, is of interest due to its potential to cause large epidemics. There are twelve (12) types of *N. meningitides*, called serogroups that have been identified, six of which are (A, B, C, W, X and Y) can cause epidemics. This disease is observed in a range of situations, from sporadic cases, little clusters, to large outbreaks throughout the world (WHO, 2000).

2.5 Types of Meningitis

2.5.1 Bacterial meningitis.

This type of meningitis is the most serious form of meningitis. Even with treatment, bacterial meningitis can be fatal most of the time. If bacterial meningitis progresses rapidly, in 24 hours or less, death may occur in more than half of those who develop it, even with proper medical treatment (Abatzoglou & Williams, 2016).

2.5.2 Viral meningitis

This is the most common but less serious form of meningitis. Enteroviruses are the most common viral cause of meningitis in the US. It is difficult to determining how many people get viral meningitis because it often remains undiagnosed and is easily confused with the flu. Its prognosis is much better than that for bacterial meningitis, with most people recovering completely with simple treatment of the symptoms. Because antibiotics do not help viral infections, they are not useful in the treatment of viral meningitis (CDC, 2016).

2.5.3 Fungal meningitis

This is a serious form of meningitis. It is normally limited to people with impaired immune systems. In 2012, fungal meningitis was linked to a contamination in a specific steroid product, methylprednisolone, manufactured in a single pharmacy and injected in the spine of people suffering from low back pain (CDC, 2014)

2.5.4 Aseptic meningitis

Aseptic meningitis is a term which refers to the broad category of meningitis that is not caused by bacteria. Approximately 50% of aseptic meningitis is due to viral infections. Other causes though less common include: drug reactions or allergies, and inflammatory diseases like lupus (CDC, 2016)

2.6 Spread of the Disease

The largest burden of meningococcal disease occurs in an area of sub-Saharan Africa known as the meningitis belt, which stretches from Senegal in the west to Ethiopia in the east (26 countries). During the dry season between December to June, dust winds, cold nights and upper respiratory tract infections combine to damage the nasopharyngeal mucosa which increases the risk of meningococcal disease. At the same time, transmission of *N. meningitidis* may be facilitated by overcrowded housing (Pandya, 2015). This combination of factors explains the large epidemics which occur during the dry season in the meningitis belt. (García *et al.,* 2014).

Epidemics in the meningitis belt were traditionally associated with *Neisseria meningitidis* serogroup A. However, the development and deployment of serogroup A meningococcal conjugate vaccine (MenAfriVac-A) in several countries within the meningitis belt of West Africa brought hope for the eradication of the disease in this region (NCDC, 2017). Unfortunately, progress was set back by the outbreak of serogroup C disease during the dry season of 2013 and 2014 in North Central (Niger) Nigeria, with more than 8,500 cases and 550 deaths. Since then, sequential outbreaks of type C strain occurred in 2014 and 2015 in North-Western Nigeria caused by sequence type (ST)-10217, which had not been previously identified elsewhere. The outbreak of serogroup C disease in two consecutive years from Nigeria suggests emergence of a new strain. Studies have shown that factors such as low socioeconomic status, climatic conditions, immunological susceptibility, migration and behavioural factors are risk factors for epidemic meningococcal disease.

The integrated Disease Surveillance and Response (IDSR) Technical Guidelines in Nigeria classify meningitis as one of the epidemic-prone diseases. Outbreaks of the disease are detected through the case-based surveillance strategy where cerebrospinal fluid sample is taken from each patient suspected of the disease. The recent 2017 outbreak in Nigeria during which 14,542 suspected cases were reported with total deaths of 1,166 Case Fatality Rate, (CFR = 8%) was predominantly due to *Neisseria meningitidis* Serogroup –C (NCDC, 2017).

Ayanlade *et al.* (2020), stated that because it is every so often problematic to explain the relationship and the effect of climate on the existence and distribution of disease, the effects of climate indices on the distributions weather related diseases like malaria and meningitis in Nigeria were evaluated over space and time. In the study, the purpose was to evaluate the relationships between climatic variables and the prevalence of malaria and meningitis, and also to develop an early warning system for predicting the prevalence of malaria and meningitis as the climate contrasts. They developed an early warning system to predetermine the months in a year that people are vulnerable to these diseases. The results showed in the Sahel, Sudan and Guinea, there was a strong relationship between temperature and meningitis with R2 > 60.0. The assessment supported the finding that the occurrence of meningitis is higher in the northern region, especially the Sahel and Sudan. Hence it was suggested that a thorough investigation of climate parameters is critical for the reallocation of clinical resources and infrastructures in economically underprivileged regions.

Molesworth *et al.* (2002), defined the meningitis belt as an area at risk of epidemic meningitis in Africa and also indicated that mapping an area at risk of epidemics of meningococcal meningitis in Africa has significant effects for their prevention and case treatment, through the targeted development of improved surveillance systems and control policies. He added that in the study, an area was described using information obtained from published and unpublished reports of meningitis epidemics between 1980 and 1999 and cases of meningococcal disease reported by surveillance systems to WHO. The Sahel he pointed bore the greatest epidemic burden, with over two-thirds of documented outbreaks and high attack rates. In addition to those already in the Meningitis Belt, countries affected included Guinea Bissau, Guinea, Côte d'Ivoire, Togo, the Central African Republic and Eritrea. Elsewhere epidemics were reported from a band of countries around the Rift Valley and Great Lakes regions extending as far south as Mozambique and from here west to Angola and Namibia in southern Africa. The cumulative pan-continental analysis provided evidence of an epidemic-susceptible area which extends beyond the region accepted as the Meningitis Belt and which, moreover, may be partially determined by the physical environment, as shown by a striking correspondence to the 300-1100mm mean annual rainfall isohyets.

Molesworth *et al.* (2002), in a study on the Environmental Risk and Meningitis Epidemics in Africa, discovered that Epidemics of meningococcal meningitis occur in areas with particular environmental characteristics. Evidence was presented that the relationship between the environment and the location of these epidemics is quantifiable of which a model was proposed based on environmental variables to identify regions at risk for meningitis epidemics. These findings, which had substantial implications for directing surveillance activities and health policy, provided a basis for monitoring the impact of climate variability and environmental change on epidemic occurrence in Africa. Climate and Meningitis in Africa is said that much about how and why the meningitis epidemics occur is unknown, but it is known that climate plays a key role. They stressed that the Meningitis Belt exists in the semi-arid zone between the dry Sahara Desert to the north, and the rain belt to the south. Having a better understanding of what drives the onset and spread of meningitis can mean the difference between life and death and that while meningitis can be prevented through vaccination, there aren't enough doses or enough workers to immunize everyone, so researchers are trying to predict when and where outbreaks will occur, which is one of the objectives this study seeks to find solutions to (Medical News Today, 2012).

2.7 Transmission of Meningitis Epidemic

Neisseria meningitidis infects only humans and is not traceable to animals. Bacterial and viral meningitis can be spread to others, however both viral and bacterial meningitis are not as contagious as colds or the flu. Transmission of meningitis requires close contact with respiratory droplets or throat secretions from carriers or saliva such as through kissing, sneezing, or coughing. Sharing drinks, utensils, or toothbrushes with an infected patient can also lead to transmission. Smoking, close and prolonged contact such as kissing, sneezing or coughing on someone, simply being in the same room with someone with meningitis is not enough to transmit the disease although living in close quarters with a carrier can enhance the spread of the disease. Transmission of *N. meningitidis* is enhanced during mass gatherings. The bacterium can be carried in the throat and sometimes overwhelms the body's defences allowing the bacterium to spread through the bloodstream to the brain. It is believed that 1% to 10% of the population carries *N. meningitidis* in their throat at any given time. However, the carriage rate may be higher (10% to 25%) in epidemic situations. Although the disease can affect anyone of any age, it mostly affects babies, toddlers and young people (WHO, 2017).

2.8 Symptoms of Meningitis

The average incubation period is four days, but can range between two and 10 days. The most common symptoms are a stiff neck, high fever, sensitivity to light, confusion, headaches and vomiting. In addition, in infants, bulging fontanels and ragdoll appearance are commonly found. A less common but even more severe (often fatal) form of meningococcal disease is meningococcal septicaemia, which is characterized by a haemorrhagic rash and rapid circulatory collapse. Even when the disease is diagnosed early and adequate treatment is started, about 8% to 15% of patients die, often within 24 to 48 hours after the onset of symptoms. If untreated, meningococcal meningitis is fatal in about 50% of cases and may result in brain damage, hearing loss or disability in about 10% to 20% of survivors (Leimkugel *et al.,* 2005).

2.9 Meningitis Diagnosis

Initial diagnosis of meningococcal meningitis can be made by clinical examination followed by a lumbar puncture showing a purulent spinal fluid. The bacteria can sometimes be seen in microscopic examinations of the spinal fluid. The diagnosis is supported or confirmed by growing the bacteria from specimens of spinal fluid or blood, by agglutination tests or by polymerase chain reaction (PCR). The identification of the serogroups and susceptibility testing to antibiotics are important to define control measures, (WHO, 2017)

Any person with a sudden onset of fever (>38.5̊C rectal or 38.0̊C axillary) and one of the following meningeal signs: neck stiffness, altered consciousness or other meningeal signs like Kerning's, Bruzinski, nuchal rigidity, raised intracranial pressure including bulging fontanel in toddlers are termed suspected case. Any suspected case with Cerebrospinal fluid (CSF) turbid, cloudy or purulent on visual inspection; or with a CSF leukocyte count >10 cells/mm^3 on doing a cell count or with bacteria identified by Gram Stain of CSF is categorized as probable meningitis case. In about 222 infants, CSF leucocyte count >100 cells/mm^3 or CSF leucocyte count 10–100 cells/mm^3 and either an elevated protein (>100 mg/dl) or decreased glucose (<40 mg/dl) level. Meningitis case is confirmed if any suspected or probable case that is laboratory confirmed by culturing or identifying (i.e. by polymerase chain reaction, immunochromatographic dipstick or latex agglutination) a bacterial pathogen (*Neisseria meningitidis, Streptococcus pneumoniae, Haemophilus influenzae type b*) in the Cerebrospinal Fluid (WHO, 2000).

2.10 Incubation Period

The incubation period of this disease depends on the causative agent. For example, the incubation period of meningococcal meningitis is 2-10 days while that of hemophilus meningitis is much shorter, this ranges from 2-4 days. However, the range of incubation for most organisms causing meningitis is 2 days to 2 weeks (WHO, 2017).

2.11 Surveillance

Surveillance, from case detection to investigation and laboratory confirmation is essential to the control of meningococcal meningitis. This should include detecting and confirmation of outbreaks, monitoring the incidence trends, including the distribution and evolution of meningococcal serogroups, to estimate the disease burden, monitor the antibiotic resistance profile, monitor the circulation, distribution and evolution of specific meningococcal strains (clones) and to estimate the impact of meningitis control strategies, particularly preventive vaccination programs.

Paireau *et al.* (2014), in a study in Togo revealed that by the end of the mass campaign, 67.3% of the target population in the region as a whole had been vaccinated, with 61% vaccinated in the Kpendjal district and 78% in the Oti district. There was an increase in the number of cases 2 weeks after the end of the mass vaccination campaign. This was attributed to the inadequate level of vaccination achieved. Only 52% of the urban population of Dapaong were vaccinated. The national surveillance system put out an alert early in the epidemic. The intervention was planned and adapted according to the progression of the epidemic, and national and international efforts were well coordinated. This emphasizes the importance of a rapid reaction from the surveillance system and of the choice of strategy for dealing with meningitis epidemics in sub-Sahelian Africa (CDC, 2016).

In Nigeria, during each epidemic season, States and Local Governments (LGAs) are expected to report CSM cases. The state epidemiologist, with support from NCDC must continue to monitor thresholds to assess attack rates since meningitis outbreak is yet to be predicted. During each meningitis season, LGAs with weekly attack rates or case counts below the alert thresholds (pre-alert phase), and LGAs in alert or epidemic phases continually collect, report, and analyse data to enable timely outbreak responses (NCDC, 2017).

2.12 Threshold by Population and Number of Cases

For Populations of 30,000–100,000 where attack rate of three suspected cases per 100,000 inhabitants in one week is reported it is in the alert threshold and also if in a population less than 30,000 there are two suspected cases in one week or increase in number of cases compared to previous non-epidemic years (CDC, 2015). It is in the epidemic threshold if in a population of 30,000–100,000, there is an attack rate of 10 suspected cases per 100,000 inhabitants in one week or in a population of less than 30,000 there are five suspected cases in one week doubling of number of cases over a three-week period (NCDC, 2017). The challenge with this is that intervention is given only when there are cases on ground. At this time, there might even be casualties but if there is a projection of the outbreak using climatic variables, early preparations be made and vaccines will be available before time rather than wait for casualties to emerge before help is sought for (NCDC, 2017).

2.13 Treatment for Meningitis

The treatment of the disease depends on the causative organism. When meningitis is first suspected, broad spectrum antibiotics is usually instituted depending on the age group of the patient. The essence is to cover for bacterial causes- as early treatment in such cases is vital. For instance, an infant should be started on Ampicillin and Cefotaxime plus Vancomycin while an older person should be started on Ceftriaxone plus Vancomycin. After the organism has been isolated from the CSF appropriate organism specific treatment should be instituted. Viral meningitis is treated supportively, and is not serious unless accompanied by encephalitis (Rashid *et al.*, 2015)

Meningococcal disease is fatal and is mostly regarded as an emergency where admission to a hospital or health centre becomes vital. While the patient is on admission, appropriate antibiotic treatment commences as soon as possible, this is preferred to be after the lumbar puncture has been carried out if such a puncture can be performed immediately. If treatment is started prior to the lumbar puncture it may be difficult to grow the bacteria from the spinal fluid and confirm the diagnosis. However, confirmation of the diagnosis should not delay treatment. A range of antibiotics can treat the infection, including penicillin, ampicillin and ceftriaxone. Under epidemic conditions in Africa in areas with limited health infrastructure and resources, ceftriaxone is the drug of choice. If viral meningitis is the case, treatment is usually less aggressive and consists of measures to make you more comfortable. Viral meningitis is often treated at home with acetaminophen (Tylenol) and other pain medications. Note that antibiotics are not helpful in treating viral meningitis (Swar, 2020)

If a patient has bacterial or fungal meningitis, they are often admitted to the intensive care unit, for either a short period of time for observation or a longer period when they are very ill. Care of bacterial meningitis begins by ensuring that the patients breathing and blood pressure is normal. An Intravenous (IV) line is inserted and antibiotics and fluids are given. Steroids may be given to try to decrease the severity of the disease. If the patient is extremely ill, more aggressive medical care may be given. A breathing tube (intubation) may be inserted to help with breathing if the patient is having difficulty breathing. Also, medications may be given to improve blood pressure and to stop seizures. A tube (catheter) may be placed in the bladder to check your hydration or fluid status (Pérez *et al.,* 2018).

2.14 Prevention of Meningitis

There are several ways of preventing meningitis but the most effective way to prevent meningitis is to get vaccinated against the disease. There are currently two vaccines available in the U.S. that protect against most types of bacterial meningitis. Getting vaccinated against meningitis at age 11 or 12, followed by a booster shot at age 16 to 18 this is because there is an increased risk of contracting meningitis between the ages of 16 and 21 and when living in close contact with others, such as in a college dormitory. Getting vaccinated against measles, mumps, rubella, and chickenpox can also help prevent diseases that can lead to viral meningitis (WHO, 2017).

Hayden *et al.* (2013), said since meningitis can be contracted when one comes in contact with respiratory or throat secretions like saliva, sputum and nasal mucus of someone who is infected, either through kissing or sharing personal items, it implies that the spread of the disease can be minimized by not sharing personal items where secretions can lurk, such as drinking glasses, water bottles, straws, glass or silver wares, toothbrushes, cigarettes, lipsticks or lip glosses. Although bacterial meningitis is not that easily transmittable but since it is found in nose and throat secretions, it can also spread through coughing and sneezing.

The Centre for Disease Control (2016), revealed that Vaccines available include: Serogroup B (Recombinant) Meningococcal Vaccines which offers a 3-year protection but do not induce herd immunity. Another type of vaccine is the Conjugate vaccines which are used in prevention (into routine immunization schedules and preventive campaigns) and outbreak response: This particular vaccine confers longer lasting immunity (5 years and more), it prevents carriage and induce herd immunity and can be used as soon as of one year of age.

Other available vaccines include, Monovalent C, Monovalent A, Tetravalent (sero groups A, C, Y, W). Also, Protein based vaccine, against *N. meningitidis B* has been introduced into the routine immunization schedule and used in outbreak response. Chemoprophylaxis is another kind of intervention where antibiotic prophylaxis for close contacts is given promptly, which can decrease the risk of transmission. Explaining further, CDC stated that outside the African meningitis belt, chemoprophylaxis is recommended for close contacts within the household. Suffice it to add that Ciprofloxacin antibiotic is the antibiotic of choice, and ceftriaxone an alternative.

The World Health Organization, (WHO, 2012) promotes a strategy comprising epidemic preparedness, prevention, and outbreak control. Preparedness focuses on surveillance, from case detection to investigation and laboratory confirmation. Prevention consists of vaccinating individuals from age groups at major risk using a conjugate vaccine targeting appropriate sero groups. Epidemic response consists of prompt and appropriate case management and reactive mass vaccination of populations not already protected through vaccination.

2.15 Eligibility for Meningitis Vaccine

WHO in 2012 noted that because of age or health conditions, some people should not get meningococcal vaccines or would have to wait before getting them if they have had a life-threatening allergic reaction after a previous dose of a meningococcal vaccine. Meningococcal conjugate vaccines may be given to pregnant women who are at increased risk for serogroup A, C, W, or Y meningococcal disease. Serogroup B meningococcal vaccines should only be given to pregnant or breastfeeding women who are at increased risk for serogroup B meningococcal disease who decide to take the vaccine at their own risk. People who have a mild illness, such as a cold, can probably get the vaccine. Those who are moderately or severely ill should probably wait until they recover.

According to Trotter *et al*. (2017), it is worthy of note that vaccines that help protect against meningococcal disease work well, but cannot prevent all cases. In a studies aimed at demonstrating the efficacy of meningococcal conjugate vaccines by CDC, the following was concluded: Menactra® in preteens and teens: Between 8 and 9 people out of every 10 vaccinated had a protective immune response one month after completing the series. In adults, between 7 and 9 people out of every 10 vaccinated had a protective immune response one month after completing the series. Menveo® in preteens and teens: Between 7 and 9 people out of every 10 vaccinated had a protective immune response one month after completing the series, while in adults, between 7 and 9 people out of every 10 vaccinated had a protective immune response one month after completing the series. In addition, for serogroup B meningococcal, vaccines showed that Besexero® in preteens, teens, and young adults, between 6 and 9 people out of every 10 vaccinated had a protective immune response one month after completing the series. Then Trumenba® in preteens, teens, and young adults, 8 people out of every 10 vaccinated had a protective immune response one month after completing the series.

Meningitis epidemics in the African meningitis belt constitute an enormous public health burden. In December 2010, a new meningococcal A conjugate vaccine was introduced in Africa through mass campaigns targeting persons 1 to 29 years of age. As of November 2017, more than 280 million persons have been vaccinated in 21 African belt countries. The vaccine is remarkably safe and cheap (around US$ 0.60 per dose while other meningococcal vaccine prices range from US$ 2.50 to US$ 117.00 per dose. In addition, its thermos ability allows its use under Controlled Temperature Chain (CTC) conditions. Its impact on carriage and the reduction in disease and epidemics is significant: a 58% decline in meningitis incidence and 60% decline in the risk of epidemics were described. It is now introduced into routine infant immunization. Maintaining high coverage is expected to eliminate meningococcal A epidemic from this region of Africa. However, other meningococcal serogroups such as W, X and C still cause epidemics and around 30 000 cases are reported each year in the meningitis belt (CDC, 2016)

The Nigerian Centre for Disease Control NCDC (2017) reiterated that Vaccination is one of the effective ways to protect against certain types of bacterial meningitis. There are vaccines for three types of bacteria that can cause meningitis; *Neisseria meningitides, Streptococcus pneumoniae and Haemophilus influenzae type-b (Hib).*

Currently in Nigeria, vaccines for *Streptococcus pneumoniae* (Pneumococcal Conjugate Vaccine: PCV) and *Haemophilus influenza type-b* (Pentavalent Vaccine) are available through the routine immunisation program for children under five years of age. However, vaccines for Neisseria meningitides (MenAfriVac-A, NeisVac-C and Conjugate ACWY Vaccine etc.) are only available through emergency request mechanisms from global stockpiles during outbreaks. The vaccines that protect against these bacteria are not 100% effective. The vaccines also do not protect against all the types (strains) of each bacterium. For these reasons, there is still a chance that bacterial meningitis can still be acquired even following vaccinations (NCDC, 2017).

2.16 Side Effects of Meningococcal Vaccines.

As it is with any medicine, including vaccines, there is a chance of side effects. Some are usually mild and go away on their own within a few days, but serious reactions are also possible. For Meningococcal Conjugate Vaccines, mild problems following this vaccination can include redness and pain where the shot was given or even a fever. It usually lasts for 1 or 2 days. For Serogroup B Meningococcal Vaccines, problems might include, Soreness, redness and swelling, feeling tired, headache, muscle or joint pain, fever or chills, nausea or diarrhoea. This can last up to 3 to 7 days (NCDC, 2017).

2.17 Inter-Tropical Discontinuity (ITD)

The ITD is the demarcation line between north eastern winds from the Sahara (hot, dry and dusty) and south western winds from Atlantic Ocean (cool and moist). The seasonal meridional oscillation of the ITD affects the characteristics of weather and climate over Nigeria (Nigerian Meteorological Agency, 2016). In 2010, the ITD was located at a mean position of latitude 7.9 ^{0}N in January. It oscillated northwards to reach its northernmost position of latitude 20.9 ^{0}N in August. Thereafter, the ITD began its southward movement to reach latitude 7.8 ^{0}N in December (Nigerian Meteorological Agency, 2011).

For instance, in 2011, the ITD was located at a mean position of 7.0 ^{0}N in January, implying about 50% of the country was above the ITD which is zone A and the characteristic feature is dry and dusty North-easterly winds. The seasonal meridional oscillation of the ITD affects the characteristics of weather and climate over Nigeria. In 2011, the ITD was located at a mean position of 7.0 ^{0}N in January, it then gradually moved northwards reaching its mean maximum position of latitude 18.6 ^{0}N in August. In September there was a rapid southward retreat of ITD, reaching a position of 7.6 ^{0}N in December. (Nigerian Climate Review Bulletin, 2011). The decadal movements and mean monthly positions of the ITD were, in most cases, above 4 ^{0}N but lagged behind long term conditions in April, and December periods. The above normal ITD positions in some cases could have been responsible for the extended rainfall into the month of October in some northern cities. (Nigerian Meteorological Agency, 2010).

The monthly anomaly of the ITD in 2016 showed that the latitudinal positions were more than 2.5 ^{0}N of its usual positions in February and March. This position brought earlier than normal rainfall to the country reaching as far as the northern cities of Gombe, Jalingo, Kaduna and Zaria in March. It was observed that the incursion of the mid latitude trough was responsible for this northward pull of the ITD. However, the ITD was more than 1.5 degrees south of its normal latitudinal positions from September to the year. This resulted in the early cessation of rains in most parts of the country especially in the North (Nigerian Meteorological Agency, 2016)

The position of the Inter-Tropical discontinuity (ITD), which is the meeting point of the dry north-easterly winds and the moist south-westerly in the first decade of January, was about 7.4 ^{0}N which was slightly below the normal, it progressively shifted northward above the normal by the second decade of January till April when it was below the normal. Its implication was evident in early rains over some parts of the country this year (Nigerian Meteorological Agency, 2017)

The latitudinal position of ITD in the first quarter of 2017 year was above the normal position up to a difference of about 3.6 ^{0}N in February which caused early rainfall especially over the southern parts. The ITD reached its peak in August at about 20.0 ^{0}N, although the last quarter of the year recorded latitudinal position that is below normal, which brought the Harmattan dust haze into the country and cessation of rains to most cities in the northern and central cities, however some cities in the northern and central region experienced precipitation in December.

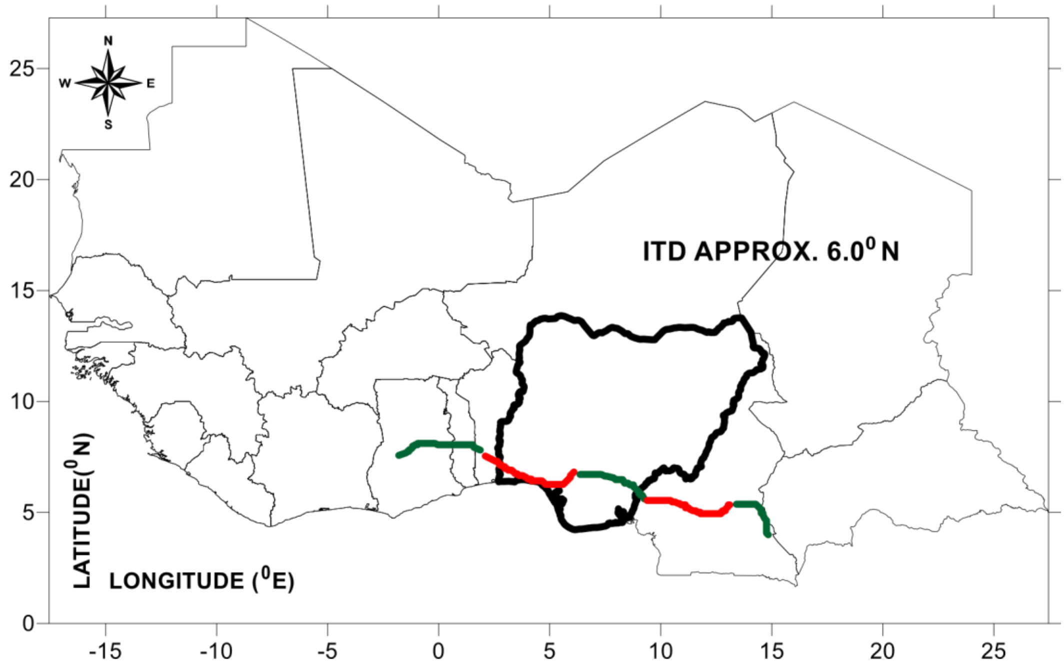

Figure 2.2: Position of the Inter tropical discontinuity

Source: Nigerian Meteorological Agency (NiMet, 2019)

This could to be attributed to the effect of extra tropical influences caused by incursion of mid-latitude trough into the country coupled with the effect of climate change experienced across the globe (Nigerian Meteorological Agency, 2017).

According to the Nigerian Meteorological Agency (2014), the ITD oscillates in pole ward – equator ward direction. It reaches its peak at about latitude 22 ^{0}N in August and lowest position at about latitude 04 ^{0}N in January/February. The position of the ITD at any point in time, plays an important role in determining the expected weather conditions over a particular region. This is so because of the established different zones at every point in time. These are Zone A, Zone B, Zone C and Zone D. Zone C may be further divided into Zone C_1 and C_2, where Zone C_1 is pole ward of C_2. Zone A is north of ITD and is characterized by dust haze. Zone B is south of the ITD and is associated with fine weather conditions as well as fair weather cumulus. Zone C on the other hand is mainly characterized by convective precipitation as well as thunderstorms. Finally, Zone D is associated with cloudy conditions and slight rains, which could be intermittent or sometimes continuous. One unique feature of Zone D is the occurrence of Little Dry Season (LDS) – short period of rainfall minimum, (Nigerian Meteorological Agency, 2016)

2.18 Relative Humidity

This is a ratio, expressed in percent, of the amount of atmospheric moisture present relative to the amount that would be present if the air were saturated. Since the latter amount is dependent on temperature, relative humidity is a function of both moisture content and temperature. Relative Humidity is derived from the associated Temperature and Dew Point for the indicated hour. Majority of adverse health effects caused by relative humidity can be minimized by maintaining indoor levels between 40% and 60%. To achieve this, it would require that the room be humidified during harmattan because humidification reduces exposure to low humidity which dries out and inflames the mucous membrane lining the respiratory tract, increasing the risk of colds, the flu, and other infections. Flu viruses survive longer, and spread more easily, when humidity levels are low (Koutangni *et al.,* 2018).

Relative humidity (RH) should be within certain limits for control of the aspect of health. Bacteria: 20% - 70%, Viruses: 40% - 80%, Fungi: 0% - 70%, Mites: 0% - 60%, respiratory infections require about 40% - 50% RH, Allergic Rhinitis and Asthma; 40% - 60% RH, Chemical interactions: 0% - 40% RH, Ozone production: 75% - 100% RH and 40 to 60% for Combined Health Conditions. In general, relative humidity for human comfort ranges between 30% and 60%. (CDC, 2014).

High humidity can have a negative effect on the human body because it makes air feel warmer and it can contribute to feelings of low energy and lethargy. In addition, hyperthermia**,** or over-heating as a result of your body's inability to effectively let out heat, can negatively impact your health in conditions of high humidity. Some health risks which result from overexposure to humidity (hyperthermia) include: dehydration, fatigue, muscle cramps, fainting, heat exhaustion and heat stroke. Thermal comfort can be achieved when relative humidity falls between 20 to 90%. Relative humidity between 40-70% does not have major impact on thermal comfort. Wind and radiation are influenced to a great extent by the immediate environment, for instance, sheltering effect of belts of trees reduces wind speed and solar radiation greatly affected by cloudiness. Temperature and humidity are less spatially variable and can give an indication of the general comfort level (Adefolalu, 1986).

2.19 Effect of Surface Pressure on Wind Pattern.

In its quarterly bulletin stated that the seasonal North to South movement of the tropical maritime winds from Atlantic Ocean, the tropical continental air mass from Northern Africa and the prevailing winds and surface pressure systems are the bases of Nigeria climates. The interaction between the two subtropical high pressure systems, namely; the Azores high pressure cell and the St. Helena high pressure cell both located at about latitude 30 ^{0}N and 30 ^{0}S respectively have great influence on the influx of moisture laden winds into the country from the Atlantic Ocean and the flow of dry and dusty winds from the Sahara Desert. The intensification of the Azores high pressure cell is prominent during the dry season (November to March) which leads to generation of strong surface winds that raises dust which are transported southward from the Sahara Desert to Nigeria causing harmattan dust haze while the intensification of the St. Helena high pressure cell favours the influx of moist southwesterly winds from the south Atlantic Ocean into the country that result in convective activities (NiMet, 2010).

Frequent outbreaks of meningitis during the dry season in sub-Saharan Africa may be related to wind-blown dust that inundates villages like this and causes respiratory and nasal problems among residents. RAL scientists have developed a prototype decision support system that integrates weather and health data to provide information that can be used to contain the spread of meningitis epidemics.

2.20 Temperature

The global temperature record represents an average over the entire surface of the planet. Temperatures experienced locally and in short periods can fluctuate significantly due to predictable cyclical events (night and day, summer and winter). The global temperature mainly depends on how much energy the planet receives from the Sun and how much it radiates back into space. The amount of energy radiated by the Earth depends significantly on the chemical composition of the atmosphere, particularly the amount of heat-trapping greenhouse gases. A one-degree *global* change is significant because it takes a vast amount of heat to warm all the oceans, atmosphere, and land by that much. (Nigerian Meteorological Agency, 2017)

The largest study to date of the potential temperature-related health impacts of climate change has shown that as global temperatures rise, the surge in death rates during hot weather outweighs any decrease in deaths in cold weather, with many regions facing sharp net increases in mortality rates (Anoruo and Okeke, 2020). Changes in the occurrence of extreme temperature events are also likely with predicted increases in more intense, frequent and longer duration episodes (heat waves) along with fewer colder episodes (IPCC, 2007). Meningitis outbreaks generally peak during periods of warm temperature, but more studies must have been conducted to affirm this correlation (Sawa and Buhari, 2011). Climate change has adverse consequences on human health as well as exacerbating health risks. Climate change is as certain as human death so long as population increases and economic activities generate gaseous wastes, thus resulting in the increase of anthropogenic carbon dioxide (CO_2). Society illusion implicated in climatic change amplifies health risks, and can increase morbidity rate to catastrophic levels. In the research, they addressed possible illusions on climatic risks and investigates health risks that could arise in Nigeria from climate change. Structured survey to elicit risk perception responses on health risks and climate change from health personnel in Nigeria and other citizens were employed. Testing the extent of relationship between climate change and morbidity rate and descriptive statistics on society illusion on climate change. This study found that there is prevailing illusion on climate change and there is significant evidence for increase in health risks and morbidity rate instantiated by climatic variability. Hence, an emergent health care strategy by government to respond to health risk pandemic caused by climate change should focus on malaria, meningitis, cholera, high blood pressure and pneumonia.

In 2010 as opined by NiMet, Mean Maximum Temperatures over the Country ranged between 31.1 ^{0}C – 42.6 ^{0}C during the warm Season. The highest temperature ranges of 40 ^{0}C – 42.6 ^{0}C was recorded over the Northeast and North-western Zone of the country while the hottest areas included Maiduguri, Potiskum, Sokoto, Nguru and Yola. The extreme Southern areas recorded temperature range of 30 ^{0}C – 35 ^{0}C, while other areas recorded temperature range of 35 ^{0}C – 40 ^{0}C. Extremely high temperatures in the range of 40 ^{0}C and above were recorded in some states especially in the northern part of the country in 2017. These high temperatures were mostly recorded in January to June. The highest temperature of 45.3 ^{0}C, 44.2^{0}C and 44.0 ^{0}C were recorded in Maiduguri, Yelwa and Nguru in April, March and May respectively. Other cities such as Sokoto and Yola, daily high temperatures of 43.0 ^{0}C and 43.5 ^{0}C were recorded respectively. Sokoto had the highest number of days with day time temperature equal to or above 40 ^{0}C. Nguru recorded these high temperatures in 64 days followed by Maiduguri with

56 days. Nguru and Yola experienced 54 and 52 days respectively of day-time temperatures in excess of 40 ^{0}C.

2.21 Health and Climate Change

Climate change refers to any significant change in the measures of weather elements such as temperature, rainfall, wind pattern etc. and lasting for an extended period of time. Climate change includes major changes in temperature, precipitation, or wind patterns, among other effects, that occur over several decades or longer, (IPCC Working Group 1 *et al*., 2013). Climate change has, and continues to influence the weather, the water cycle, weather extremes, and more –in Africa and throughout the world, (Wang *et al*., 2019). Earth's average temperature has risen by 1.5 ^{0}F (-16.9 ^{0}C) over the past century, and is projected to rise another 0.5 to 8.6 ^{0}F (-17.5 ^{0}C to -13 ^{0}C) over the next hundred years, (IPCC Working Group 1, 2013).

Rising global temperatures have been accompanied by changes in weather and climate. Small changes in the average temperature of the planet can translate to large and potentially dangerous shifts in climate and weather. Climate change represents a challenge to human health. The risks and impacts it poses on the capacity to respond varies considerably among communities. The baseline health status of a country of a community is the single largest determinant of the likely impact of climate change and the cost of adapting to it (World Health Organization, 2014).

One would ask "what is the link between the changing climate and human health?" The changing climate affects human health directly through extreme weather and climate events such as heat, storms and drought etc. it could be indirectly through changes that occur in the natural systems which in turn affects disease vectors and disease transmission. Environmental conditions such as baseline weather, soil, dust, and air and water quality also influence human health. Climate sensitive disease are a serious burden which the current focus of many countries. Warmer than normal temperatures and altered rain patterns have possibilities of lengthening the transmission season of some vector borne diseases like meningococcal meningitides. It could also alter their geographical range thus affecting regions that lack immunity to withstand the disease or even strong public health structure to absorb the pressure (WHO, 2014).

Adejuwon and Odekunle (2011), stated that climate change is a significant and emerging threat to human health, especially where infectious diseases are involved. Because of the multifaceted interactions between climate variables and components of infectious diseases (i.e., pathogen, host and transmission environment), systematically and quantitatively screening for infectious diseases that are sensitive to climate change is still a challenge. To address this, a new statistical indicator was proposed, Relative Sensitivity, to identify the difference between the sensitivity of the infectious disease to climate variables for two different climate statuses (i.e., historical climate and present climate) in non-exposure and exposure groups. The case study in Anhui Province, China has demonstrated the effectiveness of this Relative Sensitivity indicator. The application results indicate significant sensitivity of many epidemic infectious diseases to climate change in the form of changing climatic variables, such as temperature, precipitation and absolute humidity. As novel evidence, this research showed that absolute humidity has a critical influence on many observed infectious diseases in Anhui Province, including dysentery, hand, foot and mouth disease, hepatitis A, haemorrhagic fever, typhoid fever, malaria, meningitis, influenza and schistosomiasis. Moreover, some infectious diseases are more sensitive to climate change in rural areas than in urban areas. This insight provides guidance for future health inputs that consider spatial variability in response to climate change (Wang *et al.,* 2019).

Human activities have several direct and indirect impacts on health. In Nigeria, the impacts of climate change are more overwhelming due to their susceptibility and low coping capability. Studies on the impacts of climate change on health risks in Nigeria are scare. With this rationale, this study investigates the effects of climate change on health risks in Nigeria. Evidence abounds that climate change impacts in Nigeria arise from climate change-related causes such as increase in temperature, rainfall, sea level rise, extreme weather events and, especially, increased health risks. Health risks such as cerebra-spinal meningitis, cardiovascular respiratory disorder of elderly, skin cancer, malaria, high blood pressure and morbidity were identified as the direct consequences of climate change. The study concluded that government should raise awareness on adverse effects of climate change which is common among vulnerable groups, like women, children and rural dwellers in Nigeria (Femi, 2019).

2.22 Impact of Climate Change on Children.

There may be no greater increasing threat facing children globally and generations after them than the changing climate. WHO (2014) revealed that there are about 2.3 billion children in the world representing about 30% of the world's population and this number is on the increase. This makes children the largest group affected by climate change. Children are more vulnerable than adults to its harmful effect. Changes in temperatures and relative humidity have direct impact on meningococcal meningitis being a climate sensitive disease being caused by interjections favoured by hot, dry and dusty conditions. Also, exposure to high concentration of air pollutants such as carbon monoxide or particulate matter may be linked to meningitis.

The impact of climate change and global warming are worldwide and global concern. Nigeria, sadly is home to many infectious diseases. Climate change related events like temperature, rainfall, humidity etc. have direct and indirect adverse impacts on the outbreak of infectious disease among children. During the 2017/2018 meningitis outbreak, there were three hundred and three (303) number of reported cases with four (4) deaths in children less than 4 years. 46 deaths in children between 1-4 years. 5-14 years recorded 180 deaths and 19 deaths for above 30 years (WHO, 2014).

Climatic variables are of great influence to human health. Climate and weather are important components of the ecosystem because climate as constrains the range of infectious diseases whereas weather affects the timing and intensity of outbreaks. Climate can influence pathogens, vectors, hosts defences and habitation (William, 2014). Cerebrospinal meningitis (CSM) is partly weather stress disease and it shows a markedly seasonal character. They in viable begin with drier and cold weather towards the end of November and reach its peak in March and April then subside rapidly in May at the onset of rainy season.

Ceccato *et al.* (2014), revealed that during meningitis outbreak, partners focus mainly on case management and vaccination, little effort is put into dissemination of preventive messages and early detection and this gap contributes to worsening of the spread of the outbreak. Lack of this information coupled with infected persons due to overcrowding or minimal ventilation mainly caused the highest number of cases in children. The group stressed that high temperatures, extremely dusty winds and low relative humidity were contributory factors. Until meningitis outbreak is properly predicted, awareness raising campaigns are highly new to improve community awareness, case detection and referrals (WHO, 2017). Mechanisms responsible for the observed patterns of CSM outbreaks were still not clearly identified. In Mali, a West African country, there was a comparison between the information on cases and deaths due to meningitis from World Health Organization's weekly reports with atmospheric datasets. The relationship between the seasonal occurrence of meningitis, and largescale atmospheric circulation was qualified. Regional atmospheric indexes based on surface wind speed show a clear link between population dynamics of the disease and climate: the onset of epidemics and the winter maximum defined by the atmospheric index share the same mean week (sixth week of the year; standard deviation, 2 weeks) and are highly correlated. Therefore, there was a clear quantitative demonstration of the connections that exist between meningitis epidemics and regional climate variability in Africa. Moreover, this statistically robust explanation of the meningitis dynamics enables the development of an Early Warning Index for meningitis epidemic onset in West Africa. The development of such an index was suggested as it is believed to help nationwide and international public health institutions and policy makers to better control meningitis disease within the so-called westward-eastward Pan-African Meningitis Belt (Sultan *et al.,* 2005)

The composition of inhaled air varies from region to region and may include harmful particles, such as particulate matter, bacteria, fungi, and viruses. There are several types of blowing dust events that can be characterized by physical observations, including the source of dust, the direction of the wind, the density of the particulate matter, and several other physical parameters. All blowing dust events have the potential to cause adverse health effects. Inhalation of dust can cause direct respiratory effects that range from transient cough to acute fungal infection to acute respiratory failure (Reed and Nugent, 2018).

Improving the prevention and control of meningitis epidemics is the focus of numerous research projects in Africa and internationally. Under a collaborative partnership initiative known as Meningitis Environmental Risk Information Technologies 'MERIT' constituted by WHO, WMO, the International Research Institute for Climate and Society and other leaders within the environmental and public health communities, research projects have been designed and developed to respond directly to public health questions and priorities (WMO, 2012). The combined output of operational research activities is being assessed to determine the effectiveness of predictive models in strengthening the public health strategy. For example, the expected probability of an epidemic occurring based on climatic and environmental factors combined with epidemiological spatio-temporal models at the district level, may in the future help public health officials respond to potential outbreaks. The climate service in support of the public health officials in meningitis affected countries, should supply forecasts of the likely duration and end of the dry season and update these with any pertinent meteorological forecasts (World Health Organization, 2011).

There is a clear seasonal pattern of meningitis cases that corresponds to the period of the year when there are increases in dust concentrations as well as reductions in humidity levels linked to the movement of the Inter Tropical Convergence Zone. While the temporal association between climate and meningitis is evident, what triggers or ends an epidemic is as yet unknown. One hypothesis is that dry, hot and dusty air irritates the respiratory mucosa thus facilitating invasion of the bacteria.

Woringer *et al.* (2018), in a study on Atmospheric Dust, Early Cases, and Localized Meningitis Epidemics in the African Meningitis Belt: An Analysis Using High Spatial Resolution Data, compiled weekly reported cases of suspected bacterial meningitis at the Health Centre's resolution for 14 districts of Burkina Faso for the period 2004-2014. Using logistic regression, they evaluated the association of epidemic HC-weeks with atmospheric dust [approximated by the Aerosol Optical Thickness (AOT) satellite product] and with the observation of early meningitis cases during October-December. Results showed that although Aerosol Optical Thickness was strongly associated with epidemic HC-weeks in crude analyses across all HC weeks during the meningitis season [odds ratio (OR); 95% CI: 4.90, 9.50], the association was no longer apparent when controlling for calendar week (OR; 95% CI: 0.60, 1.50). The number of early meningitis cases reported during October-December was associated with epidemic HC-weeks in the same HC catchment area during January-May of the following year (OR for each additional early case; 95% CI: 1.06, 1.21). In conclusion, over Burkina Faso, spatial variations of atmospheric dust load do not seem to be a factor in the occurrence of localized meningitis epidemics, and the factor triggering them remains to be identified. The pathophysiological mechanism linking early cases to localized epidemics is not understood, but their occurrence and number of early cases could be an indicator for epidemic risk. Could this be same for Nigeria?

Koutangni *et al.* (2019), in a study "Compartmental models for seasonal hyperendemic bacterial meningitis in the African meningitis belt", suggested that the pathophysiological mechanisms underlying the seasonal dynamic and epidemic occurrence of bacterial meningitis in the African meningitis belt remain unknown. Regular seasonality (seasonal hyperendemicity) is observed for both meningococcal and pneumococcal meningitis and understanding this is critical for better prevention and modelling. The two principal hypotheses for hyper-endemicity during the dry season imply (1) an increased risk of invasive disease given asymptomatic carriage of meningococci and pneumococci; or (2) an increased transmission of these bacteria from carriers and ill individuals. In this study, they formulated three compartmental deterministic models of seasonal hyperendemicity, featuring one (model1-'inv' or model2-'transm'), or a combination (model3-'inv-transm') of the two hypotheses. The models were parameterized based on current knowledge on meningococcal and pneumococcal biology and pathophysiology. The three models' performance were compared in reproducing weekly incidences of suspected cases of acute bacterial meningitis reported by health centres in Burkina Faso during 2004–2010, through the meningitis surveillance system. The three models performed well (coefficient of determination R^2, 0.72, 0.86 and 0.87, respectively). Model2-'transm' and model3'inv-transm' better captured the amplitude of the seasonal incidence. However, model2-'transm' required a higher constant invasion rate for a similar average baseline transmission rate.

The results suggest that a combination of seasonal changes of the risk of invasive disease and carriage transmission is involved in the hyper endemic seasonality of bacterial meningitis in the African meningitis belt. Consequently, both interventions reducing the risk of nasopharyngeal invasion and the bacteria transmission, especially during the dry season are believed to be needed to limit the recurrent seasonality of bacterial meningitis in the meningitis belt. Epidemics of meningococcal meningitis in Africa have plagued the continent for over a century. These epidemics have a strong association with the environment and efforts are being made to develop models to predict both their location and their incidence. This review describes the predictive models based on climate/environmental information currently available, describes work in progress, and presents evidence that the distribution of the epidemics is changing in a pattern that is compatible with changes in the environment (Barry and Annesi-Maesano, 2017).

Markus (2012), while studying the influence of weather elements on the Occurrence of some common diseases in Kafanchan, Kaduna state, he assessed critical elements of weather such as rainfall, temperature and relative humidity on how they influence diseases. Although medical science has made remarkable progress in fighting diseases through modern technology, the health of the human population is still influenced to a great extent by weather and climate. The study determined the role weather elements play in diseases outbreak and transmission. The objectives of the study are to identify weather induced common diseases in Kafanchan, assess the nature of the relationship between common diseases and weather elements responsible for them and to examine the seasonality of common diseases in the study area. The methodology used in this research involved the collection of monthly data of temperature (minimum and maximum), rainfall and relative humidity for 10 years (1999 to 2008) in Kafanchan from the Water Board of the same town. Medical records of the diseases: malaria, typhoid, meningitis, measles, diarrhoea, cough, pneumonia and cholera were obtained from three hospitals using purposive sampling method based on their spatial spread within the study area and the duration of their existence, if up to 10 years and availability of records. These diseases are among the common diseases in Kafanchan. Correlation and Regression analysis statistic were used to assess relationship between weather elements (rainfall, temperature and relative humidity) of Kafanchan and the occurrence of common diseases. ANOVA was used to find out if there is significant difference in the seasonality of occurrences of the common diseases. The Pearson Product Moment Correlation Coefficient and stepwise and enter methods of Regression Analysis were used. The descriptive statistics indicated that malaria and typhoid have the highest number of frequency of occurrence in all the variables. According to the Professional Nurses Journal, October 2001, Meningitis is more likely in childhood than at any other age and there an estimated 1,600 cases per year in England and Wales in children under the age of five years.

Despite much progress in surveillance and biological research, there seem to be no explanation for the epidemic pattern of meningitis in the African meningitis belt, which is required to mathematically model the impact of vaccine strategies or to predict epidemics. A hypothetical explanatory model for epidemic meningococcal meningitis was initiated. Four incidence patterns were defined as model states, including endemic incidence during the rainy season, ubiquitous hyper endemicity during the dry season, occasional localized epidemics, and–at the regional level– regular epidemic waves traversing over communities or years. While the transition from endemic to hyper endemic situation in a community is caused by an increase in risk of meningitis given colonization by a virulent meningococcus (due to damage of the pharyngeal mucosa by dry climate), the transition from hyper endemic to epidemic situation involves increased pharyngeal colonization and transmission which is maybe caused by viral respiratory infection epidemics. The described mechanisms are sufficient to explain the 10- to 100-fold incidence increase that both transitions usually imply. Epidemic waves occur if new meningococcal strains which escape pre-existing immunity, enter the population. Future research should include the impact of viral co-infection on bacterial colonization and invasion (Woringer et al, 2018)

2.23 Meningitis and Climatic Variables

Chowdhury *et al.* (2018) while studying the association between temperature, rainfall and humidity with common climate-sensitive infectious diseases in Bangladesh noted that Bangladesh is one of the world's most vulnerable countries for climate change, hence the observational study examined the association of temperature, humidity and rainfall with six common climate-sensitive infectious diseases in adults which includes malaria, diarrheal disease, enteric fever, encephalitis, pneumonia and bacterial meningitis in north-eastern Bangladesh. Patients admitted in the hospital adult ward from 2008 to 2012 with a diagnosis of one of the six chosen climate sensitive infectious diseases were enrolled in the study.

During the study, climate related data were collected from the Bangladesh Meteorological Institute and disease incidence analysed against mean temperature, relative humidity and average rainfall for the Sylhet region in Bangladesh. In the study, statistical significance was determined using Mann-Whitney test, Chi-square test and ANOVA testing. About 5,033 patients were enrolled where 58% were male and 42%, female in the ratio 1.3:1. All six diseases showed highly significant where $p = 0.01$. Rises in incidence between the study years 2008 with 540 cases and 2012 with about 1330 cases, compared with no significant rise in overall all-cause hospital admissions in the same period *($P = 0.19$).* The highest number of malaria cases were 135, diarrhoea, 266 and pneumonia, 371 cases occurred during the rainy season. On the other hand, the maximum number of enteric fever was 408; encephalitis, 183 and meningitis, 151 cases occurred during autumn, which follows the rainy season. A positive *($P = 0.01$)* correlation was observed between increased temperature and the incidence of malaria, enteric fever and diarrhoea, and a negative correlation with encephalitis, meningitis and pneumonia. Higher humidity correlated *($P = 0.01$)* with a higher number of cases of malaria and diarrhoea, but for meningitis and encephalitis, Relative humidity was inversely correlated. Higher incidences of encephalitis and meningitis occurred while there was low rainfall. Incidences of diarrhoea, malaria and enteric fever, increased with rainfall, and then gradually decreased. The findings in this study supports a relationship between weather patterns and disease incidence, and provide essential reference point for future research.

Broman *et al.* (2014), investigated the Spatiotemporal Variability and Predictability of Relative Humidity over West African Monsoon Region. A K-means cluster analysis was performed to identify spatially coherent regions of relative humidity variability during the two periods. The cluster average of the relative humidity provides a robust representative index of the strength and timing of the transition periods between the dry and wet periods. Correlating the cluster indices with largescale circulation and sea surface temperatures indicates that the land–ocean temperature gradient and the corresponding circulation, tropical Atlantic sea surface temperatures (SSTs), and to a somewhat lesser extent tropical Pacific SSTs all play a role in modulating the timing of the monsoon season relative humidity onset and retreat. These connections to large-scale climate features were also found to be persistent over inter seasonal time scales, and thus best linear predictive models were developed to enable skilful forecasts of relative humidity during the two periods at 15 to 75-day lead times. The public health risks due to meningitis epidemics are of grave concern to the population in this region, and these risks are strongly tied to regional humidity levels. Because of this linkage, the understanding and predictability of relative humidity variability is of use in meningitis epidemic risk mitigation, which motivated this research.

This study covered the historical background of meningococcal meningitis in Africa since the menace of the disease was first revealed around 100 years ago. It is conceivable that a scourge strain of the *meningococcus* was brought into West Africa from the Sudan by travellers coming back from the Haj around the end of the century. Since 1905 significant pandemics of meningococcal meningitis have occurred in nations of the Sahel and sub-Sahel at regular intervals, finishing in colossal pestilence in which about 200 000 cases were accounted for in 1996. Efforts to control the plague of meningococcal meningitis in Africa by immunization with meningococcal polysaccharide antibodies have met with just unassuming achievement since pandemics can spread with incredible speed and vaccination is often started late. This circumstance ought to be improved because of an ongoing initiative by the International Coordinating Group (ICG), which is adding to better reconnaissance in countries that are in danger and guaranteeing that antibody is accessible when required. Be that as it may, in the medium term, the best prospect for the control of meningococcal meningitis in Africa lies in the recent development of polysaccharide protein conjugate vaccines which, unlike polysaccharide vaccines, are immunogenic in the very young, induce immunological memory and are likely to give long-lasting protection.

Spatial and temporal variability of relative humidity over the West African monsoon (WAM) region was investigated by (Broman et al., 2014) in the American Meteorological Society journal, in particular, the variability during the onset and retreat periods of the monsoon was considered. A K-means cluster analysis was performed to identify spatially coherent regions of relative humidity variability during the two periods. The cluster average of the relative humidity provides a robust representative index of the strength and timing of the transition periods between the dry and wet periods. The cluster indices were correlated with large-scale circulation and sea surface temperatures indicates that the land-ocean temperature gradient and the corresponding circulation, tropical Atlantic sea surface temperatures (SSTs), and to a somewhat lesser extent tropical Pacific SSTs all play a role in modulating the timing of the monsoon season relative humidity onset and retreat.

Relative Humidity Forecast was used to manage Meningitis in the Sahel. It was mentioned that Meningitis epidemics in the Sahel occur quasi-regularly and with devastating impact. In 2008, for example, eighty-eight thousand people contracted meningitis and over five thousand died and until very recently, the protection provided by the only available vaccine was so limited and short-lived that the only practical strategy for vaccination was reactive like waiting until an epidemic occurred in the region before vaccination in that region to prevent the epidemic's further growth. They confirmed that even with that strategy, there were still times when demand outpaced available vaccine. While a new vaccine has recently been developed that is effective and inexpensive enough to be used more largely and proactively, it is only effective against the strain of bacteria that causes the most common kind of bacterial meningitis, not all kinds. As a result, there will likely be continued need for reactive vaccination strategies. It is generally known that meningitis epidemics in the Sahel occur only in the dry season, hence their project investigated the relationship between meningitis and relative humidity and several independent lines of evidence demonstrate a robust relationship between the onset of the rainy season, as marked by weekly average relative humidity above 40%, and the end of meningitis epidemics.

These lines of evidence they said include statistical analysis of two years of weekly meningitis and weather data across the Sahel, cross-correlation of ten years of meningitis and weather data in the Upper East region of northern Ghana, and high resolution weather simulations of past meningitis seasons to interpolate available weather data. They also adapted two techniques that have been successfully used in public health studies which are the generalized additive models that have been used to relate air quality and health, and a linearized version of the compartmental epidemics model that has been used to understand MRSA. Based on these multiple lines of evidence, average weekly relative humidity forecast two weeks in advance appears consistently and strongly related to the number cases of meningitis in the Sahel. They suggested that using available forecast models contributed through the WMO Thorpex-Tigge project, however the model is not available anymore and applying quantile regression to enhance their accuracy, it will be possible to forecast the average weekly relative humidity to two weeks in advance which allows us to anticipate the end of an epidemic in a region of the Sahel up to four weeks in advance. This they pointed out would allow public health officials to deploy vaccines to areas in which the epidemics are likely to persist due to continued dryness and avoid vaccinating in areas where the epidemics will end with higher humidity. They concluded their study by introducing the relative humidity decision-information tool developed for use by public-health officials. In addition, they intended to summarize the results of a weekly meningitis forecast exercise held during the 2011-2012 dry season with public health decision makers from several African countries and the World Health Organization. In conclusion, the study highlighted some results of concurrent socio-economic research that suggests other interventions for managing meningitis and helps quantify the economic impact of the disease in Ghana. Generally, while their research had demonstrated an actionable relationship between weather and disease, this relationship they say is only one factor in a complex and coupled human-natural system which merits continued investigation. Based on this assertion, this study decided to look out for other climatic variables in addition to relative humidity.

Meningococcal meningitis is a climate sensitive infectious disease. The regional extent of the Meningitis Belt in Africa, where the majority of epidemics occur, was originally defined by Lapeysonnie in the 1960’s. A combination of climatic and environmental conditions and biological and social factors have been associated to the spatial and temporal patterns of epidemics observed since the disease first emerged in West Africa over a century ago. However, there is still a lack of knowledge and data that would allow disentangling the relative effects of the diverse risk factors upon epidemics.

The Meningitis Environmental Risk Information Technologies Initiative (MERIT), a collaborative research-to-practice consortium, seeks to inform national and regional prevention and control strategies across the African Meningitis Belt through the provision of new data and tools that better determine risk factors. In particular MERIT seeks to consolidate a body of knowledge that provides evidence of the contribution of climatic and environmental factors to seasonal and year-to-year variations in meningococcal meningitis incidence at both district and national scales. Here we review recent research and practice seeking to provide useful information for the epidemic response strategy of National Ministries of Health in the Meningitis Belt of Africa. The research and derived tools described by MERIT focused at “getting science into policy and practice” by engaging with practitioner communities under the umbrella of MERIT to ensure the relevance of their work to operational decision making. We limit our focus to that of reactive vaccination for meningococcal meningitis. Important but external to our discussion is the development and implementation of the new conjugate vaccine, which specifically targets meningococcal A. (García-Pando *et al.*, 2014) .

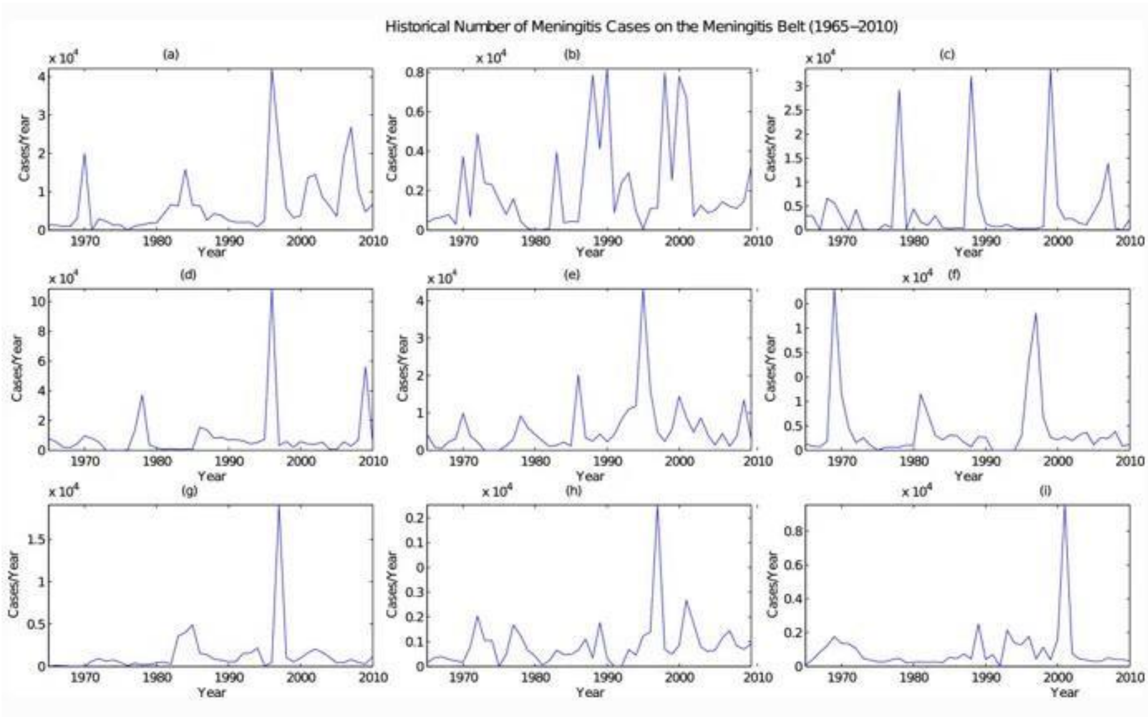

Figure 2.3: Time series of number of meningitis cases between 1965 and 2010 in

(a) Burkina Faso, (b) Chad, (c) Sudan, (d) Nigeria, (e) Niger, (f) Mali. (g) Ghana,

(h) Togo, and (i) Benin.

Source: WHO (2017)

The emergence and spread of meningococcal meningitis in the Meningitis belt of Africa has been shown frequently in research to have links to weather and climate (Pandya *et al,* 2015); However, onset of the disease also depends on intricate interaction of environmental, economic, and sociological factors, as well as patterns, causes, and effects of health and disease conditions often called epidemiological factors. To precisely predict the onset of meningitis, therefore, researchers and others cannot look at the environmental factors of weather and climate in isolation, but rather must investigate a confluence of interrelated factors known to contribute to onset including smoke from fires, agriculture burning, or indoor cooking. There is also divergent proneness to the disease based on age, poverty, and access to health care; and adaptive capacity such as education about the disease's symptoms and the importance of early intervention and hospitalization. Socio-economic factors that may also contribute to the disease's onset include external drivers such as climate change, El Nino influences, and patterns of human migration. In contrast, substantial evidence exists that shows environmental conditions, like Relative Humidity (RH), can be used to determine the end of a meningitis outbreak. In effect, when relative humidity reaches 40 percent, various research work steadily shows a positive correlation beckoning the end of meningitis outbreaks following periods of high temperatures, high humidity, and the beginning of the rainy season and African monsoon, (IRI, 2011)

Molesworth *et al.* (2002), interestingly noted that being outside the meningitis belt does not mean an absence of meningitis because in the last decades, some African countries south of the belt have experienced large meningitis epidemics and there has been an extension of the belt into countries like Togo, Cameroon, Côte d'Ivoire and Benin. This revelation informed the inclusion of the southern Savanna in Nigeria to ascertain what other factors are responsible for outbreak of meningitis in region with ample amount of rainfall and humidity, that is if the statement hold water.

Abdussalam *et al.* (2014) in a study on the Climate Influences on Meningitis Incidence in Northwest stated that Northwest Nigeria is a region with a high threat of meningitis. In his study, the influence of climate on monthly meningitis incidence was examined where monthly counts of clinically diagnosed hospital-reported cases of meningitis were collected from three hospitals in northwest Nigeria for the 22-yr period spanning 1990–2011. Generalized additive models and generalized linear models were fitted to accumulated monthly meningitis counts. Other variables included monthly time series of maximum and minimum temperature, humidity, rainfall, wind speed, sunshine, and dustiness from weather stations nearest to the hospitals, and the number of cases in the previous month. The effects of other unobserved seasonally varying climatic and non-climatic risk factors that may be related to the disease were collectively accounted for as a flexible monthly varying smooth function of time in the generalized additive models. Results reveal that the most important explanatory climatic variables are the monthly means of daily maximum temperature, relative humidity, and sunshine with no lag; and dustiness with a 1-month lag. Accounting for $s(t)$ in the generalized additive models explains more of the monthly variability of meningitis compared to those generalized linear models that do not account for the unobserved factors that $s\ (t)$ represents. The skill score statistics of a model version with all explanatory variables lagged by 1 month suggest the potential to predict meningitis cases in northwest Nigeria up to a month in advance to aid decision makers.

CHAPTER THREE

3.0 MATERIALS AND METHODS

3.1 Types and Sources of Data.

Secondary data were used for this research because the data collection had been done by various institutions of interest such as the Federal Ministry of Health (FMoH), Federal Medical Centres (FMC), Primary Health Care centres (PHC), Nigerian Centre for Disease and control (NCDC), International research institute for climate and society (IRI), Bureau of Statistics and National Oceanic and Atmospheric Administration (NOAA).

Data on climatic variables were sourced online for the period of twelve years from 2008 to 2019 for twelve (12) states within the country via data base of NOAA, International research institute for climate and society (IRI). These variables were Maximum Temperature, Mean air temperature, Relative Humidity, Rainfall amount and wind speed. The choice of twelve years was due to the limited availability of meningitis data. Cases of Meningitis were collected from the Nigerian Centre for Disease control (NCDC) and Bureau of statistics for a period of twelve (12) years for twelve (12) states within the country. Also, field work was embarked on to ascertain credibility of data collected.

3.2 Methods of Data Collection

Basically, secondary data were used for this research. Data on climatic variables from

2008 to 2019 were collected and collated. Data were also gotten from World Meteorological Organization (WMO), International research institute for climate and society (IRI), Bureau of Statistics and National Oceanic and Atmospheric Administration (NOAA). Daily meningitis cases for corresponding stations were gathered from the World Health Organization (WHO), Federal ministry of Health, Federal Medical Centres, Public health centres, Nigerian Centre for Disease and control and Bureau of statistics. The data was aggregated to weekly.

3.3 Sampling Frame

Sampling which is a subset of a selected population is an unbiased representative of the larger population. Studying the entire population of the three geographical zones might be cumbersome hence the need for sampling. This ensured that the sample group was a representative of the larger population without error. In this study, for number of reported cases of meningitis, everyone with suspected case of cerebrospinal meningitis be it a child or an adult; both male and female were eligible. Meningitis variables and climatic variables were collected from four (4) states each from each geographical zone. This served as a representation of the regions.

3.4 Research Instruments.

Basically, for the purpose of this research, secondary data were used from medical records from Primary health care centres, Federal ministry of health, general hospitals and federal medical centres and climatic variables sourced from the online platforms. Also from journals and publications, data collected by individual organizations which associated with qualitative databases. Field work was embarked upon as well.

3.5 Method of Data Analysis.

Models, based on biological properties of disease transmission dynamics or on statistical associations between environmental variables and health outcomes, are being increasingly used to gain insights into how climate change could affect future patterns of climate-sensitive health outcomes.

Models range from simple, i.e. considering only one key variable that will change with climate change, such as temperature extremes, to fully integrated models that incorporate all known processes of significance (WHO, 2017)

Climatic variables from 2008 to 2019, meningitis cases were computed and analysed. Also, the impact of climatic risks factors such as maximum temperature, mean air temperature, wind speed and relative humidity on Meningitis occurrence in the study area was assessed.

3.5.1 **Objective one**

To examine the trend in spatio-temporal occurrence of meningitis in Sudano- Sahelian and Guinea Savanna zones of Nigeria. Weekly Moving Averages of meningitis cases and afore mentioned climatic variables were used to aggregate daily data to weekly and presented in form of spatial maps.

3.5.2 Objective two

To investigate whether there is a relationship between Climatic variables (relative humidity, rainfall, temperature and wind speed) and meningitis occurrence in the study areas by using Pearson's product moment correlation *(r)* where:

$$\boldsymbol{r} = \frac{n\sum xy-(\sum x)(y)}{\sqrt{n(\sum x^2\ )-(\sum x)2}\sqrt{n(\sum x^2\ )-(\sum x)2}} \qquad \textit{(1)}$$

The quantity *r*, called the Pearson's correlation *(r)*, measures the statistical association or relationship between two continuous variables.

x = values of the independent variable which are the climatic variables (relative humidity, maximum temperature, mean air temperatures, wind speed and rainfall) y = values of the mean of the dependent variable which is Meningitis cases

$\sum x$ = Sum of individual climatic variable

$\sum y$ = Sum of Meningitis cases

$\sum x^2$ = Sum of square of each climatic variable.

$\sum y^2$ = Sum of square of meningitis n=
Number of pairs of variables

3.5.3 Objective three

To analyze the impact of the climatic variables on Meningitis occurrence in the study areas.

Multivariate Multiple Regression Analysis was used as a tool in analysing the impact of the independent variables using the correlation coefficient which measures the strength of relationship between two variables. The strength of the relationship between meningitis occurrence which is the dependable variable and other independent variables like mean air temperature, wind speed, Relative Humidity,

Rainfall and maximum temperature was established.

$$\boldsymbol{Y} = \boldsymbol{\beta}_0 + \boldsymbol{\beta}_1\boldsymbol{X}_1 + \cdots + \boldsymbol{\beta\rho X\rho} \qquad \textbf{(2)}$$

The model parameters $\beta^0 + \beta^1 + \cdots + \beta\rho$ *and* σ *must be estimated from the data.*

$Y = Annual\ total\ of\ Meningitis\ occurrence$

$\beta_o \quad = Constant,$

$X = Climatic\ variable \quad \beta = corresponding\ regression\ coefficient$

Coefficient of Multiple regression is given as $R^2 = \frac{1-\sum(Y-Y_e)}{\sum(Y-Y_ə)}$ where R^2 = Coefficient of multiple determination.

Y_e = Total dependable variable which is meningitis cases

$Y_ə$ = Multiple regression

3.5.3 Objective four

To attempt to generate a model for predicting CSM outbreak in the study areas. Risk modelling here involves predicting meningitis outbreak and a formal, quantitative estimation of the probability of adverse effect from meningitis cases across the country. Artificial Neural Network was used. This used the trend equation to calculate the forecast for specific time values.

3.5.3.1 *Method*

The Poisson loglinear regression analysis which is a special case of Generalized linear models used for modelling count data was used as a forecasting tool because it could be used to estimate the number of times an event will occur over a given duration of time, and in this case, it was the future occurrence of meningitis within the study area based on two or more climatic variables entered for analysis. During model development, collinearity diagnostics were performed, and explanatory variables were selected through a process of step wise selection process, with a criterion of elimination being a *p* value of ≤ 0.05 when testing the significance of the coefficient estimate.

3.5.3.2 *Generalized linear model for counts (GLM)*

$$E\ (y_i) = b_0 + b_1x_1 + b_2x_2 \ldots + b_kx_1 \qquad (3)$$

where

$E\ (yi)$ = effect on the mean of Y b_0 =

Constant b_1x_1= Corresponding regression

coefficient

Based on the Poisson regression model above, with every unit increase in X, the predictor variable has multiplicative effect of $exp\ (\beta)$ on the mean of Y that is µ.

3.5.3.3 *Interpretation of parameter estimates:*

1. *If $\beta = 0$,* then *$exp\ (\beta) = 1$,* and the expected count, $\mu = E(y) = exp(y) = exp$

   (α) and Y and X are not related.

2. *If $\beta > 0$,* then *$exp\ (\beta) > 1$,* and the expected count $\mu = E(y)$ *is* $exp(\beta)$ times

   larger than when $X= 0$

3. *If $(\beta) < 0$,* then *$exp\ (\beta) < 1$,* and the expected count $\mu =E(y)$ *is* $exp\ (\beta)$ times smaller

   than when $X = 0.$

CHAPTER FOUR

4.0 RESULTS AND DISCUSSIONS

In this chapter, results gotten from several findings in the course of study are discussed.

4.1 Distribution of Sampled States in Nigeria.

To have a better understanding of the spatio-temporal variability in the occurrence of meningitis *(meningococci)* in the Sudano-Sahelian and Guinea Savanna zones (North and south Savanna) of Nigeria as it relates to climatic variables the states have been zoned as depicted in Table 4.1.

Table 4.1 Zoning of Selected States in Nigeria

S/N	States	Zones
1	Katsina	Sudano-Sahel
2	Borno	Sudano-Sahel
3	Jigawa	Sudano-Sahel
4	Sokoto	Sudano-Sahel
5	Kaduna	Northern Savanna
6	Adamawa	Northern Savanna
7	Niger	Northern Savanna
8	Abuja	Northern Savanna

9	Benue	Southern Savanna
10	Kogi	Southern Savanna
11	Kwara	Southern Savanna
12	Enugu	Southern Savanna

Source: Author's compilation, 2019.

Table 4.1 shows the distribution of selected states in Nigeria according to their respective zones. The Sudano-Sahelian region includes: Katsina, Borno, Jigawa and Sokoto. Northern Savanna includes Kaduna, Adamawa, Niger and Abuja while Southern Savanna includes: Benue, Kogi, Kwara and Enugu.

4.2 Objective One

4.2.1 Trend in spatial-temporal occurrence of meningitis and climatic Variables in the Northern Savanna region for Three Time Periods from 2008 – 2011, 2012 – 2015 and 2016 - 2019.

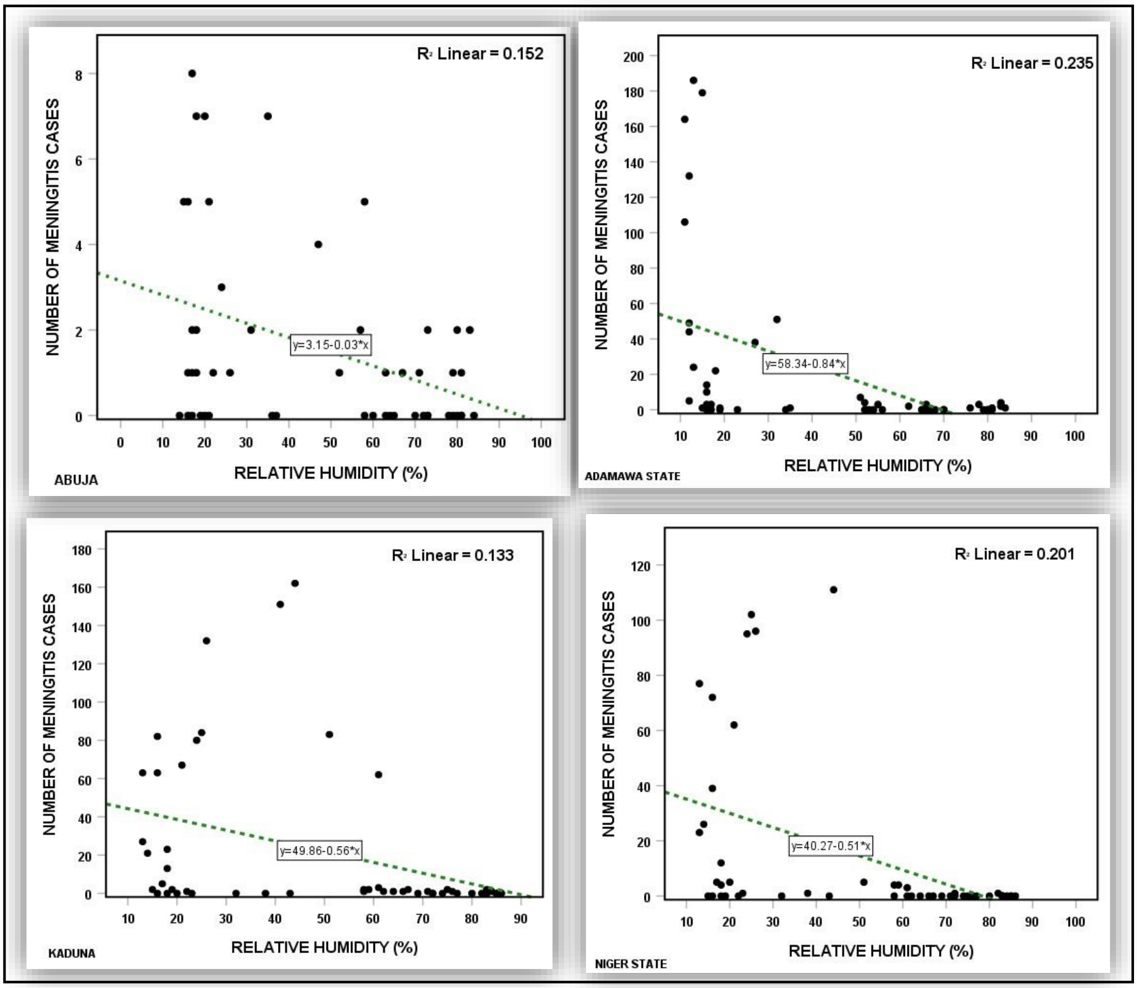

Figure 4.1: Trend in Spatial Occurrence of Meningitis and Relative Humidity in The Northern Savanna region from 2008 to 2011.

In Figure 4.1, during the period 2008 – 2011 in Abuja, the strength of the relationship between meningitis and relative humidity is about 15%. In Kaduna, it was 13%, 24% over Adamawa, and 20% in Niger. Although a weak impact is noticeable, that which exists between meningitis and relative humidity over Adamawa and Niger is more than Kaduna and Abuja between 2008 and 2011.

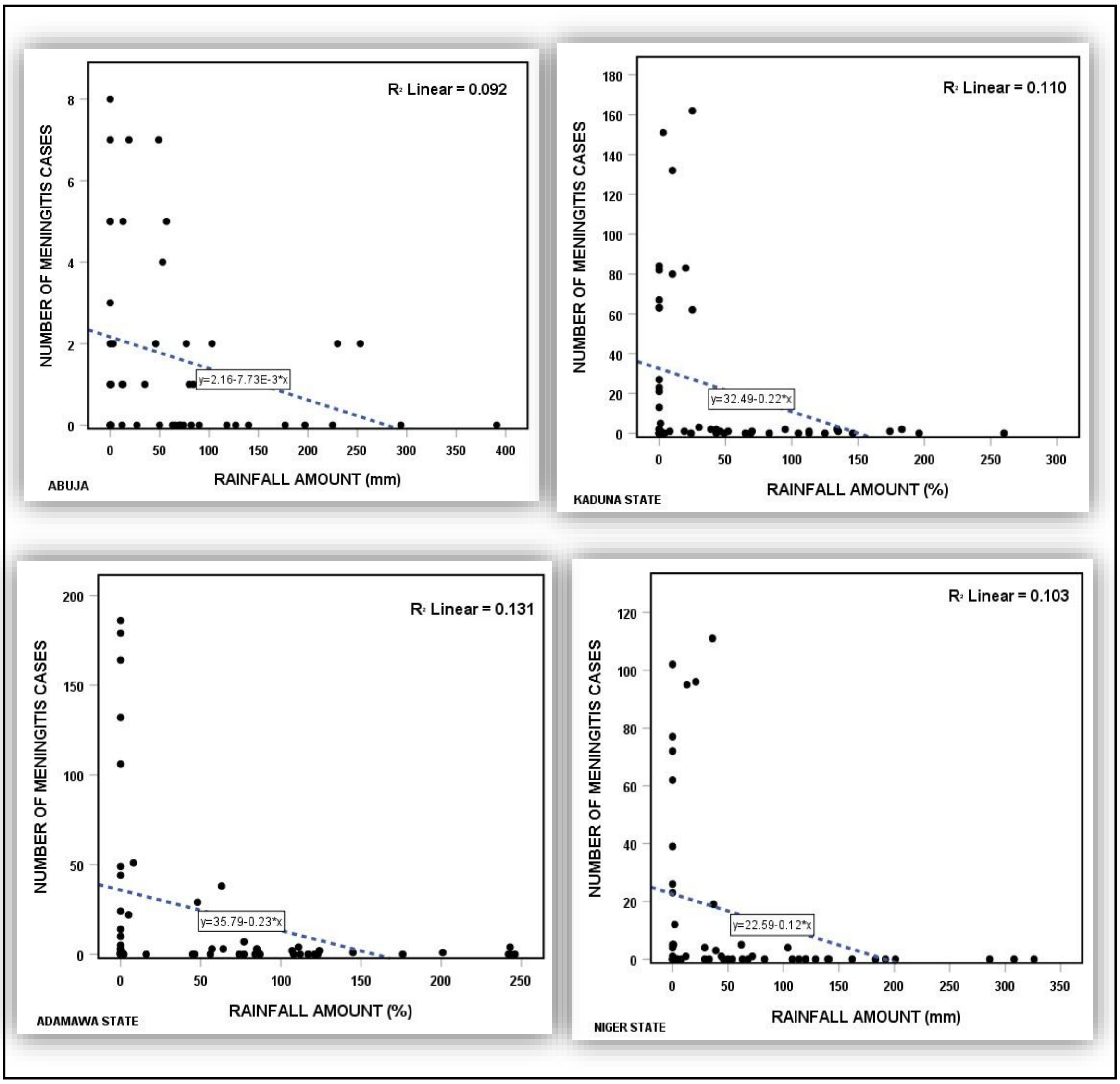

Figure 4.2 Trend in Spatial Occurrence of Meningitis and Rainfall Amount in The Northern Savanna region from 2008 to 2011

For rainfall in Figure 4.2, the impact it has on meningitis is minimal over Abuja at R^2 = 9%, R^2 =11% over Kaduna state, R^2 = 13% over Adamawa, and R^2 =10% over Niger state. This signifies that on a scale of 0 to 100%, rainfall accounts for less than 15% of the cases of meningitis in the Northern Savanna. This influence is weak. Noticeable across states is that meningitis cases are high when rainfall amount is less than 50mm.

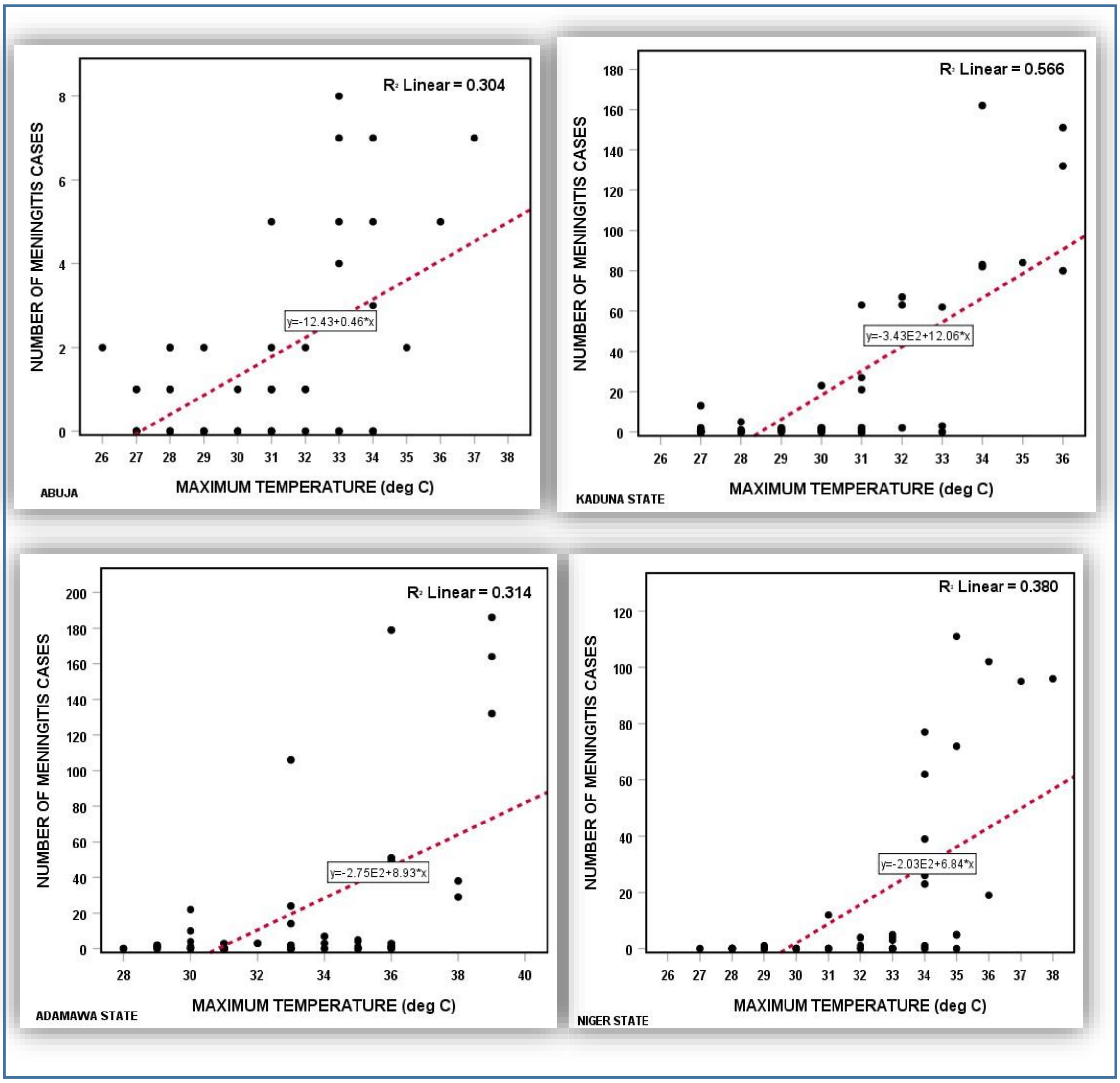

Figure 4.3 Trend in Spatial occurrence of Meningitis and Maximum Temperature in The Northern Savanna region from 2008 to 2011.

From 2008 to 2011 in Figure 4.3, 30% of the increase in meningitis cases were accounted for by maximum temperature over Abuja, then maximum temperature influenced 57% of CSM incidence in Kaduna, 31% in Adamawa and 38% in Niger state. Maximum temperature contributes more to meningitis cases over Kaduna state, next, Niger state followed by Adamawa state and the least impact on number of CSM cases is over Abuja. However, a common trend visible to all states is that meningitis cases are more when temperatures are in the range of 32 ^{0}C – 37 ^{0}C.

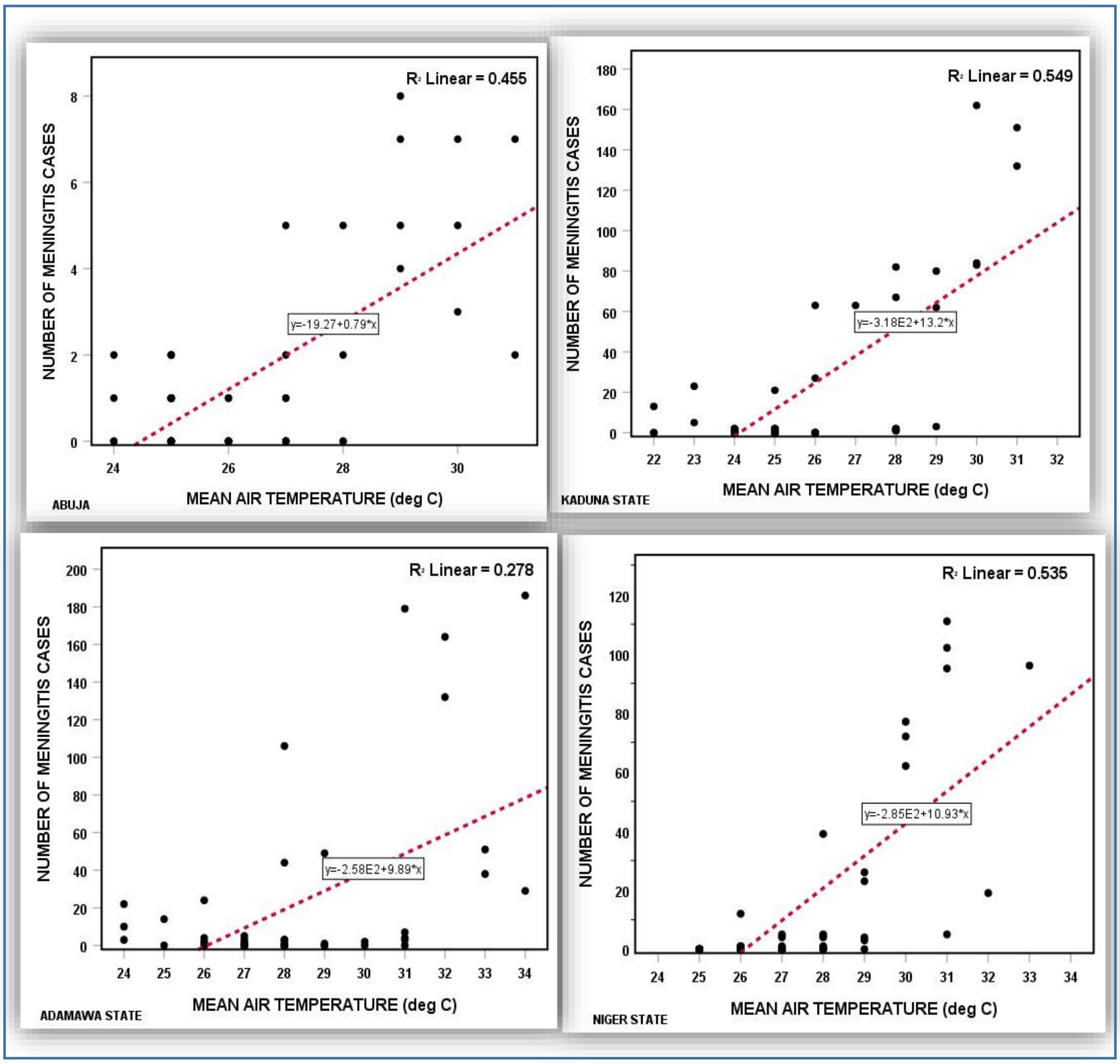

Figure 4.4 Trend in spatial occurrence of meningitis and mean air temperature in the northern Savanna region from 2008 to 2011.

The Percentage contribution of mean air temperature to the number of meningitis cases over Abuja in Figure 4.4 is about 46%, 54% over Kaduna, 28% over Adamawa and 53% in Niger state. Within this period, the mean air temperature contributes more to the number of meningitis cases in Niger state than Adamawa state. The number of meningitis cases is seen to increase with increasing mean temperature in the range of 30 ^{0}C -34 ^{0}C.

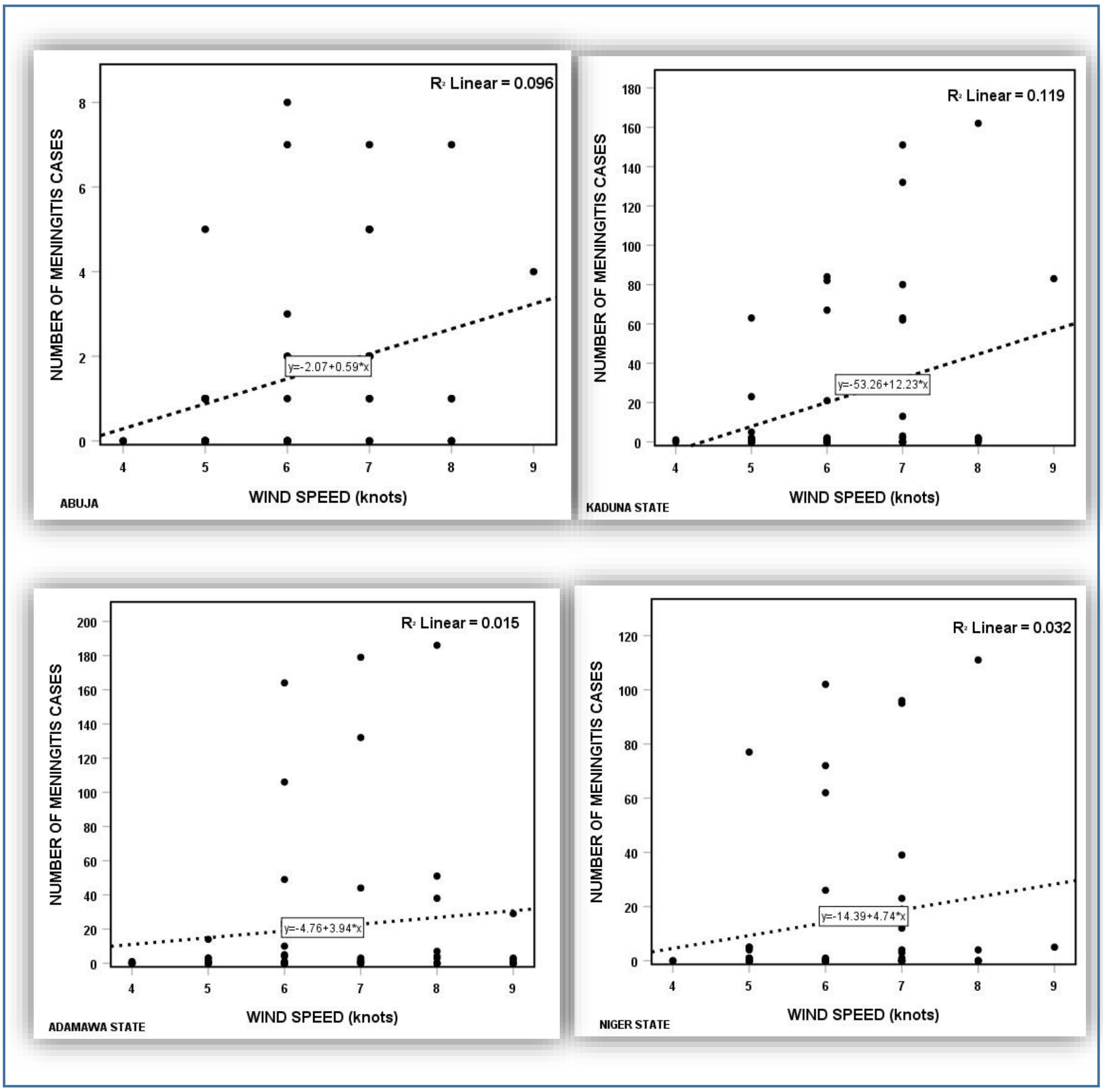

Figure 4.5 Trend in spatial occurrence of meningitis and wind speed in the northern Savanna region from 2008 to 2011.

Within the period 2008 to 2011, the percentage contribution of wind speed to meningitis cases across states in the zone is less than 10% which is low on a scale of R^2 = 0 to 100%. Over Abuja, coefficient of determination, R^2 =9%, R^2 =11% over Kaduna state, R^2 =1% over Adamawa and R^2 =3% in Niger state. Common among Abuja, Adamawa, Niger and Kaduna states is that meningitis cases are higher when wind speed is at about 5 knots to 7 knots. On the whole, the largest contributor to meningitis cases in the Northern Savanna between 2008 and 2011 is the mean air temperature, except for Kaduna where the maximum temperature topped the chat at 57% against mean air temperature at 54%, implying a difference of 2%.

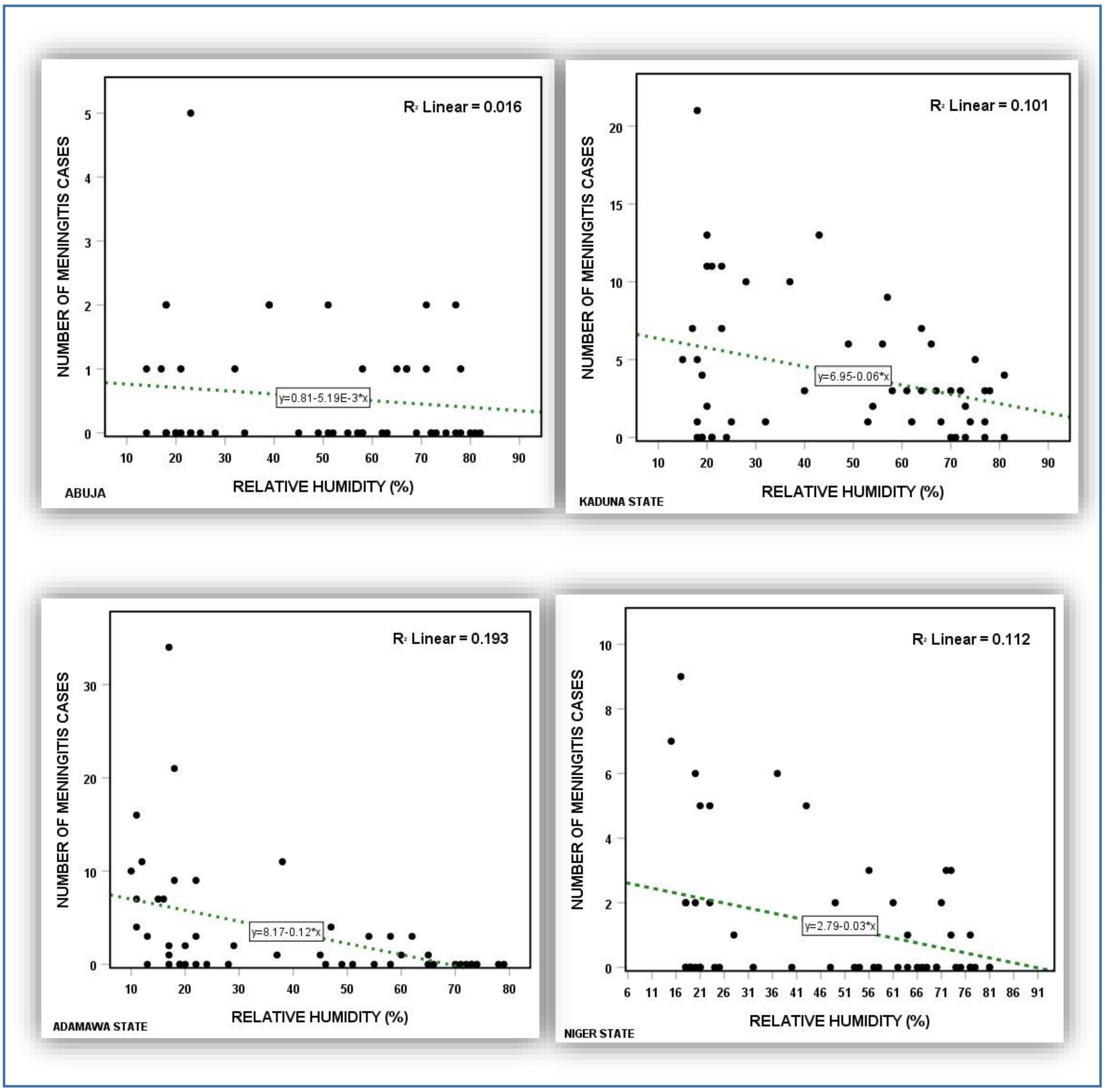

Figure 4.6 Trend in spatial occurrence of meningitis and relative humidity in the northern Savanna region from 2012 to 2015.

Considering the next period, from 2012 to 2015 the influence relative humidity had on the number of meningitis cases recorded is $R^2 \leq 20\%$ with $R^2 = 2\%$ over Abuja, $R^2 = 10\%$ in Kaduna state, $R^2 = 19\%$ in Adamawa and $R^2 = 11\%$ in Niger State. Howbeit, meningitis cases are high with corresponding relative humidity values of less than 40%   which corroborates ACMAD threshold for CSM high vigilance.

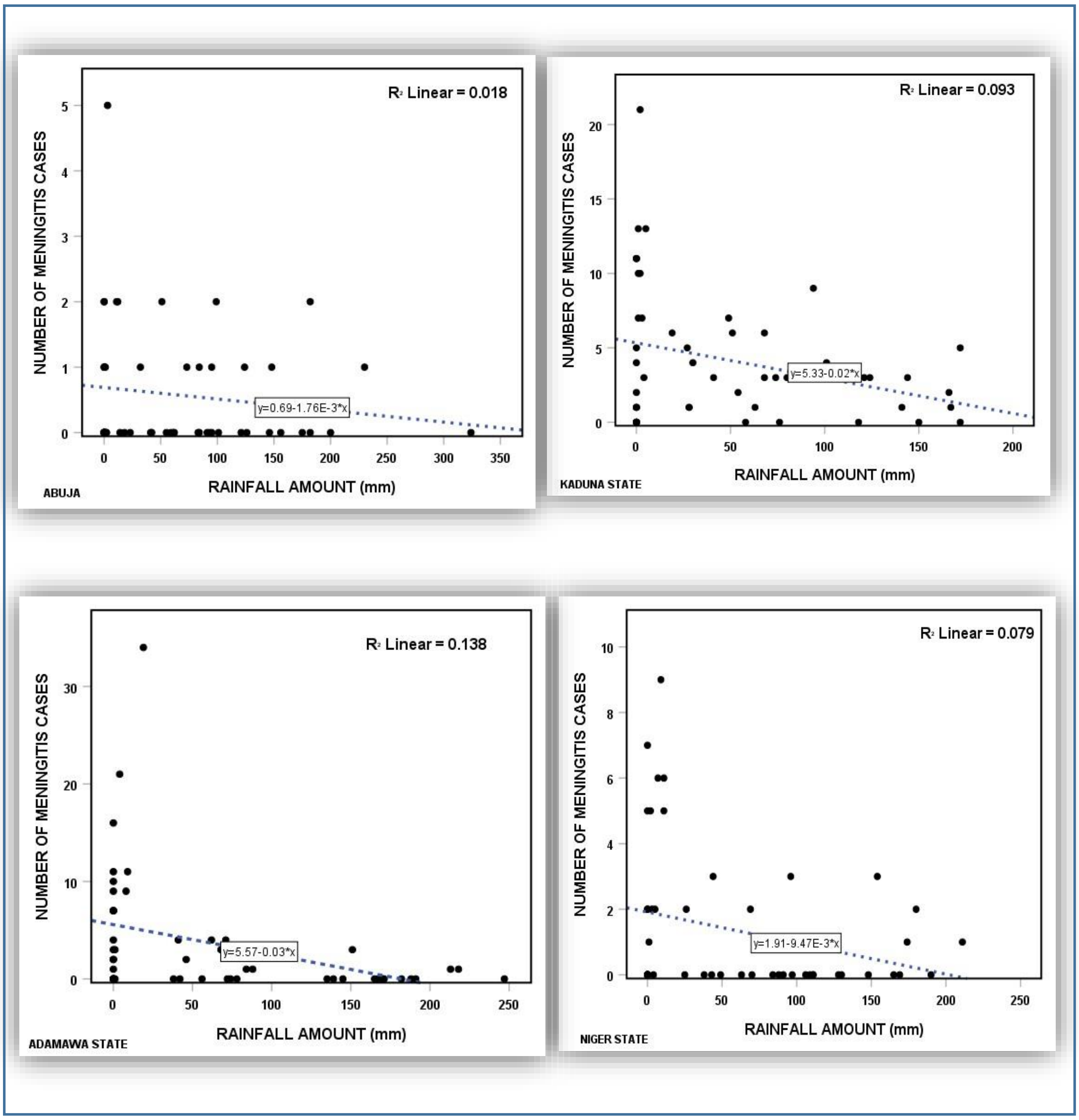

Figure 4.7 Trend in spatial occurrence of meningitis and rainfall amount in the northern Savanna region from 2012 to 2015.

The variation in meningitis cases accounted for by rainfall over Abuja is 2%, 9% in Kaduna State, 13% in Adamawa state, and 8% in Niger state. This indicates that the contribution of rainfall to the number of meningitis cases recorded is less than 15% during this period. However, high cases of meningitis were recorded with rainfall amount less than 40 mm across the states.

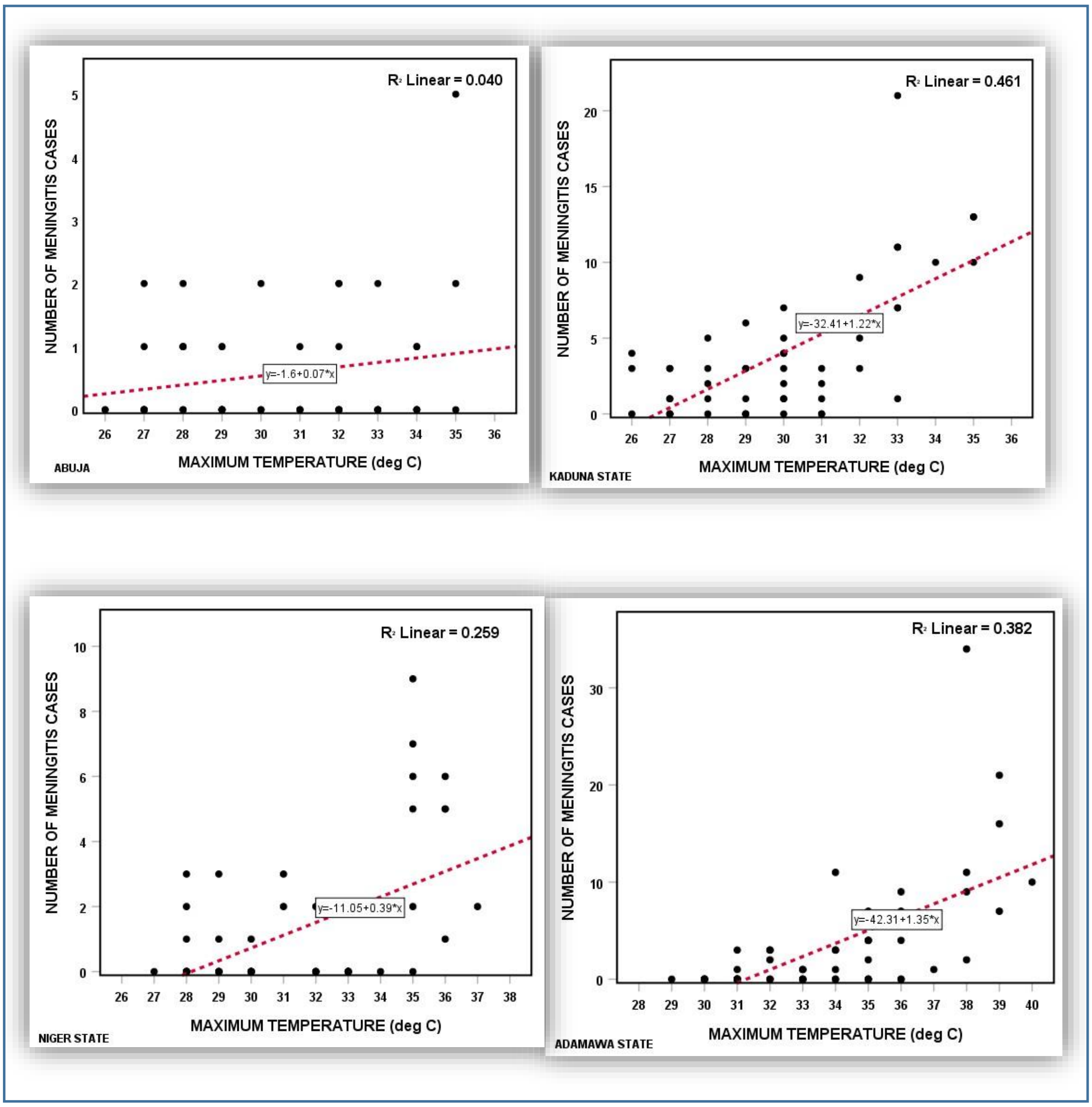

Figure 4.8 Trend in spatial occurrence of meningitis and maximum temperature in the northern Savanna region from 2012 to 2015.

Between 2012 and 2015, maximum temperature accounted for a 4% increase in meningitis cases in Abuja, 46% increase in Kaduna, 26% in Niger, and 38% in Adamawa state. Except for Abuja, the highest number of CSM cases are being witnessed at 32 ^{0}C – 35 ^{0}C. Over Abuja, cases were spread across the various temperature ranges.

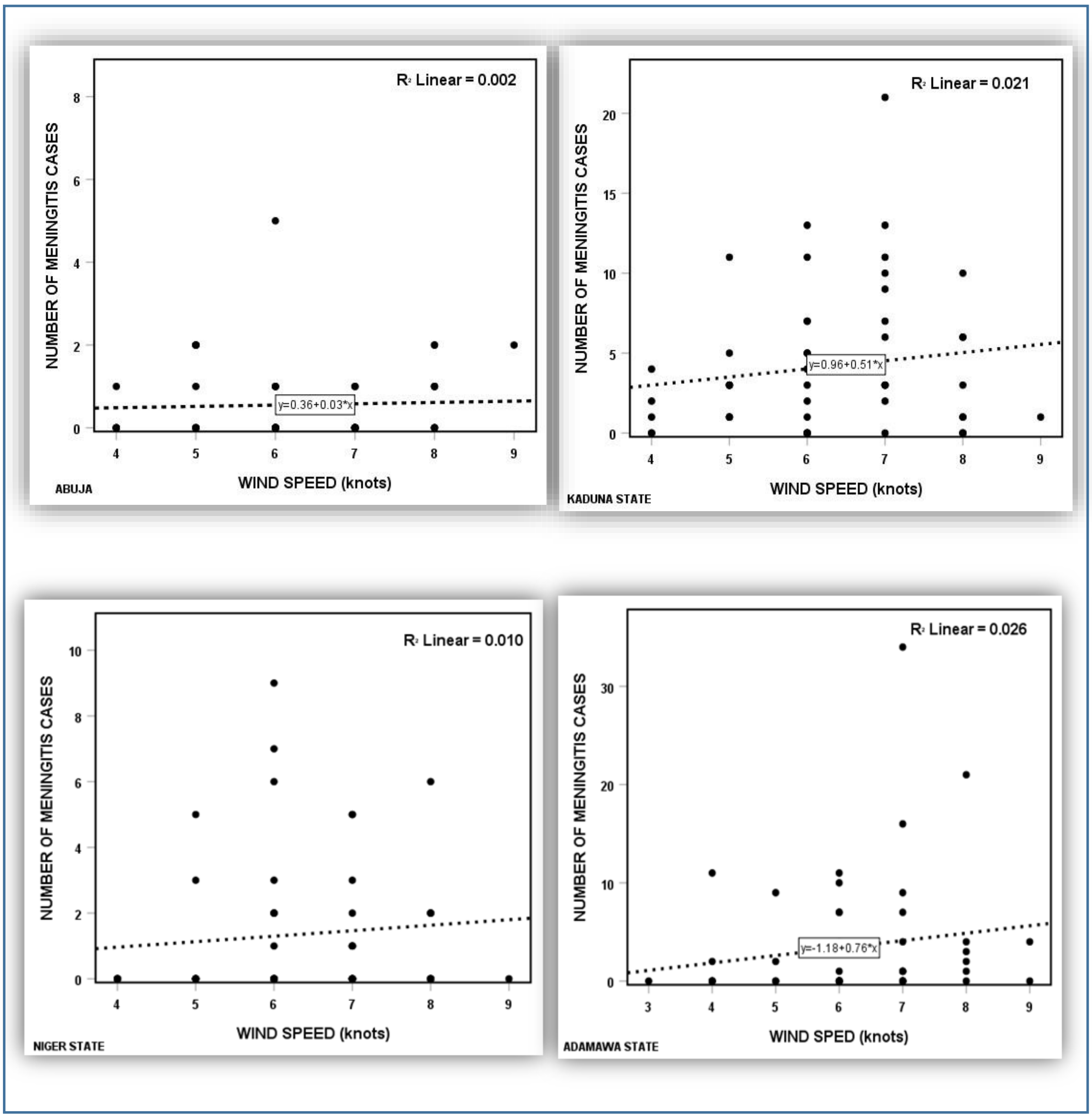

Figure 4.9 Trend in spatial occurrence of meningitis and wind speed in the northern Savanna region from 2012 to 2015.

From 2012 to 2015, the impact of wind speed on meningitis cases is very minimal with $R^2 \leq 1\%$ over Abuja, $R^2 = 2\%$ in Kaduna, $R^2 = 1\%$ in Niger and $R^2 = 3\%$ in Adamawa state. Notably however is that, high cases of meningitis were recorded when wind speed was between 5 and 8 knots. This scenario spans through all the states in the region.

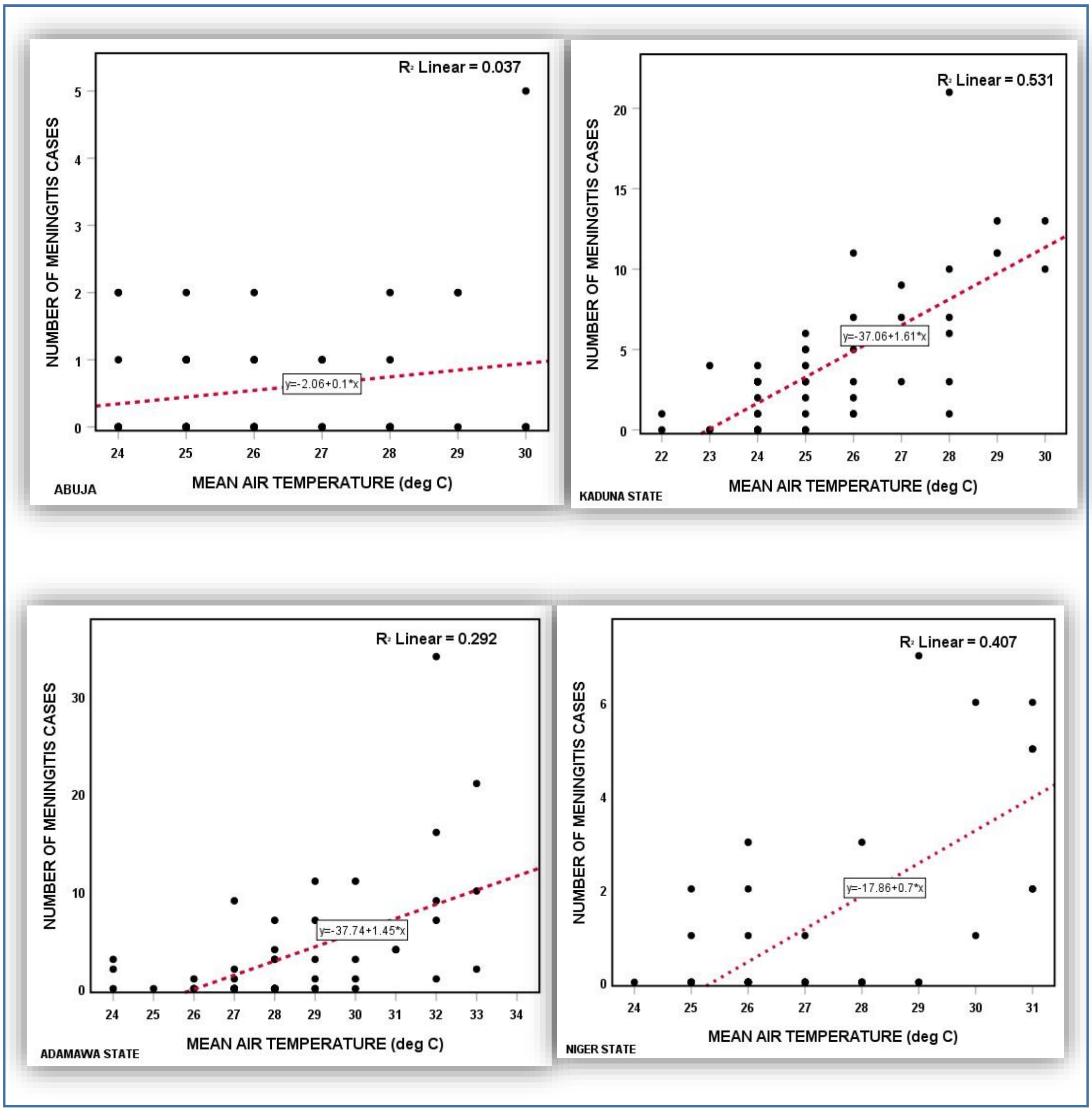

Figure 4. 10 Trend in spatial occurrence of meningitis and mean air temperature in the northern Savanna region 2012 to 2015.

Spanning 2012 to 2015, 3% of meningitis cases in Abuja were accounted for by mean air temperature. Similarly, 53% of meningitis cases in Kaduna state were also accounted for by mean air temperature, 29% in Adamawa, and 40% in Niger state. Mean air temperature impacted Abuja the least during this period. Peak cases were recorded when mean air temperatures were in the range of 27 to 30 ^{0}C.

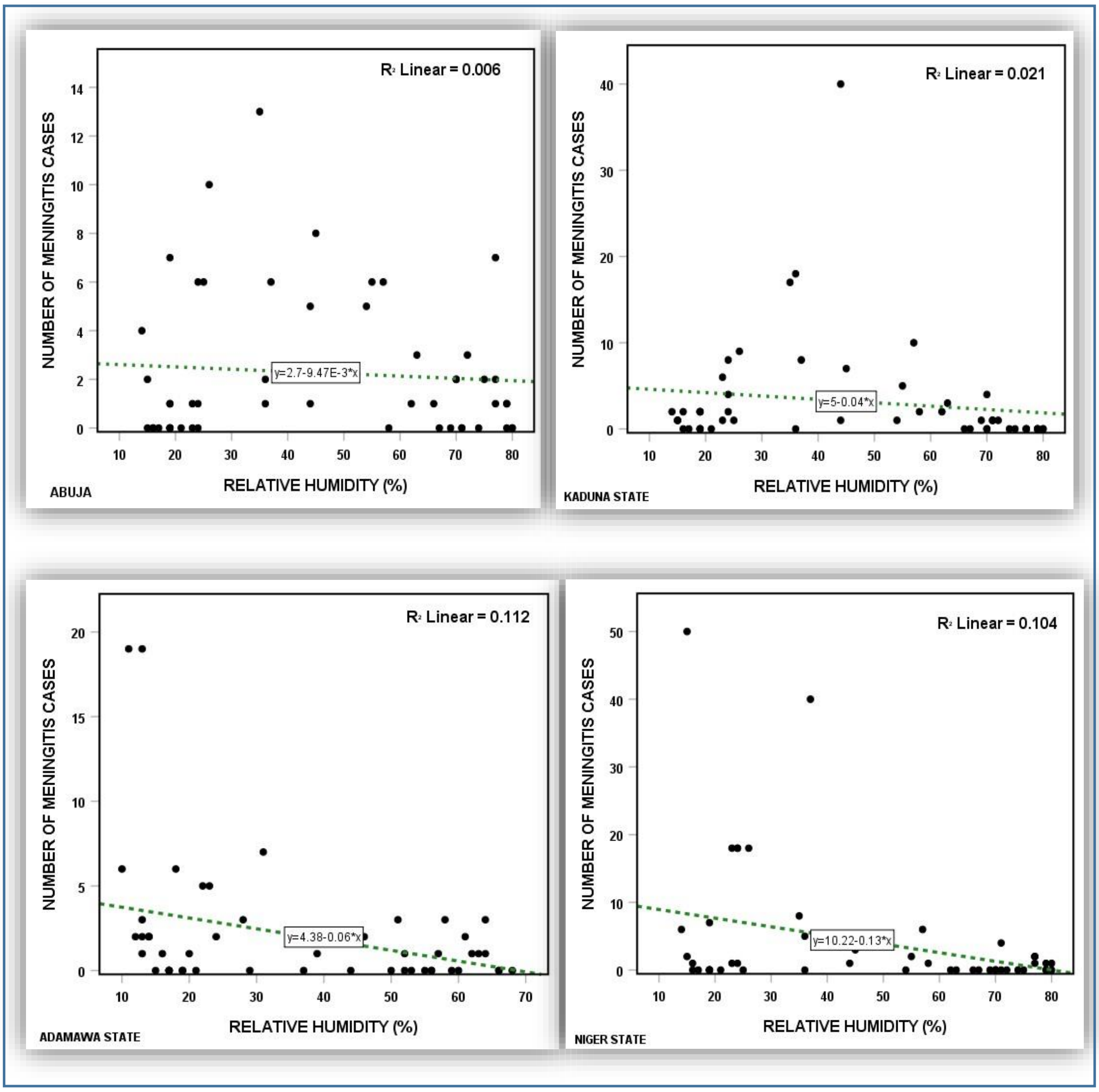

Figure 4. 11 Trend in spatial occurrence of meningitis and relative humidity in the northern Savanna region from 2016 to 2019.

Within this period, in Abuja, less than 1% of meningitis cases are attributed to the influence of relative humidity. The percentage impact in Kaduna is 2%, 11% in Adamawa State and 10% in Niger state. This indicates the larger portion of meningitis cases in the region and season are justified by factors other than relative humidity.

However, between 0 and 40%, a higher number of meningitis cases were recorded.

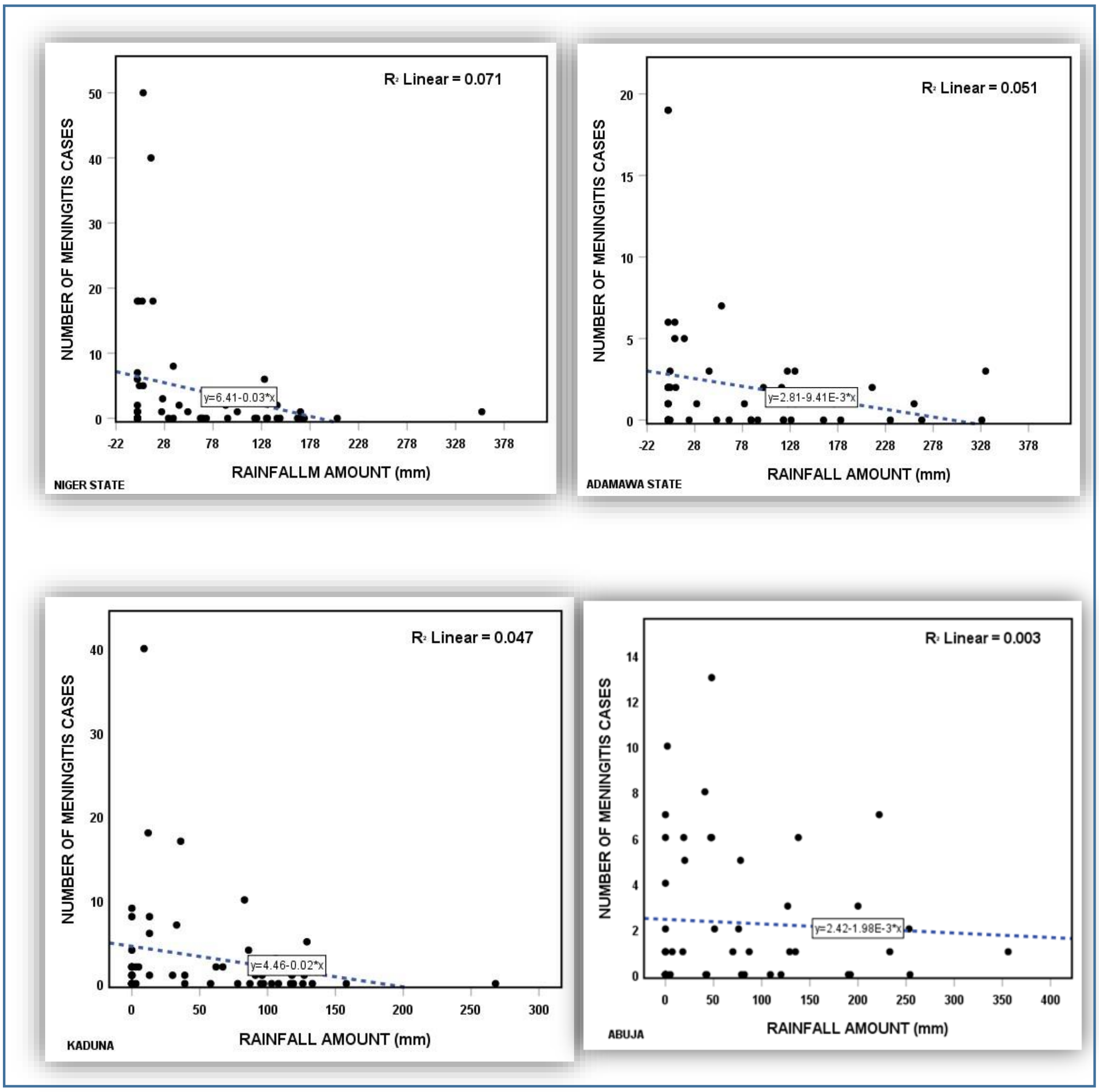

Figure 4.12 Trend in the spatial occurrence of meningitis and rainfall in the Northern Savanna region from 2016 to 2019.

Rainfall elucidates about 7% of meningitis cases in Niger state within 2016 and 2019, 5% in Adamawa, 4% in Kaduna and less than 1% in Abuja. This connotes that the impact of rainfall on increasing number of CSM cases between 2016 and 2019 is small. However, an increasing number of cases were reported when the rainfall amount was less than 50 mm.

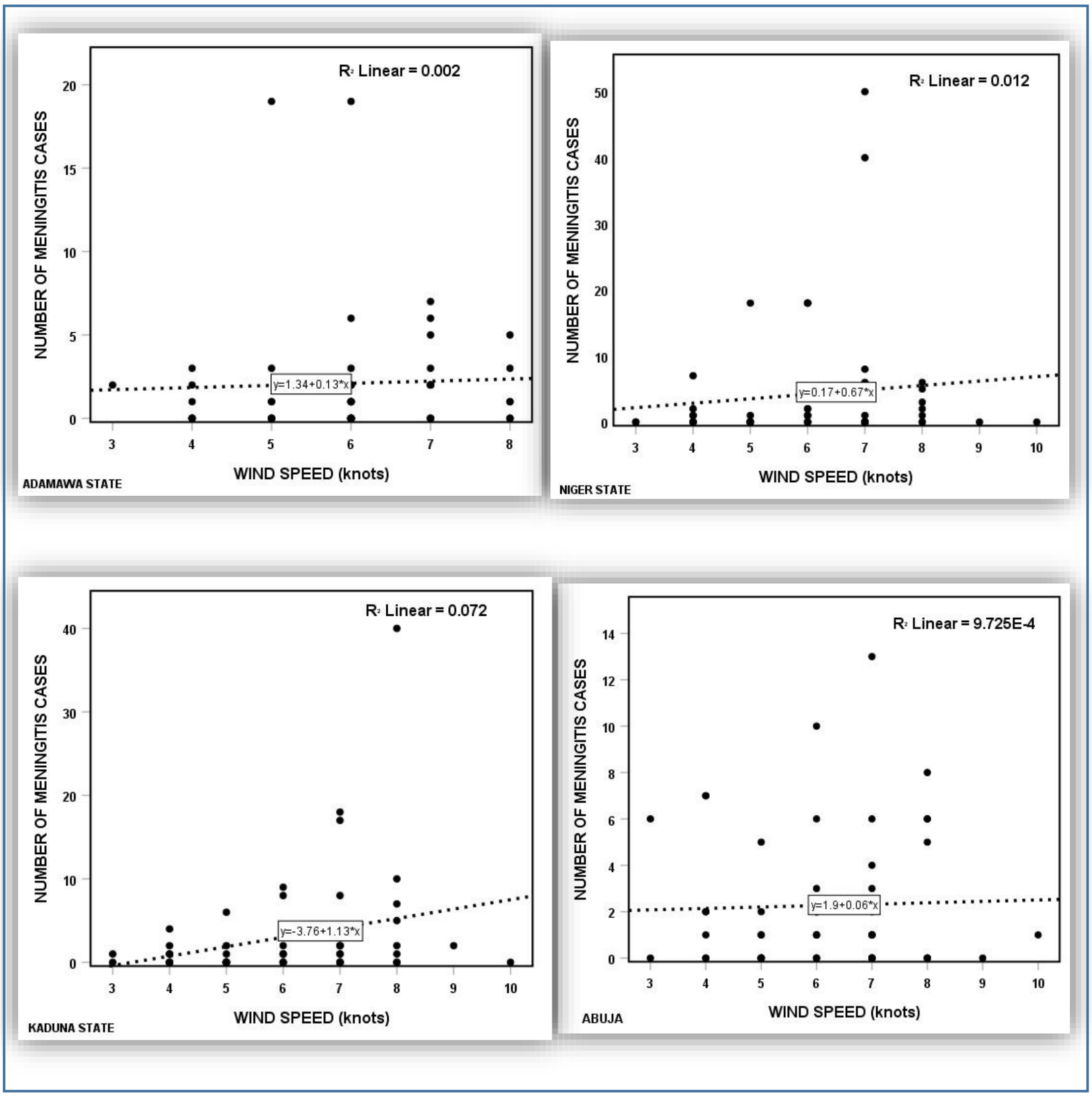

Figure 4.13 Trend in spatial occurrence of meningitis and wind speed in the northern Savanna region from 2016 to 2019.

From 2016 to 2019 over Kaduna, wind speed influenced 7% of the CSM cases in the region with less than 1% in Abuja, Niger and Adamawa states. This means that the impact of wind speed in the occurrence of CSM in this region is minute. Despite the little impact, high cases of meningitis are recorded when wind speed is about 5 to 8 knots.

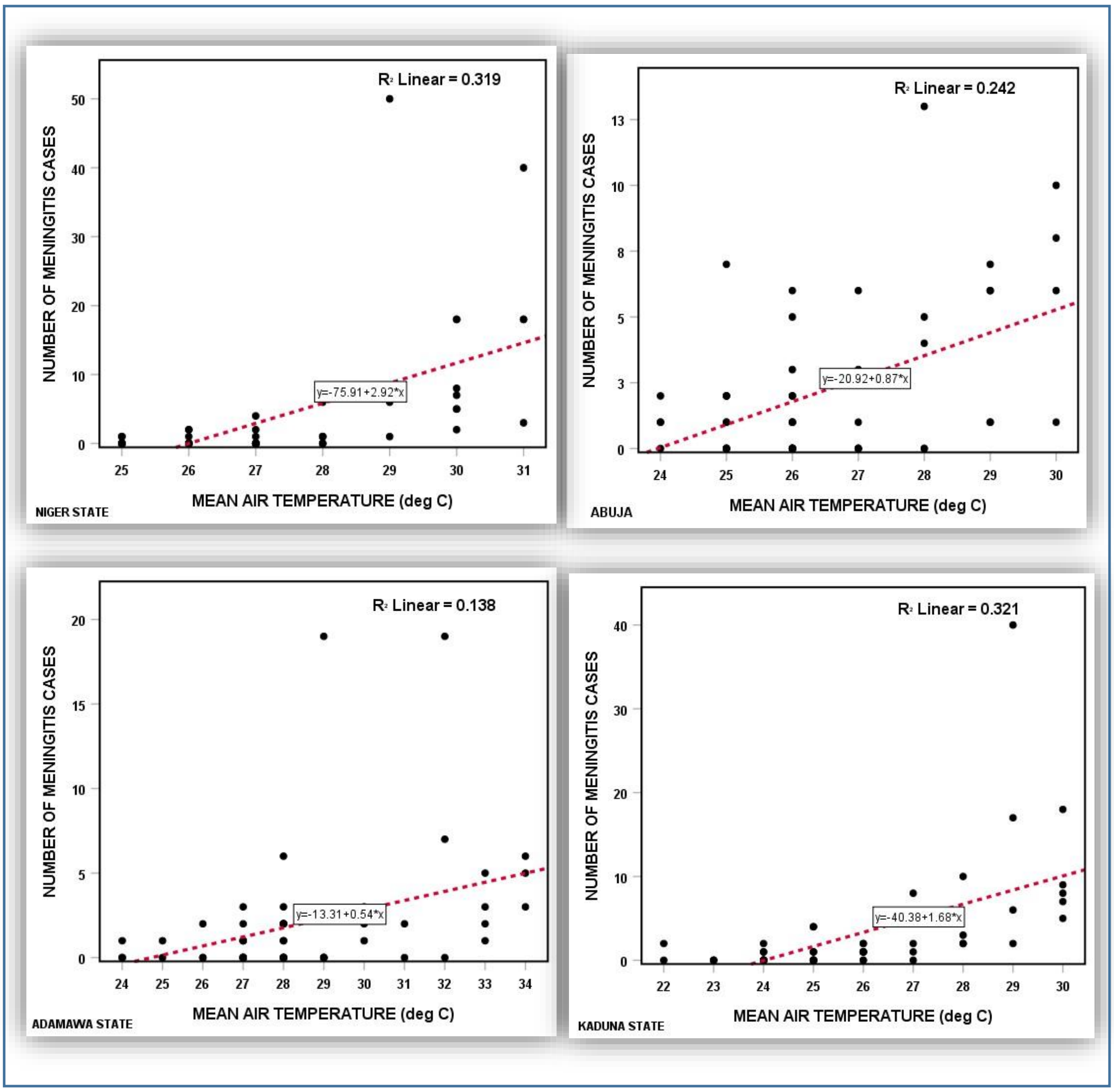

Figure 4.14 Trend in the spatial occurrence of meningitis and mean air temperature in the Northern Savanna region from 2016 to 2019.

About 32% of meningitis cases can be satisfactorily explained by mean air temperature values. For Abuja it is 24%, then 13% over Adamawa and 32% for Kaduna State. For the region, the percentage is smaller for Adamawa state compared to other states. More cases of meningitis were recorded when temperatures were within 27 ^{0}C and 30 ^{0}C.

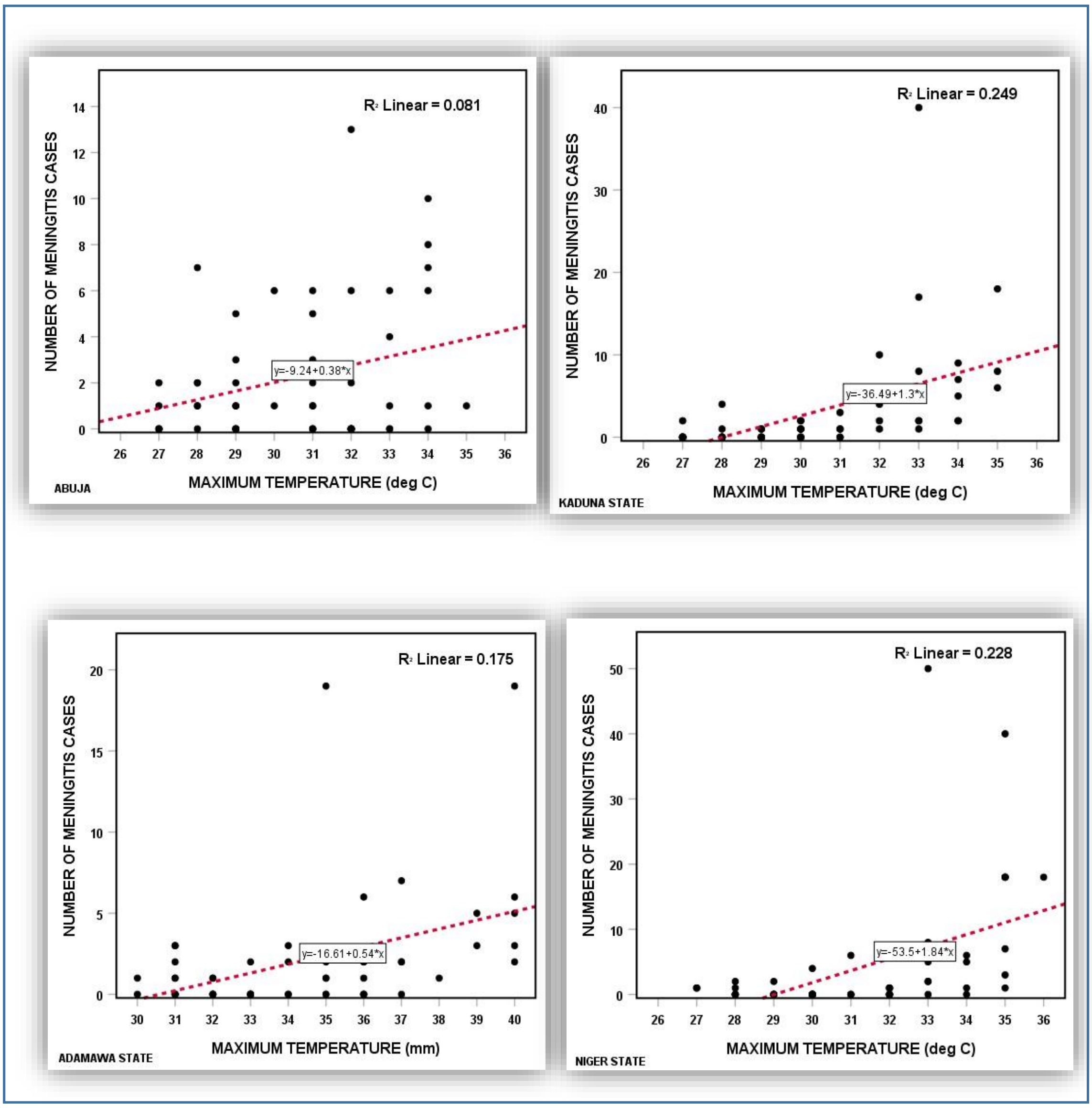

Figure 4.15 Trend in the spatial occurrence of meningitis and maximum temperature in the Northern Savanna region from 2016 to 2019.

During this period, maximum temperature over Abuja accounted for 8% of CSM cases. In Kaduna State, it accounted for 25% of cases of meningitis in the reported period with 17% of cases recorded over Adamawa and 23% in Niger state. Maximum temperature accounted for more CSM cases over Kaduna state. Even though the impact of these variables are slight for each of the states, it is established that they contribute to meningitis cases.

4.2.2 Trend in spatial-temporal occurrence of meningitis and climatic

variables in the Southern Savanna region for three time periods from 2008 – 2011, 2012 – 2015 and 2016 - 2019.

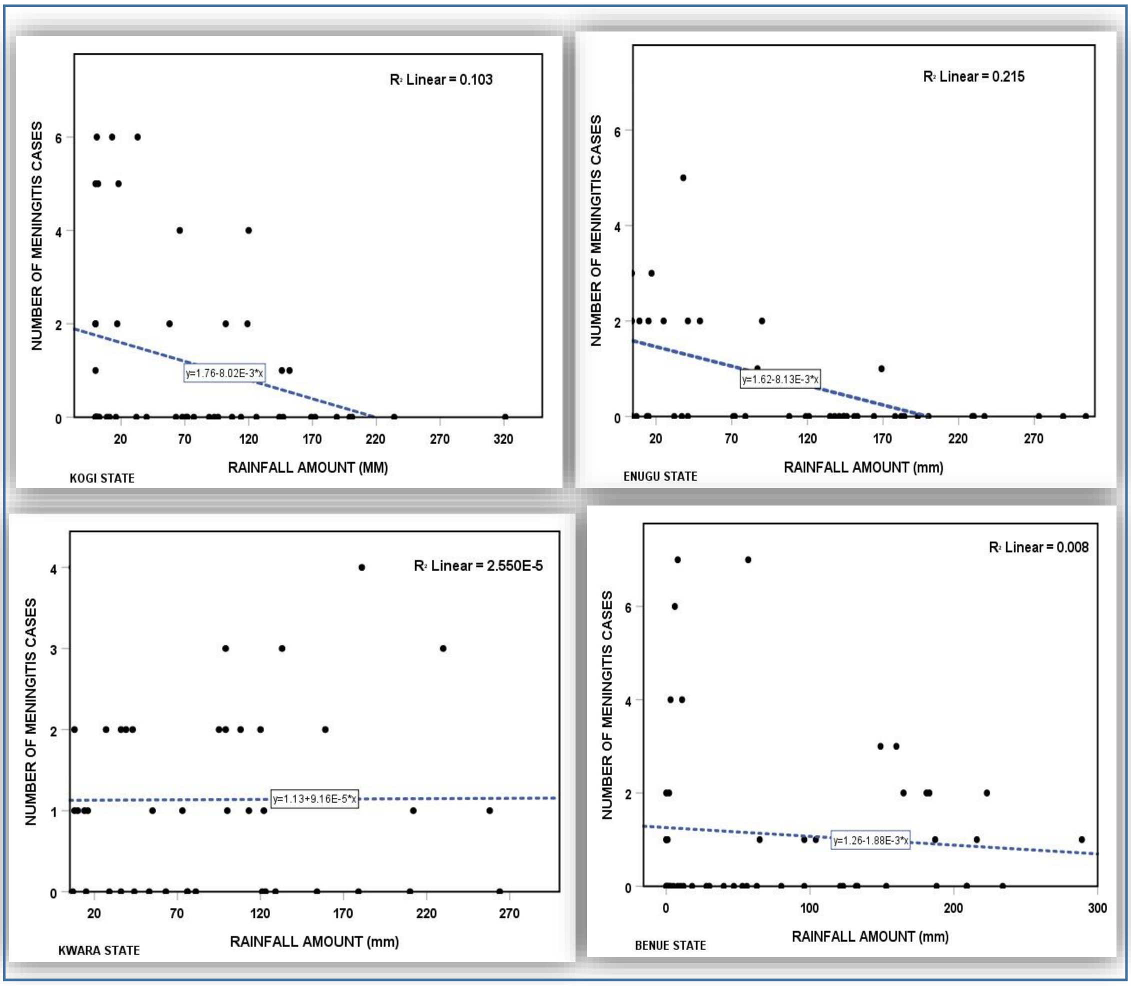

Figure 4.16 Trend in Spatial occurrence of meningitis and rainfall in the Southern Savanna region from 2008 to 2011.

Rainfall accounted for certain percentage of meningitis occurrence during the fouryear period for each of the states although the impact was frail. $R^2 \leq 1$ in Kwara, $R^2 = 0.008$ in Benue, $R^2 = 0.10$ in Kogi and $R^2 = 0.21$ in Enugu being the state with stronger relationship existing between variables. Peak cases occurred at rainfall values of over 100mm across the region during this period,

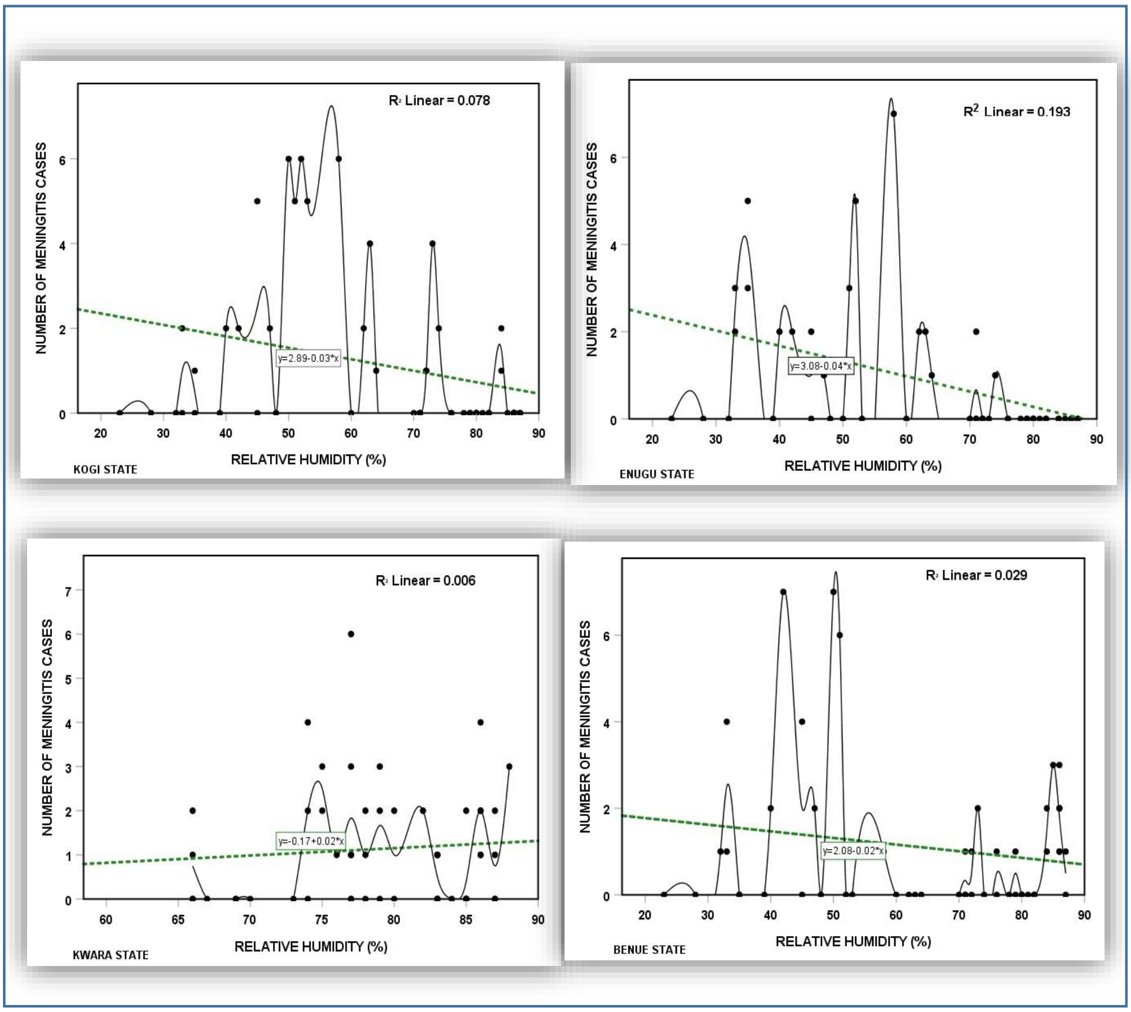

Figure 4.17 Trend in Spatial occurrence of meningitis and relative humidity in the Southern Savanna from 2008 to 2011.

In Kogi State 8% of CSM cases are accounted for by relative humidity. In Enugu about 19% of the cases were accounted for by relative humidity and less than 1% in Kwara State and about 2% in Benue state. In Kwara State high cases of CSM were recorded in spite of high relative humidity value of about 80%. This Scenario played out in other states like Enugu, Kogi and Benue but at RH values slightly lower than that obtainable over Kwara state. This defied the notion that meningitis incidence begins to decrease at the beginning of raining season (Jackou – Boulama, 2005).

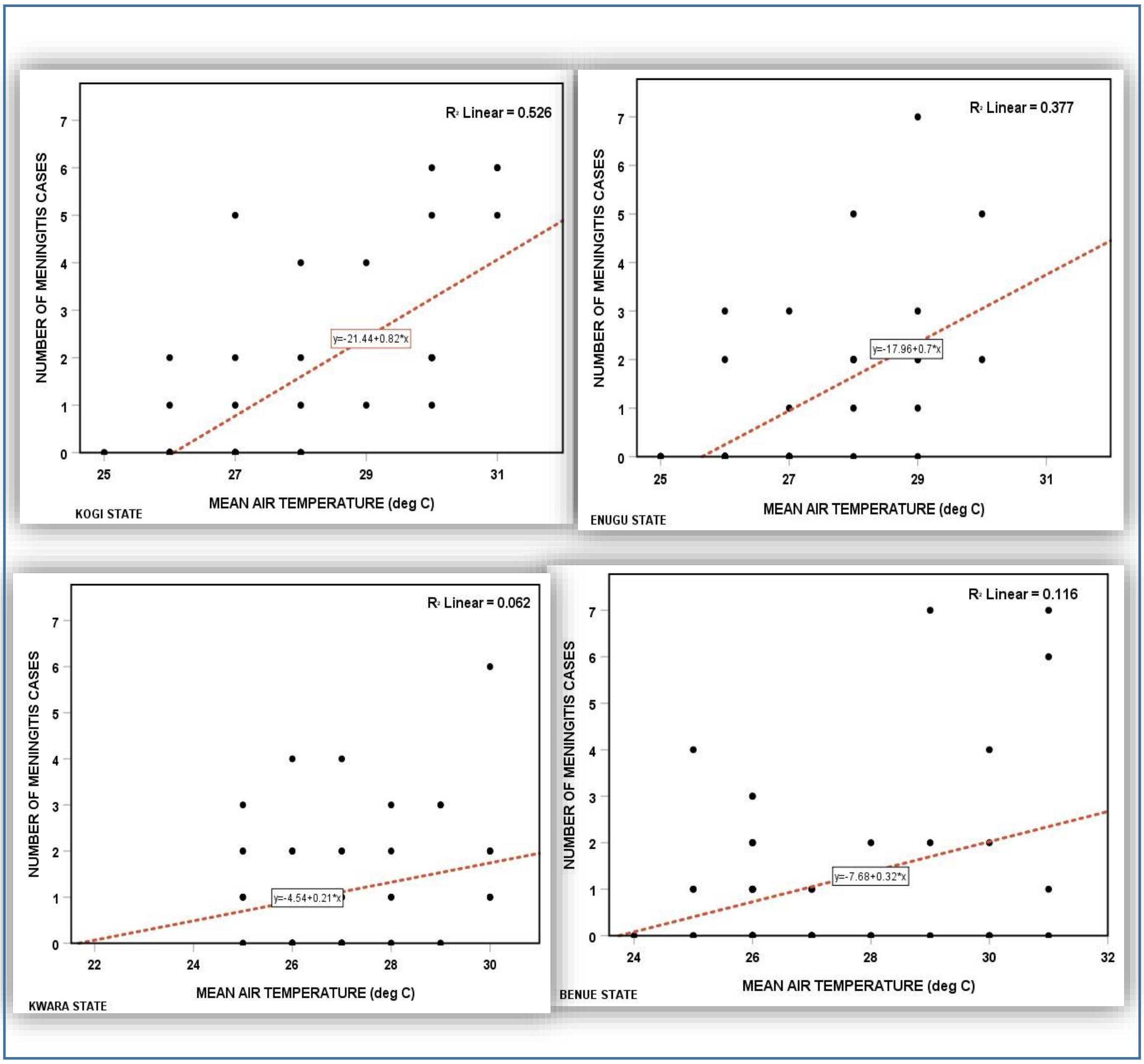

Figure 4.18 Trend in spatial occurrence of meningitis and mean air temperature in the Southern Savanna region from 2008 to 2011.

The relationship between meningitis cases and mean our temperature was moderate at with R^2= 53 over Kogi. The relationship was weak in Enugu with R^2 = 37. The relationship was very weak at R^2 = 6% and 11% in Kwara and Benue states respectively. Frequency in occurrence of meningitis was highest at mean temperature between 29 and 31^{0}C.

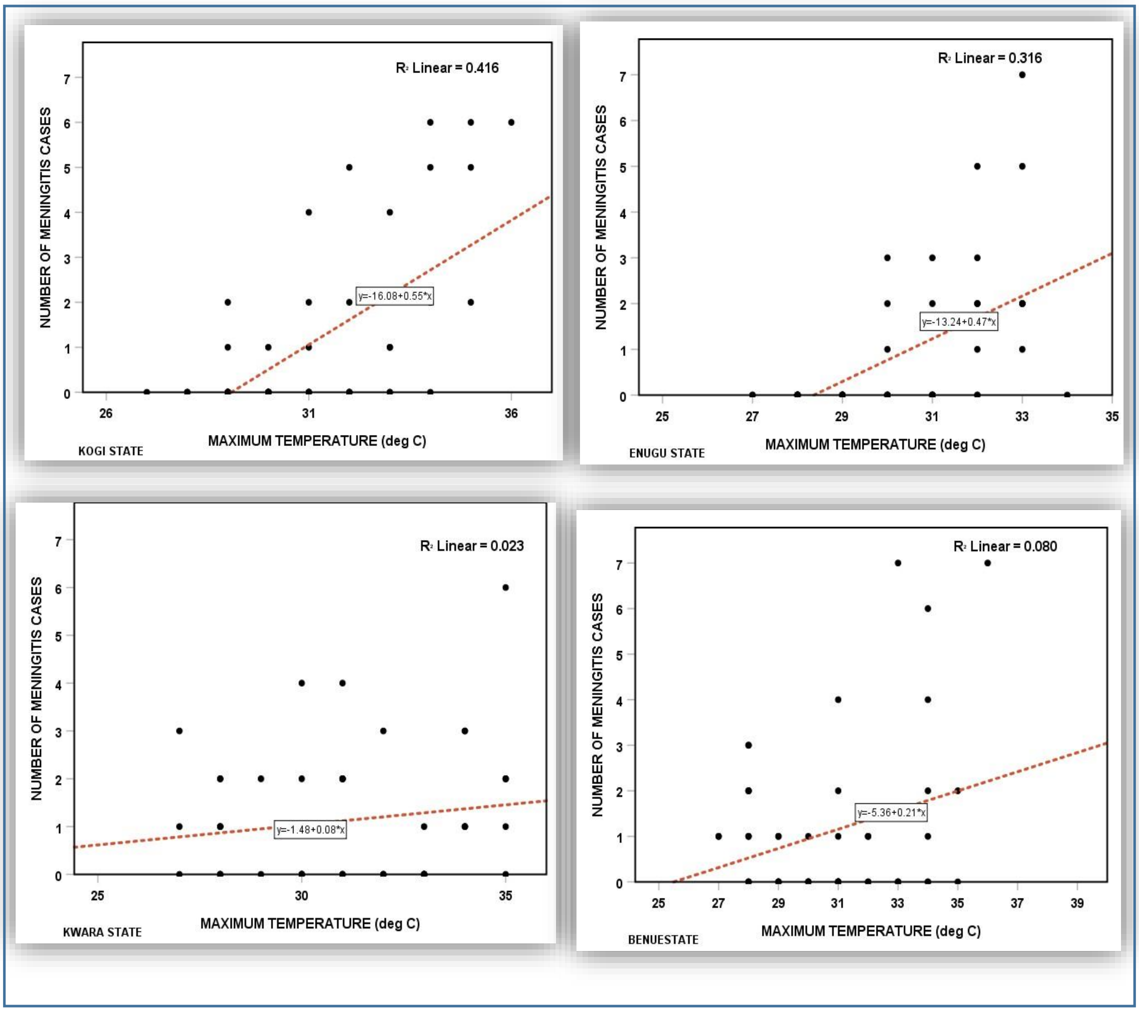

Figure 4.19 Trend in spatial occurrence of meningitis and maximum temperature in the Southern Savanna region from 2008 to 2011.

The relationship between maximum Temperature and prevalence of meningitis in Kogi state from 2008 to 2011 displays to be slightly weak with R^2 of 41%, a weak relationship in Enugu State with R^2 at 31%. A very weak relationship of R^2 at 2% and 8% is established over Kwara and Benue state. Peak cases of meningitis were recorded at temperatures of 33 ^{0}C to 35 ^{0}C.

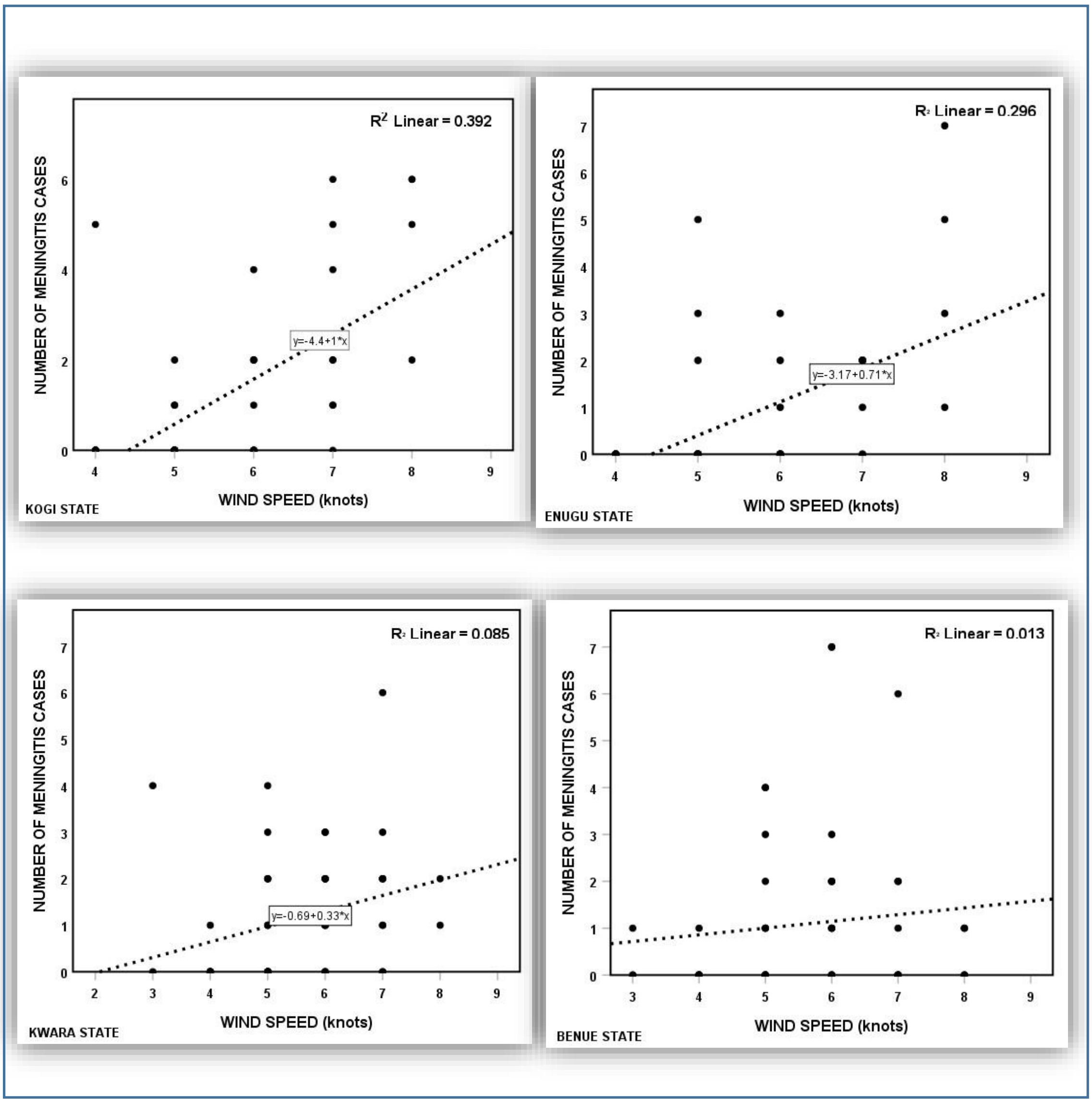

Figure 4.20 Trend in spatial occurrence of meningitis and wind speed in the Southern Savanna region from 2008 to 2011.

In 2008 to 2011, the relationship between wind speed and CSM cases in Kogi and Enugu was moderately weak with R^2 of 39%, and 30% respectively but extremely weak at 8% and 1% over Kwara and Benue respectively. Worthy of note is that CSM cases prevailed most at wind speed of 6 to 7 knots across the region with an upward trend across all the states.

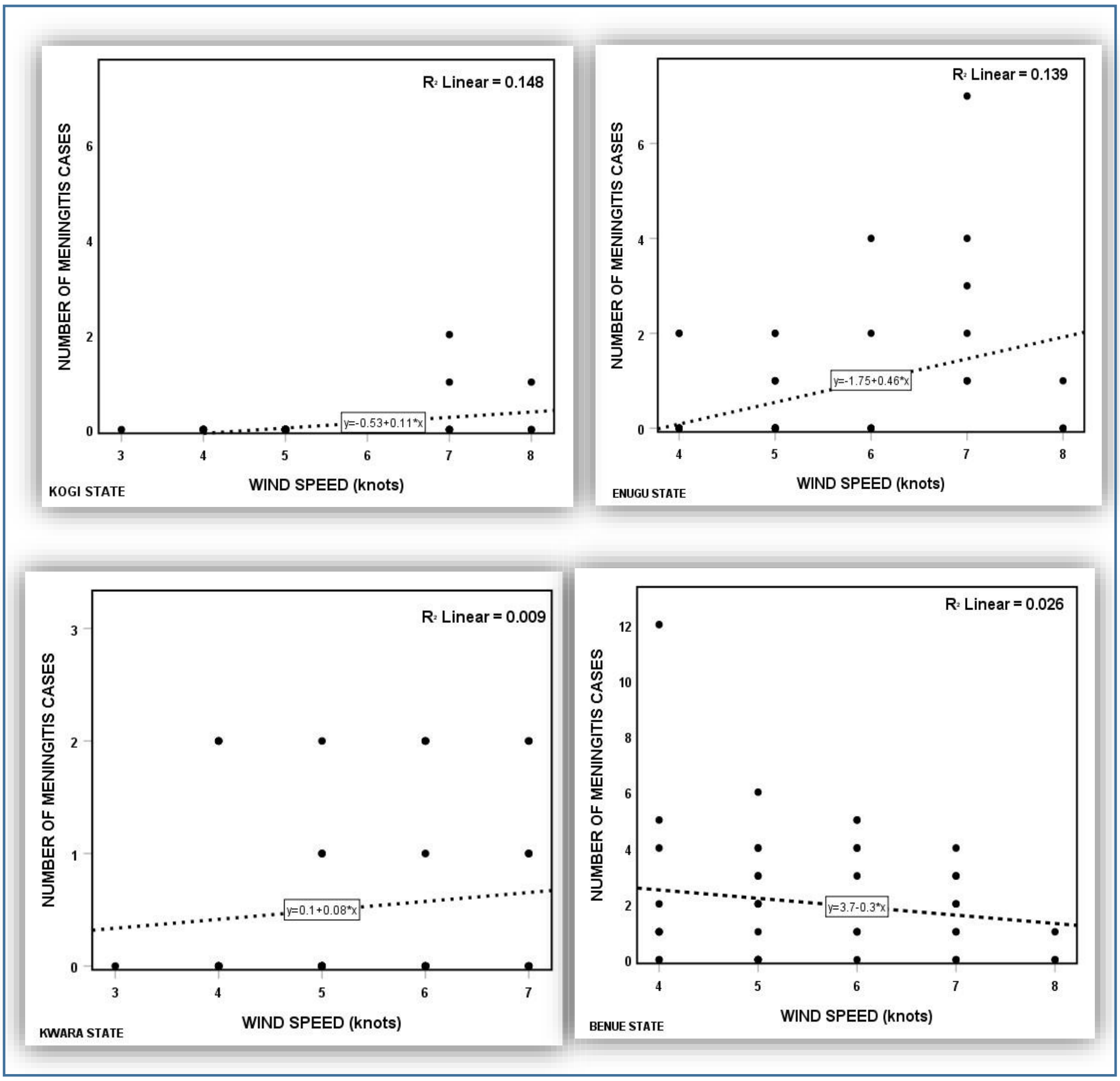

Figure 4.21 Trend in spatial occurrence of meningitis and wind speed in the Southern Savanna region from 2012 to 2015.

During this period the relationship between meningitis prevalence and wind speed is weak with R^2 value of about 14% in Kogi, 13% in Enugu and less than 1% over Kwara and Benue. The relationship between CSM and meningitis in Benue was

slightly stronger than that seen in other states in the region. Meningitis cases occurred more at wind speed of 6 to 7 knots across the region with an upward trend over Kogi,

Kwara and Enugu state.

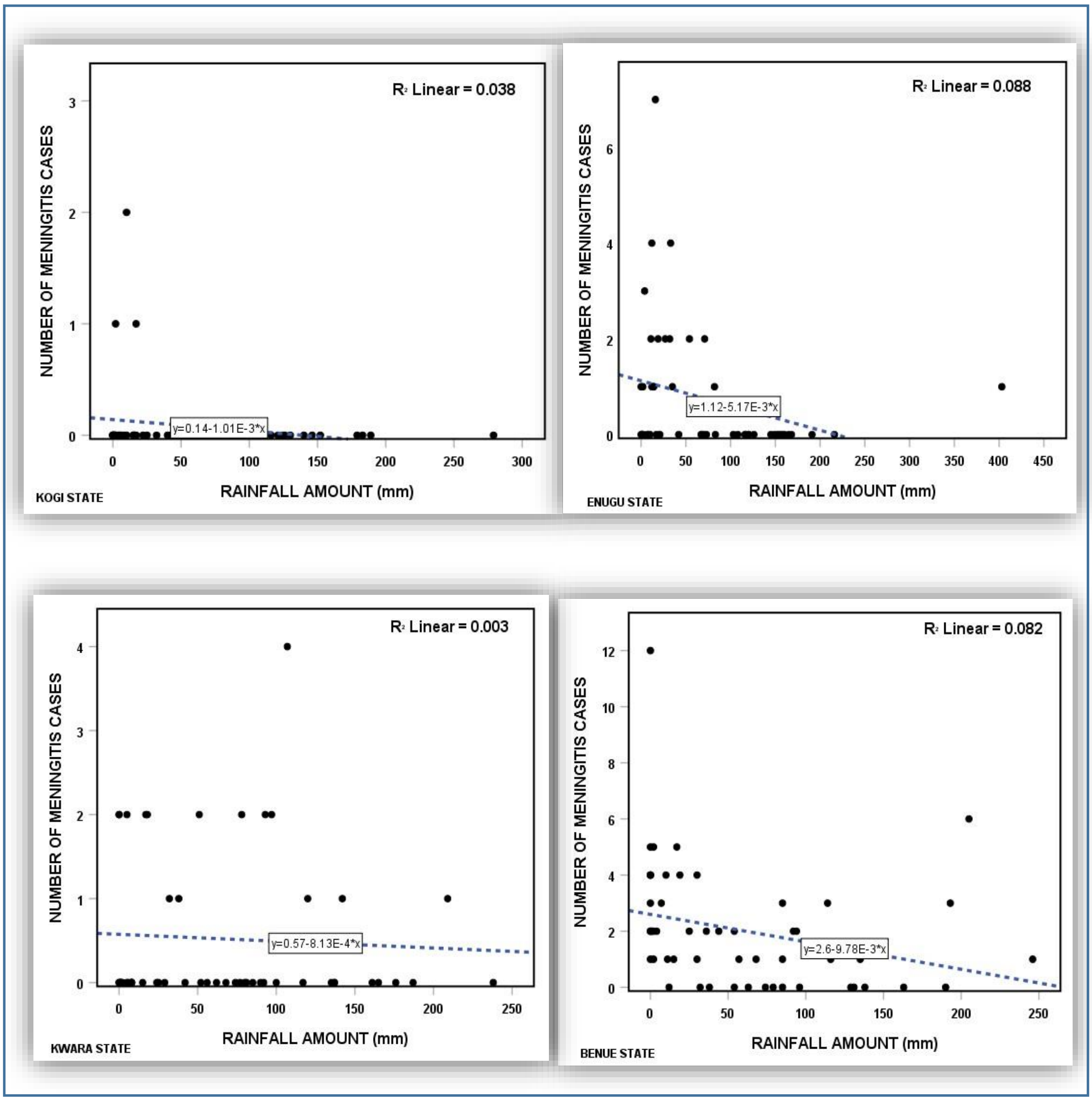

Figure 4.22 Trend in spatial occurrence of meningitis and rainfall in the Southern Savanna region from 2012 to 2015.

During this period, a weak relationship is seen between rainfall and meningitis occurrence at 4% in Kogi, 8% in Enugu and Benue and less than 1% in Kwara State. The percentage of CSM cases accrued to rainfall indices in the region is negligible.

Howbeit, CSM prevailed more when rainfall amount was less than 80 mm.

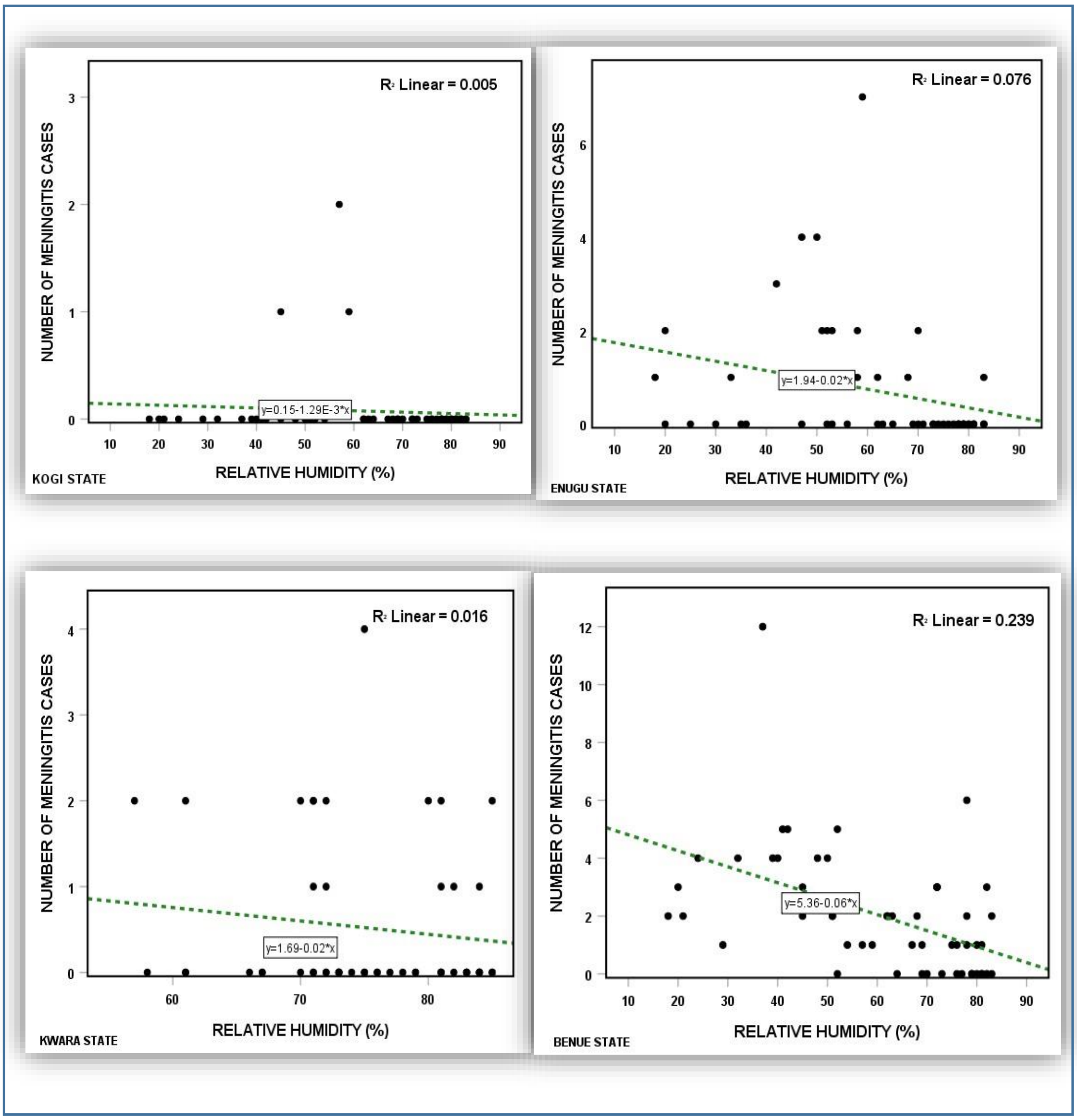

Figure 4.23 Trend in spatial occurrence of meningitis and relative humidity in the Southern Savanna from 2012 to 2015.

The strength of relationship between relative humidity and meningitis occurrence was weak with R^2 = 0.005 in Kogi, R^2 =0.076 in Enugu, R^2 = 0.016 in Kwara and R^2 = 0.23 in Benue. Only over Benue did high cases of meningitis occur at relative humidity less than 40% during the period. For other states, cases occurred irrespective of RH values.

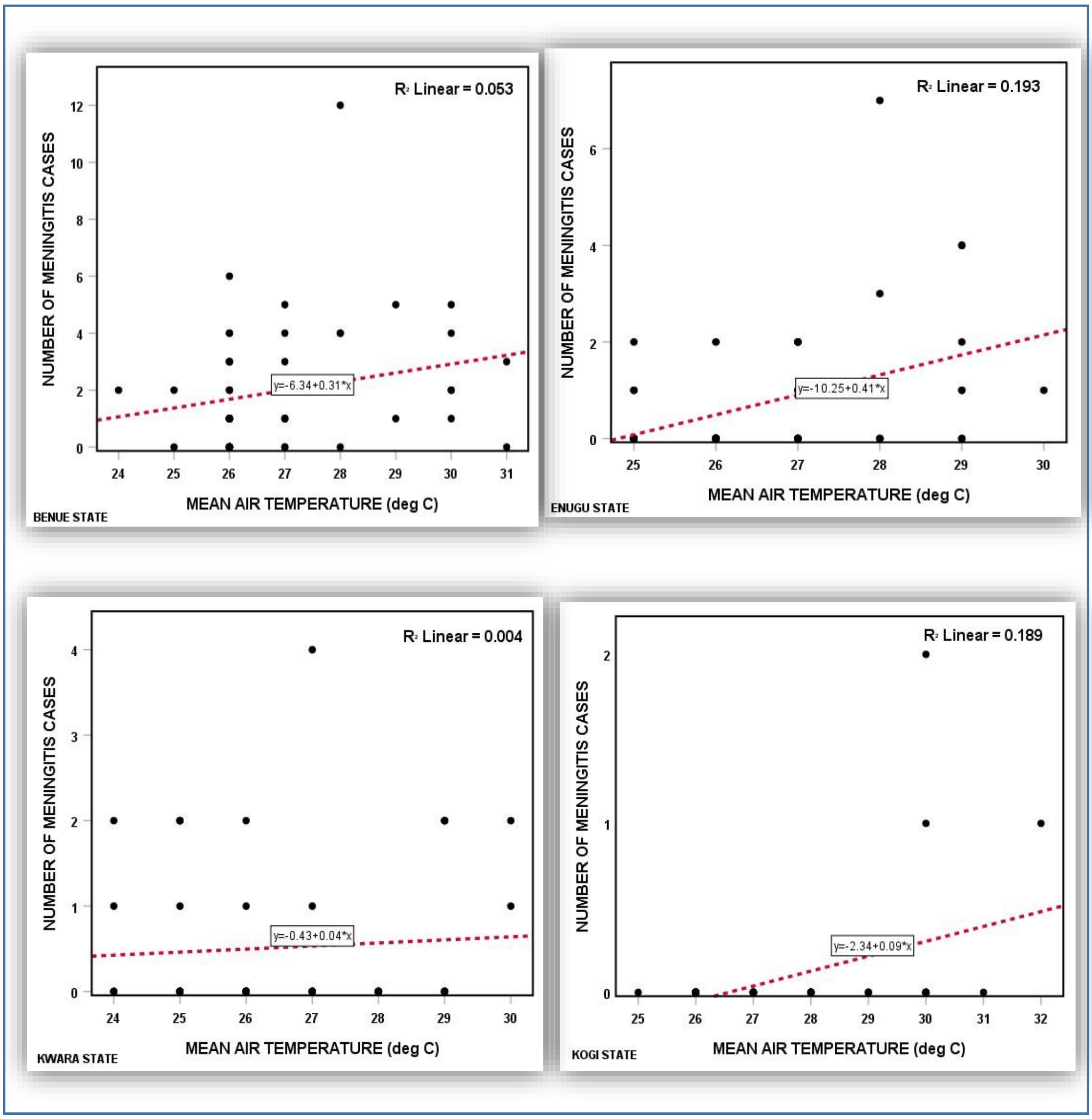

Figure 4.24 Trend in spatial occurrence of meningitis and mean air temperature in the Southern Savanna region from 2012 to 2015.

Mean air temperature elucidated that the relationship existing between it and meningitis occurrence in the region to be weak relationship with R^2 = 0.053 over Benue, R^2 = 0.19 in Enugu, R^2 = 0.004 in Kwara which in the weakest and R^2 = 0.18 in Kogi. Meningitis cases prevailed more at mean air temperature of between 28 ^{0}C and 29 ^{0}C, depicting an upward trend with regards to mean air temperature.

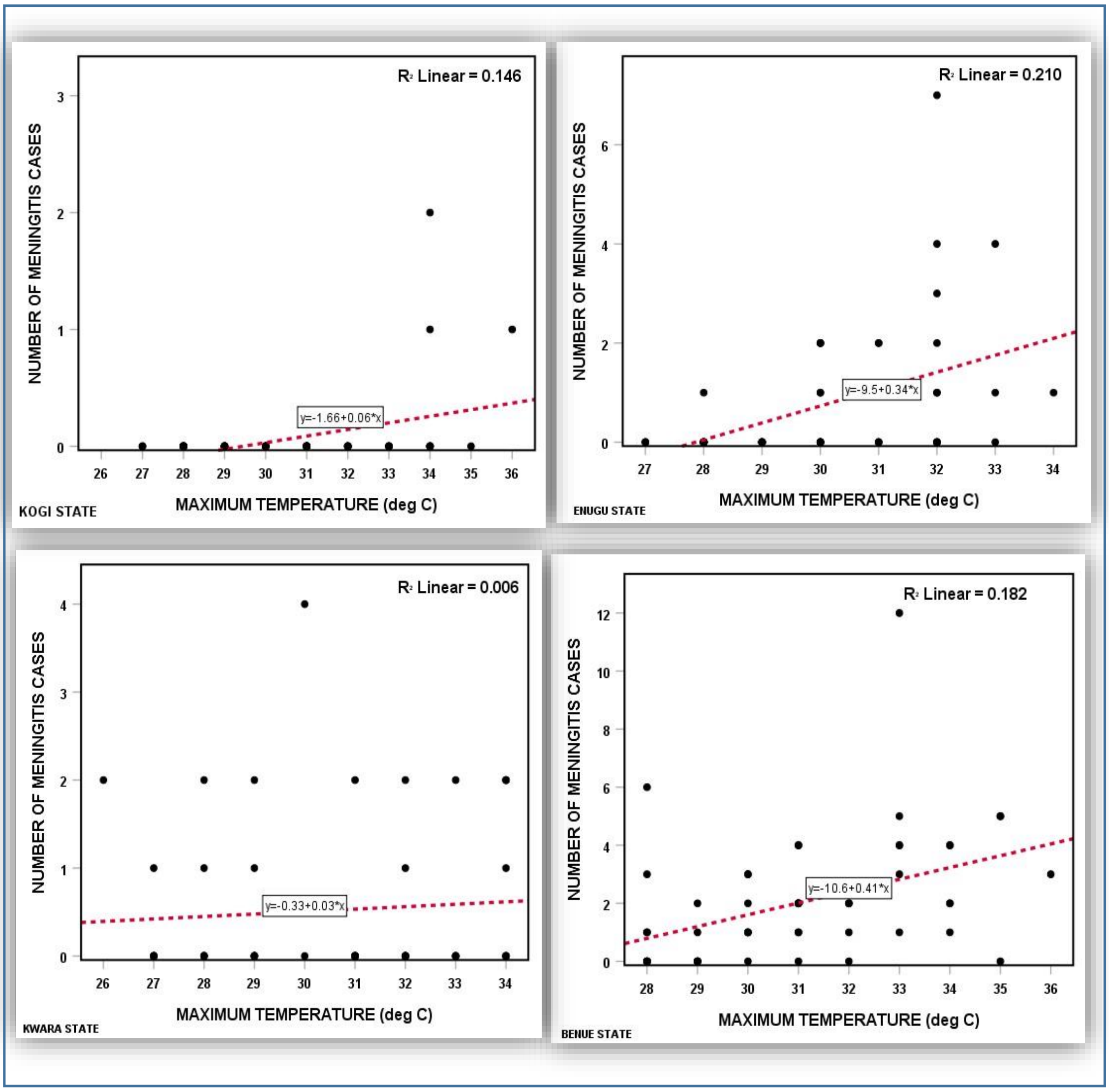

Figure 4.25 Trend in spatial occurrence of meningitis and maximum temperature in the Southern Savanna region from 2012 to 2015.

Meningitis occurrence was influenced by maximum temperature. Generally, the relationship between maximum temperature and meningitis prevalence from 2012 – 2015 in the region for this four-year period is weak with R^2 = 0.15 in Kogi, R^2 = .21 in Enugu, R^2 = 0.006 in Kwara being the weakest and R^2 = 0.18 in Benue state. CSM prevailed more when maximum temperature was in the range of 31 ^{0}C to 33 ^{0}C.

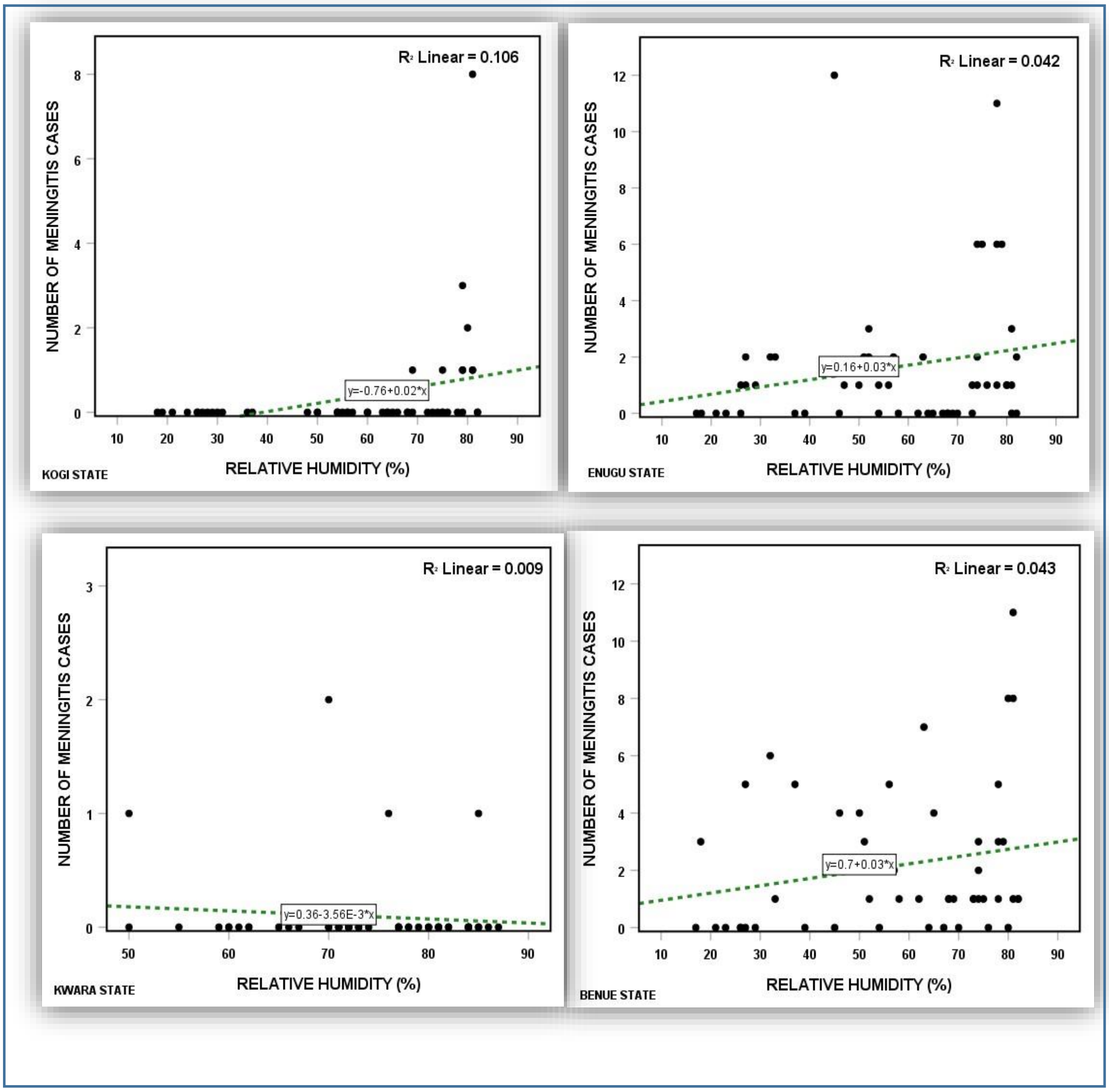

Figure 4.26 Trend in spatial occurrence of meningitis and relative humidity in the Southern Savanna region from 2016 to 2019.

There is a weak relationship between prevalence of CSM and relative humidity where the R^2 value of 0.10 is established in Kogi, R^2= 0.042 in Enugu, R^2= 0.009 in Kwara and R^2= 0.043 over Benue. Meningitis prevailed more in Benue and Enugu states.

CSM cases were also caused by relative humidity during the four-year period.

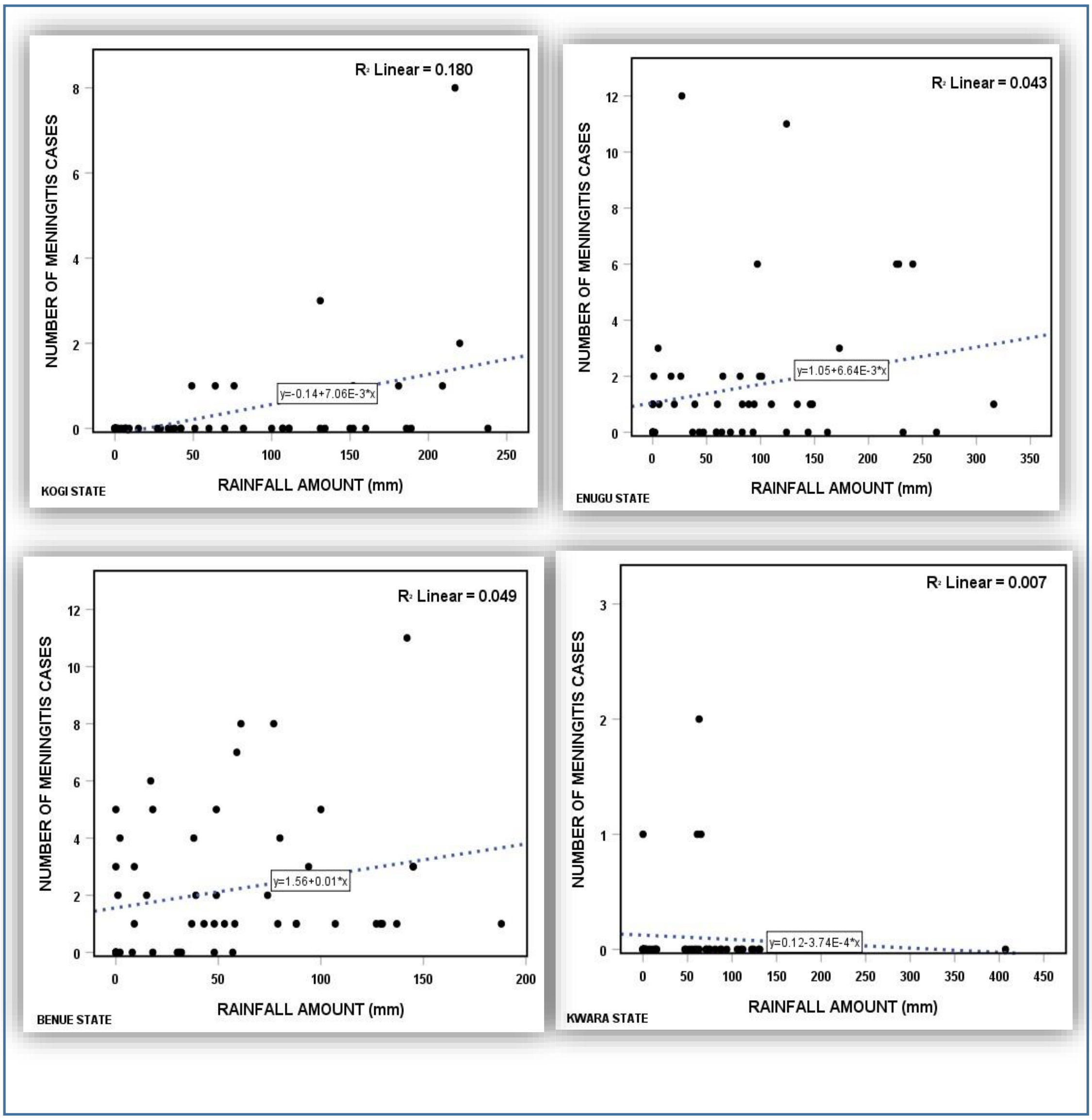

Figure 4.27 Trend in spatial occurrence of meningitis and rainfall in the Southern Savanna from 2016 to 2019.

From 2016 to 2019, the relationship between meningitis prevalence and rainfall amount was weak because over Kogi state at an R^2 value of 18%, in Kwara state, R^2 = 0.007 which is less than 1%. In Enugu state and Benue state, it is at 0.043 and 0.49 respectively. CSM cases occurred more when rainfall was less than 50 mm only over Kwara, Benue, Enugu and Kogi reported peak incidence of meningitis when rainfall was as high as 150 mm to 200 mm

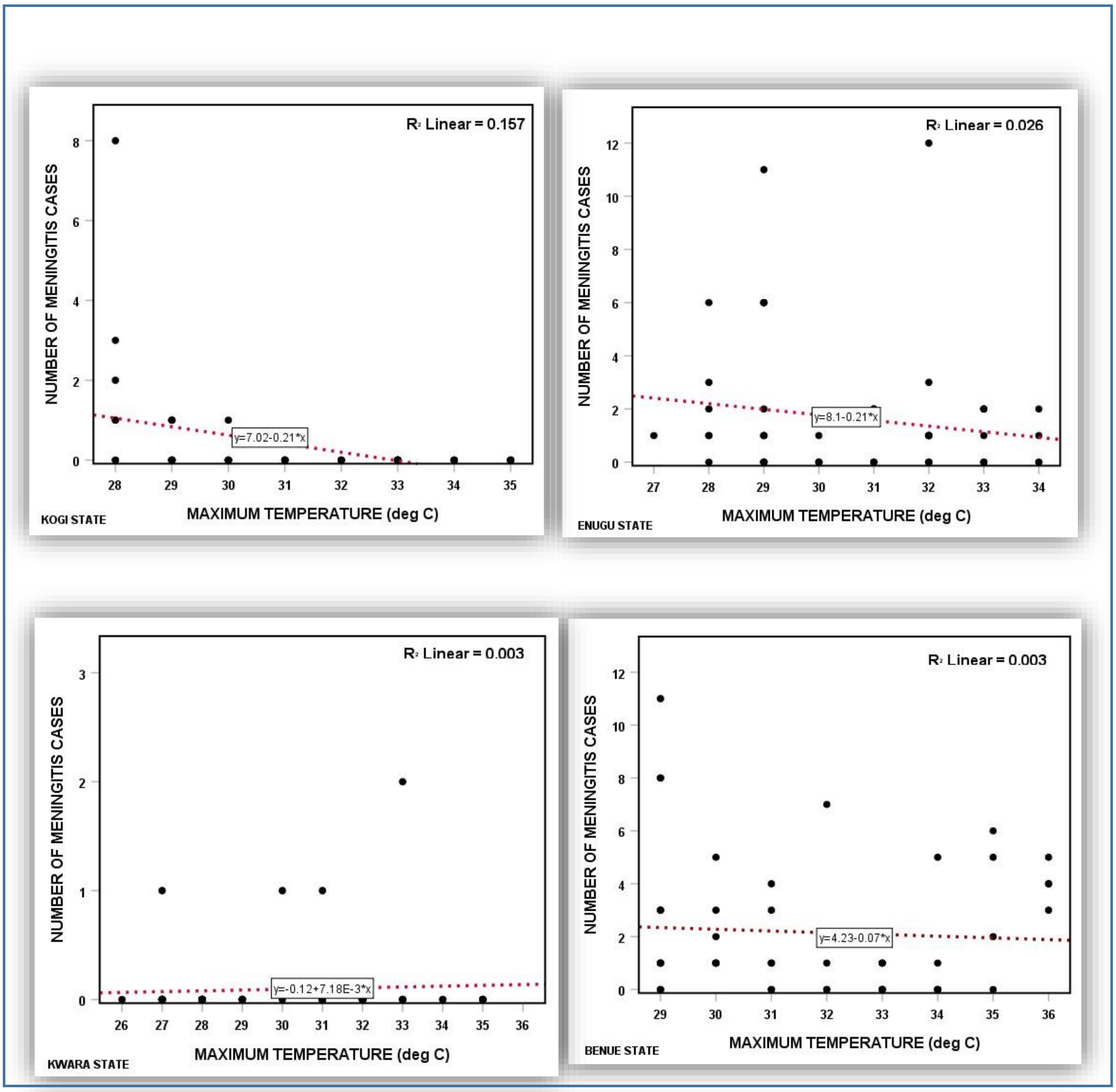

Figure 4.28 Trend in spatial occurrence of meningitis and maximum temperature in the Southern Savanna region from 2016 to 2019.

Maximum temperature had a level of impact on meningitis cases within the four-year period in view. However, the impact in each state varied in intensity. For instance, R^2 was 0.003 in Benue and Kwara State, 0.15 in Kogi state and 0.26 in Enugu state. Temperatures at about 28 ^{0}C – 29 ^{0}C had more CSM cases in Kogi and Enugu state then 29 ^{0}C to 33 ^{0}C in Kwara and Benue.

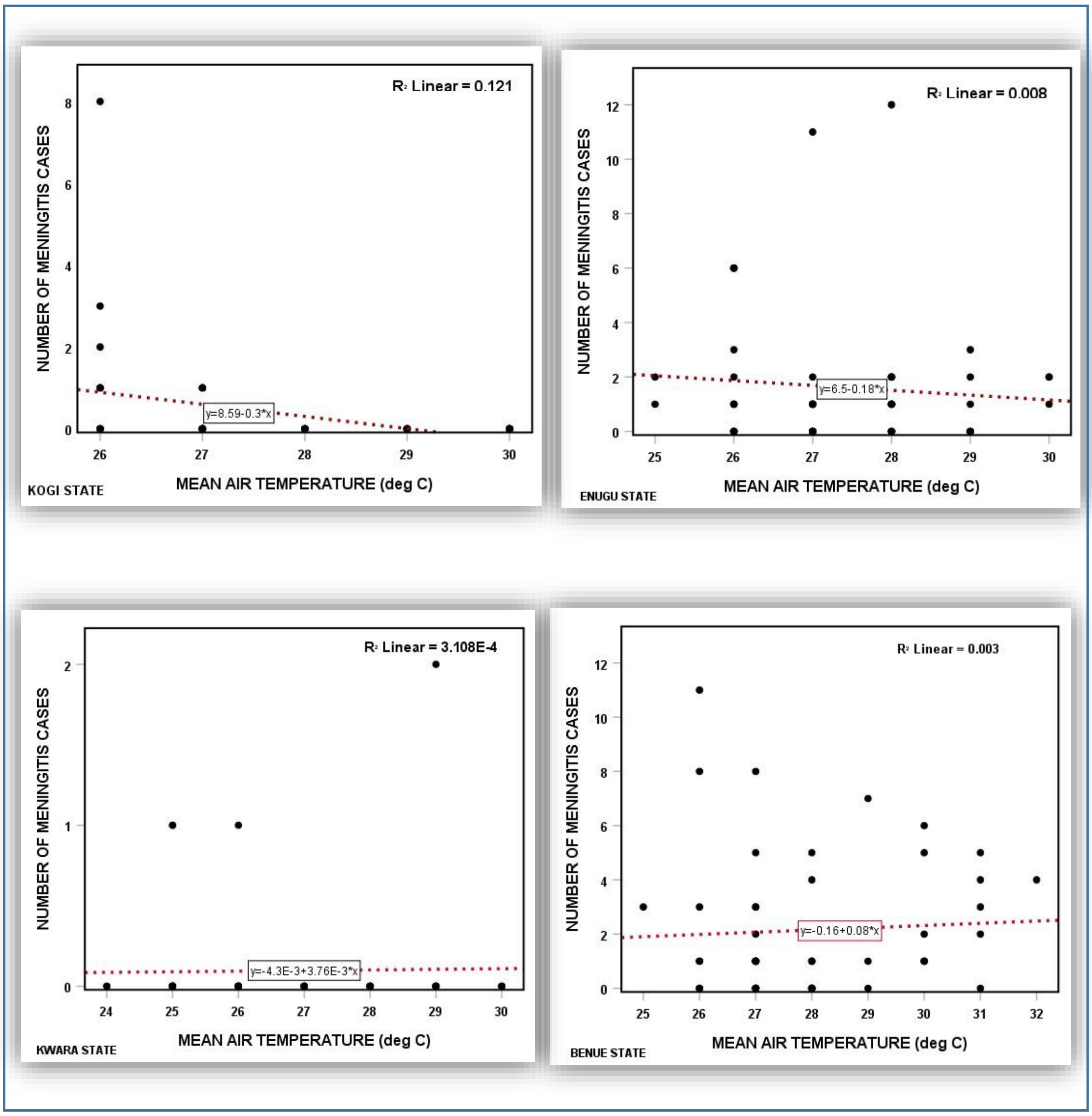

Figure 4.29 Trend in spatial occurrence of meningitis and mean air temperature in the Southern Savanna from 2016 to 2019.

Mean air temperature like other climate parameters had impact on meningitis cases within the four-year season although the impact was marginal. In Kwara, R^2 was less than one, in Benue, R^2= 0.003, R^2= 0.008 in Enugu and R^2= 0.12 in Kogi. In conclusion, mean air temperature influenced CSM cases in the region. No state was without the impact of mean air temperature.

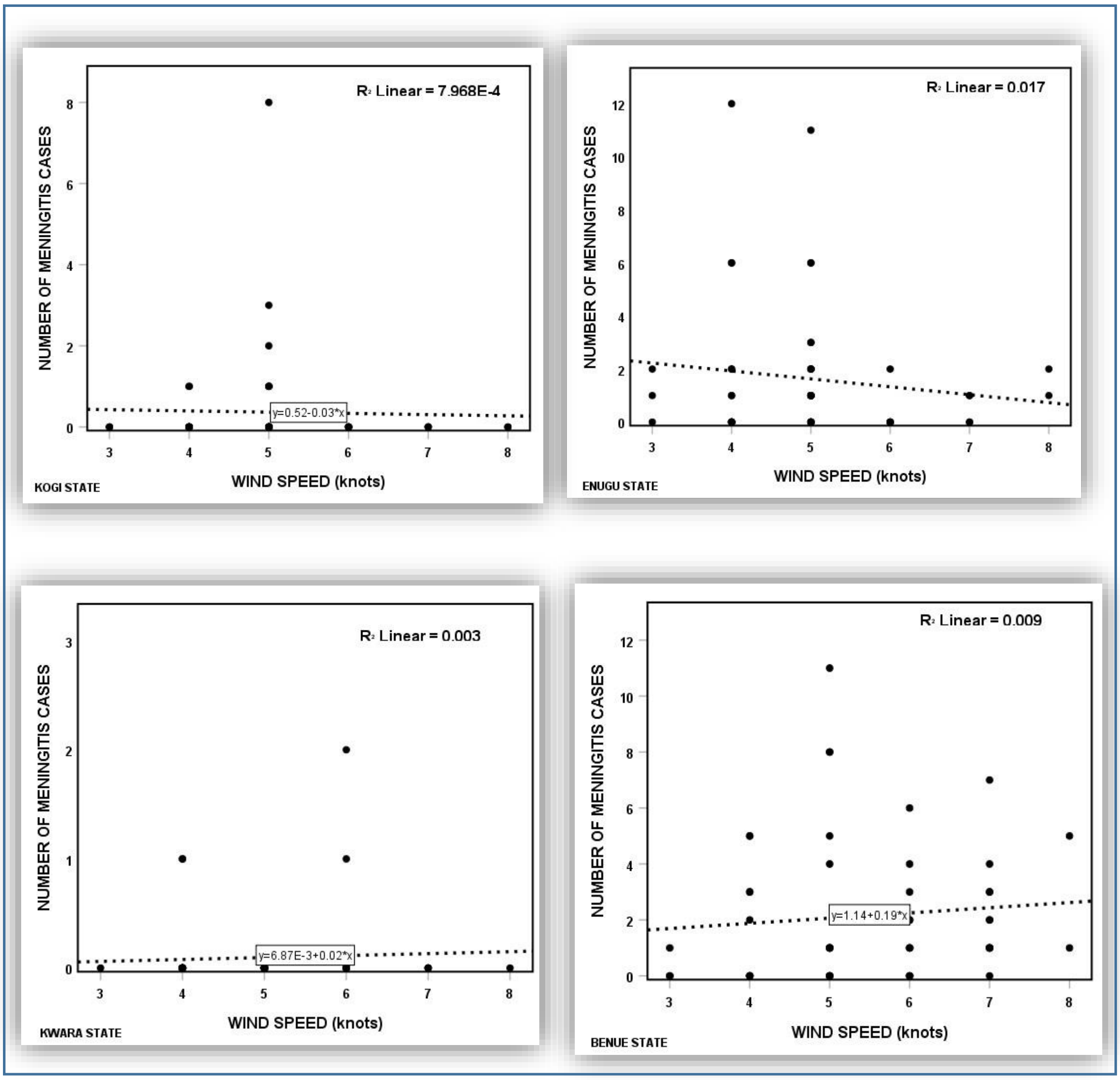

Figure 4.30 Trend in spatial occurrence of meningitis and wind speed in the Southern Savanna region from 2016 – 2019).

Wind speed had impact on meningitis cases in this region. In a span of four years, the R^2 values were 0.003 in Kwara State, 0.009 in Benue State, R^2= 0.17 in Enugu and less than 1.0 in Kogi. Common to all states in the region is that meningitis were at their peak at a wind speed of 5 to 6 knots.

4.2.3 Trend in spatial Occurrence of meningitis and weather parameters in the Sudano-Sahelian Region for three time periods from 2008 – 2011, 2012 – 2015 and 2016 - 2019.

The trend in occurrence of meningitis with respect to the weather variables in consideration over the Sudano-Sahelian region is being discussed.

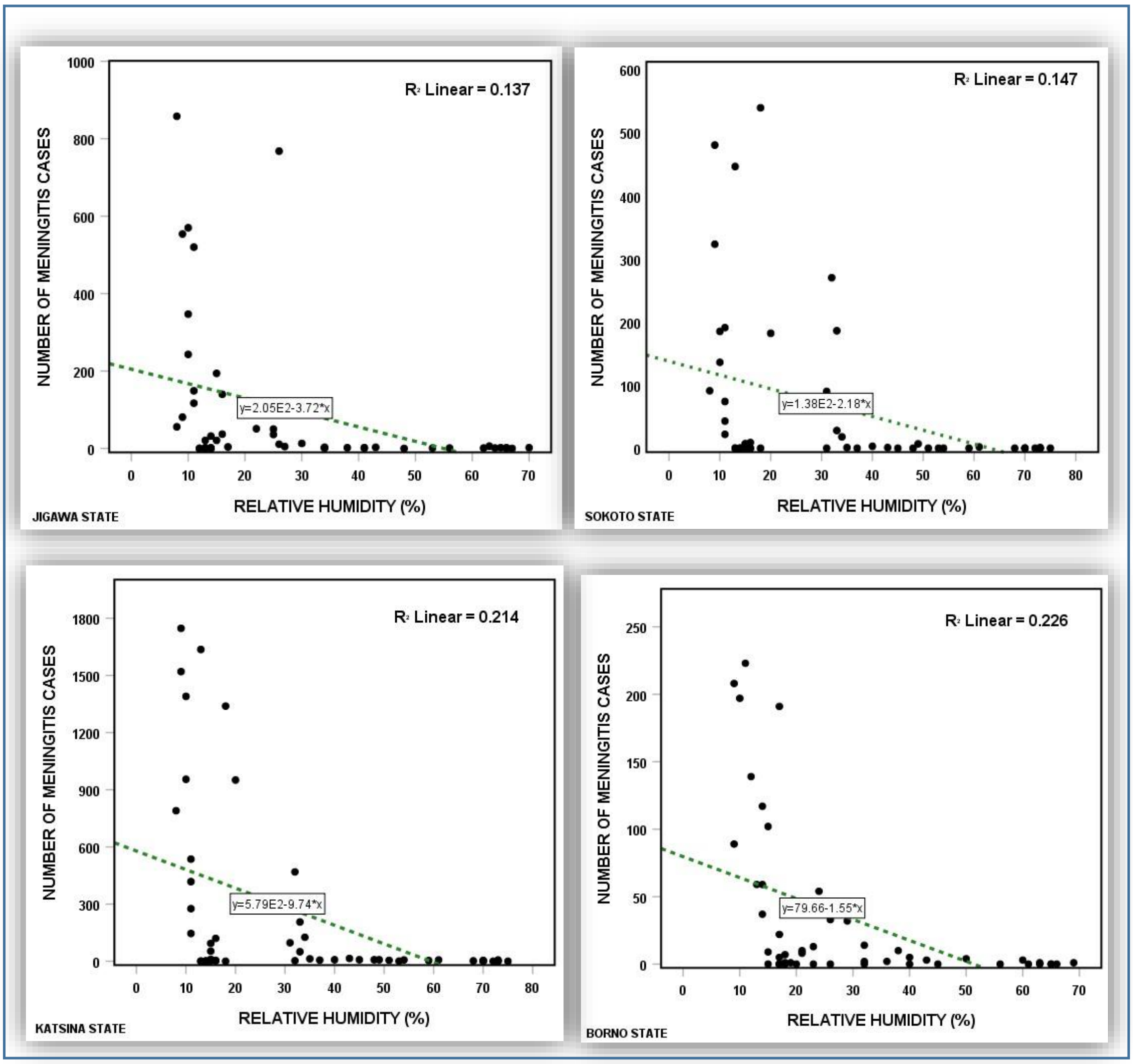

Figure 4.31 Trend in spatial occurrence of meningitis and relative humidity in the Sudano-Sahelian region from 2008 to 2011.

In Katsina state, 21% of CSM cases were accounted for by relative humidity, 23% of the cases in Borno State and 13% in Jigawa State. In Sokoto, it was at about 16%. Highest cases of meningitis were recorded when RH was within 10 and 15% across all the states.

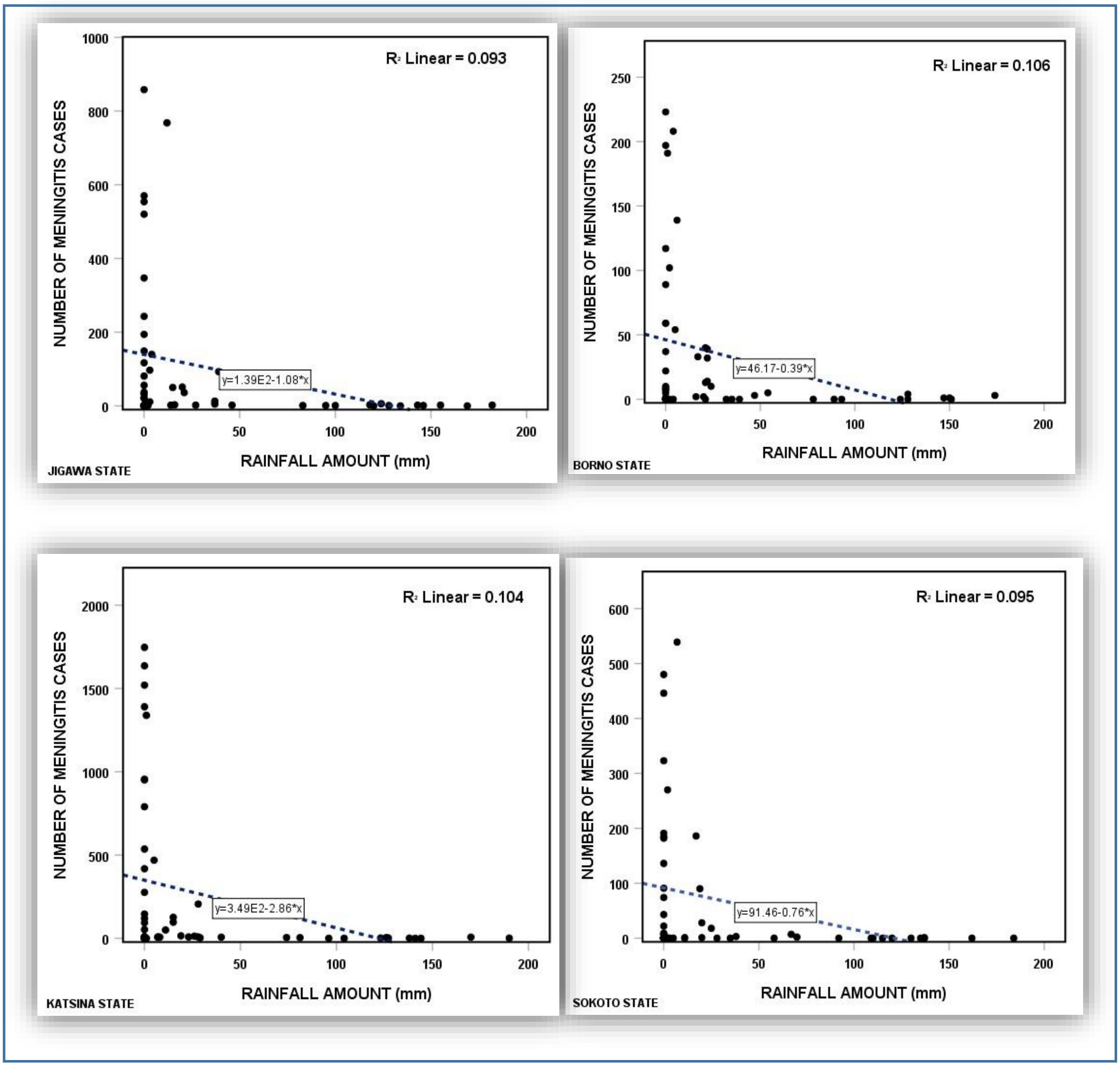

Figure 4.32 Trend in spatial occurrence of meningitis and rainfall amount in the Sudano-Sahelian region from 2008 to 2011

Rainfall impacted CSM cases in the region with an impact of about 10% in Katsina,

10% in Sokoto, Jigawa 9% and 10% over Borno. Meningitis incidence was more at rainfall amount less of than 40%. This corroborates ACMAD's stance on the

influence of rainfall on meningitis.

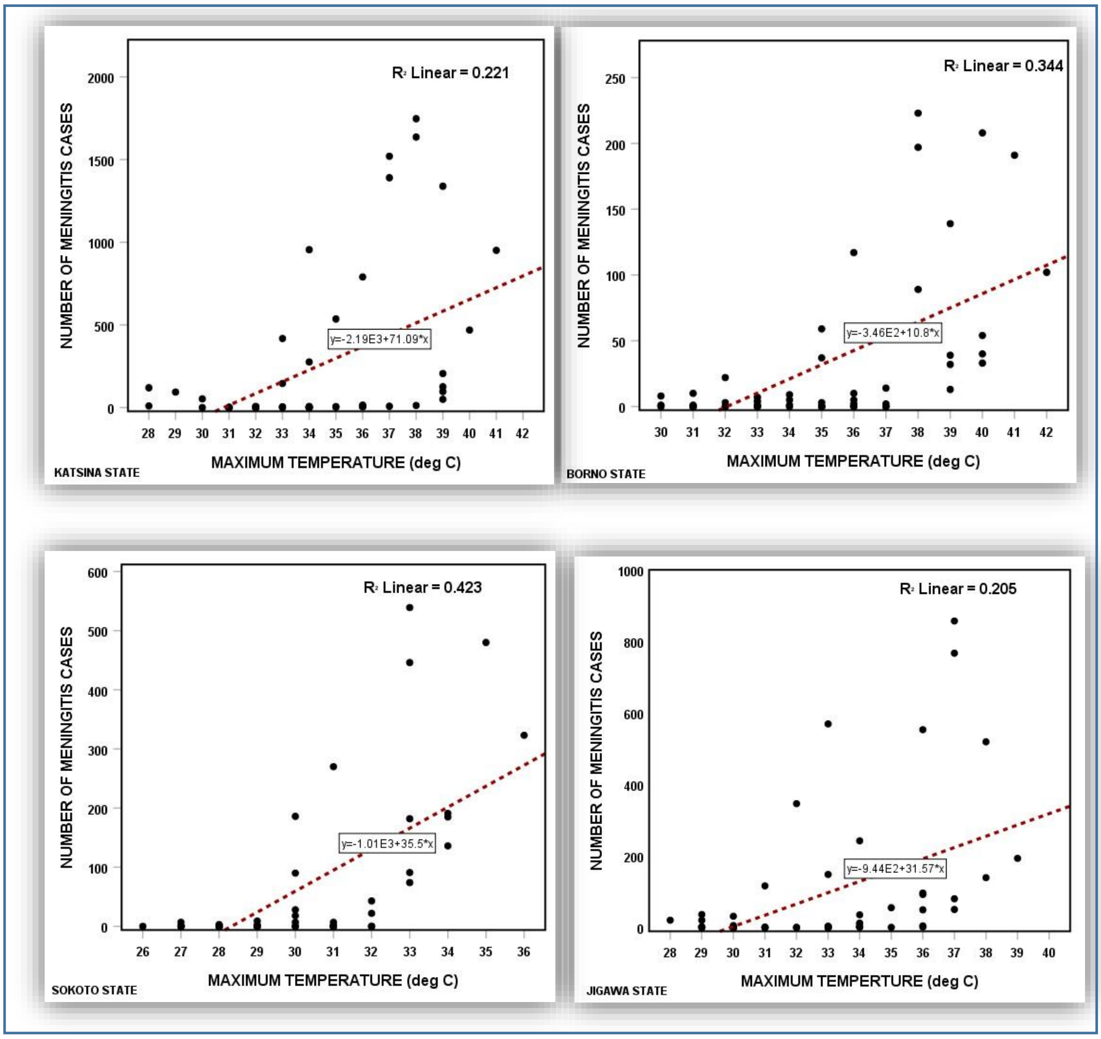

Figure 4.33 Trend in spatial occurrence of meningitis and maximum temperature in the Sudano-Sahelian region from 2008 to 2011.

The relationship between maximum temperature and meningitis prevalence in the region from 2008 to 2011 is generally weak with R^2 = 0.221 over Katsina State, 0.34 in Borno State, 0.43 in Sokoto and 0.20 over Jigawa. Of the four States the relationship was stronger in Sokoto State. CSM cases surged at a maximum temperature of 38 – 39^{0}C in the region.

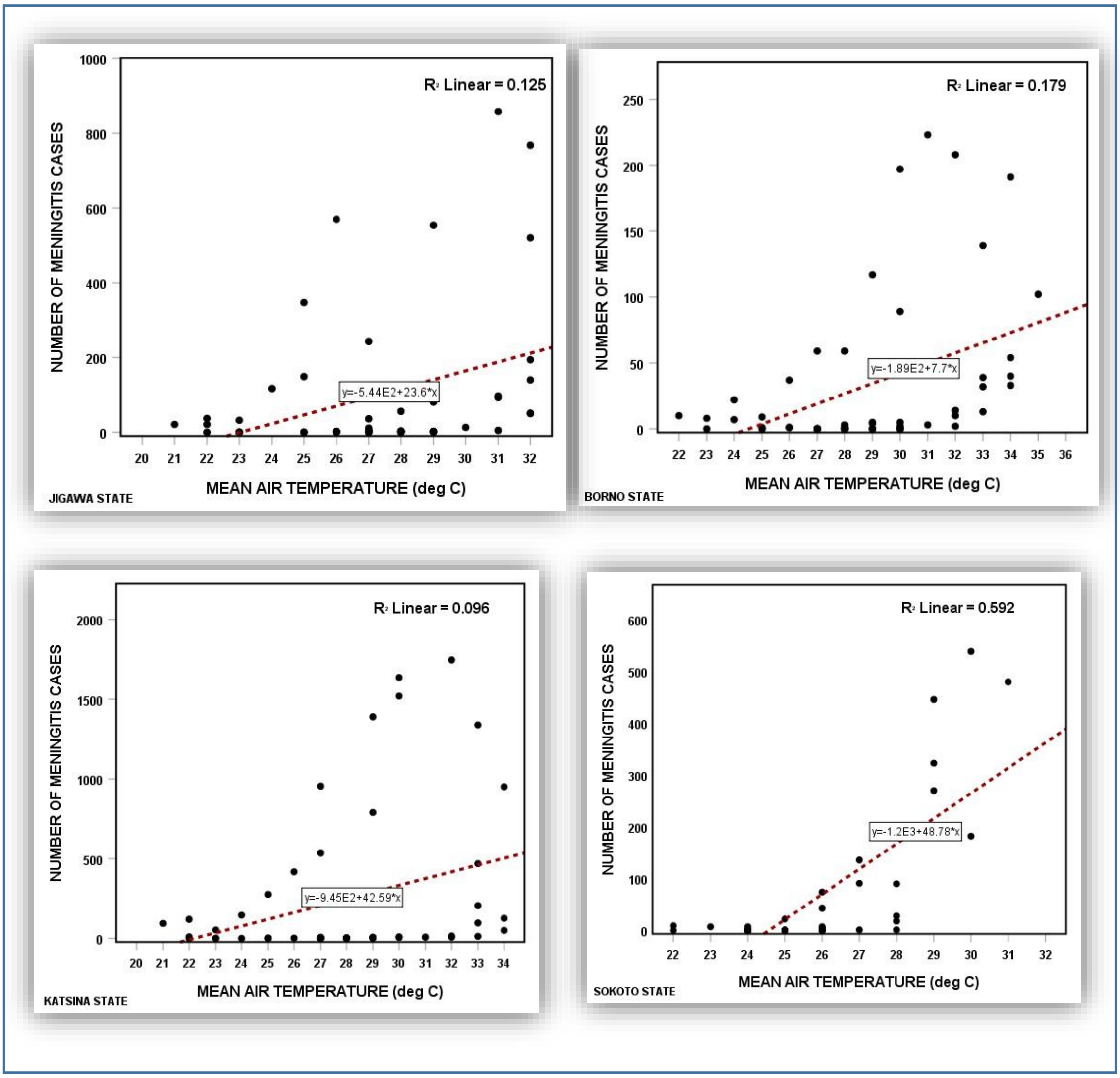

Figure 4.34 Trend in spatial occurrence of meningitis and mean air temperature in the Sudano-Sahelian region from 2008 to 2011.

A weak relationship is witnessed in Jigawa with R^2 value of 0.125, R^2= 0.17 in Borno, 0.096 in Katsina but strong over Sokoto State with R^2 value of 0.59. Meningitis prevailed more at mean temperature value of 29 ^{0}C – 30 ^{0}C across the region. This supports ACMAD's stand point that mean temperatures within the range of 18 ^{0}C –

32 ^{0}C favour high CSM cases.

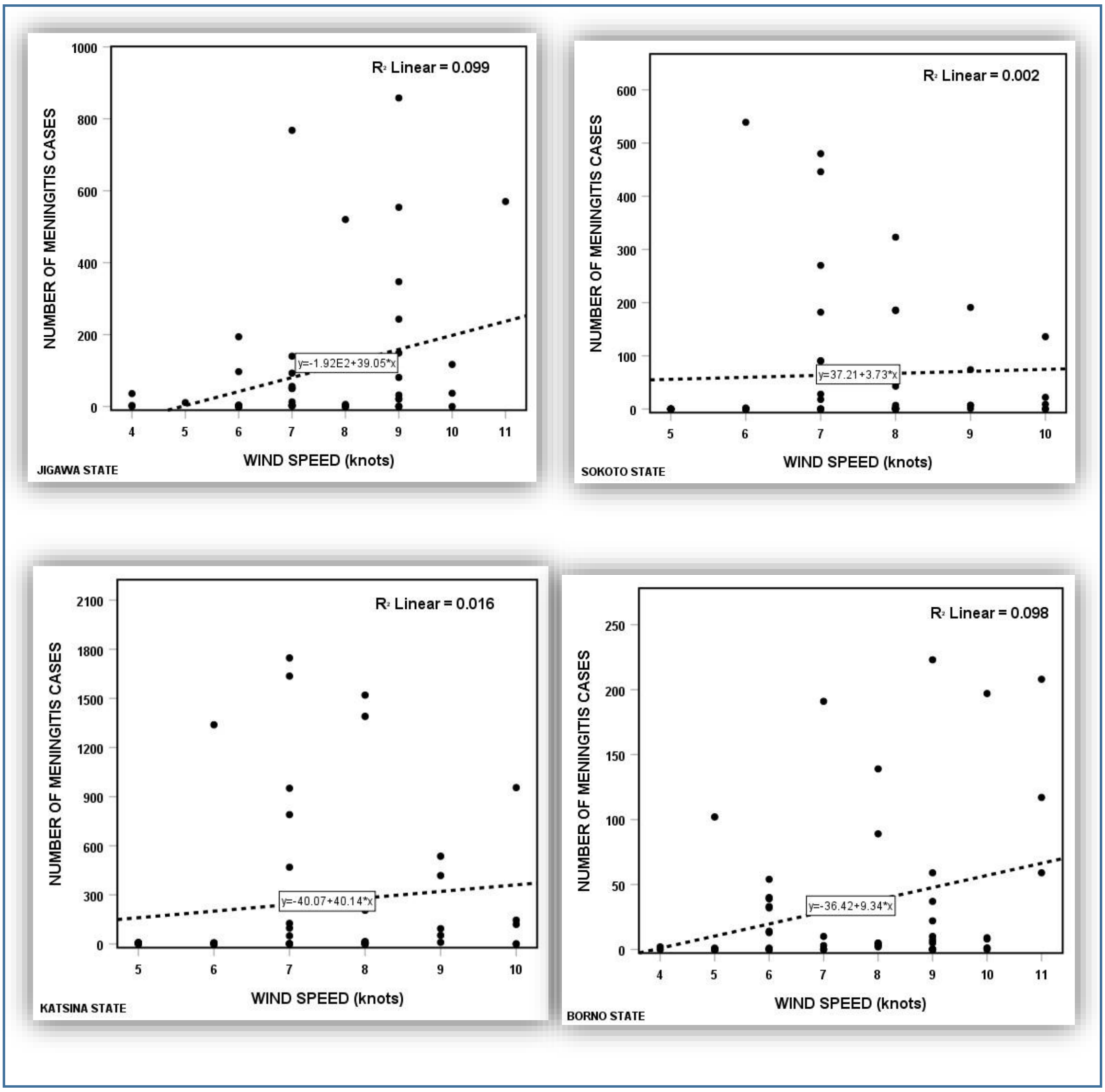

Figure 4.35 Trend in spatial occurrence of meningitis and wind speed in the Sudano-Sahelian region from 2008 to 2011.

Wind speed only accounted for 9% of CSM prevalence in Jigawa, 10% in Borno, 2% in Katsina and less than 1% in Sokoto State. Generally, the relationship between the dependent and independent climate variable is weak. Meningitis cases pealed at wind speed of 6 – 7 knots.

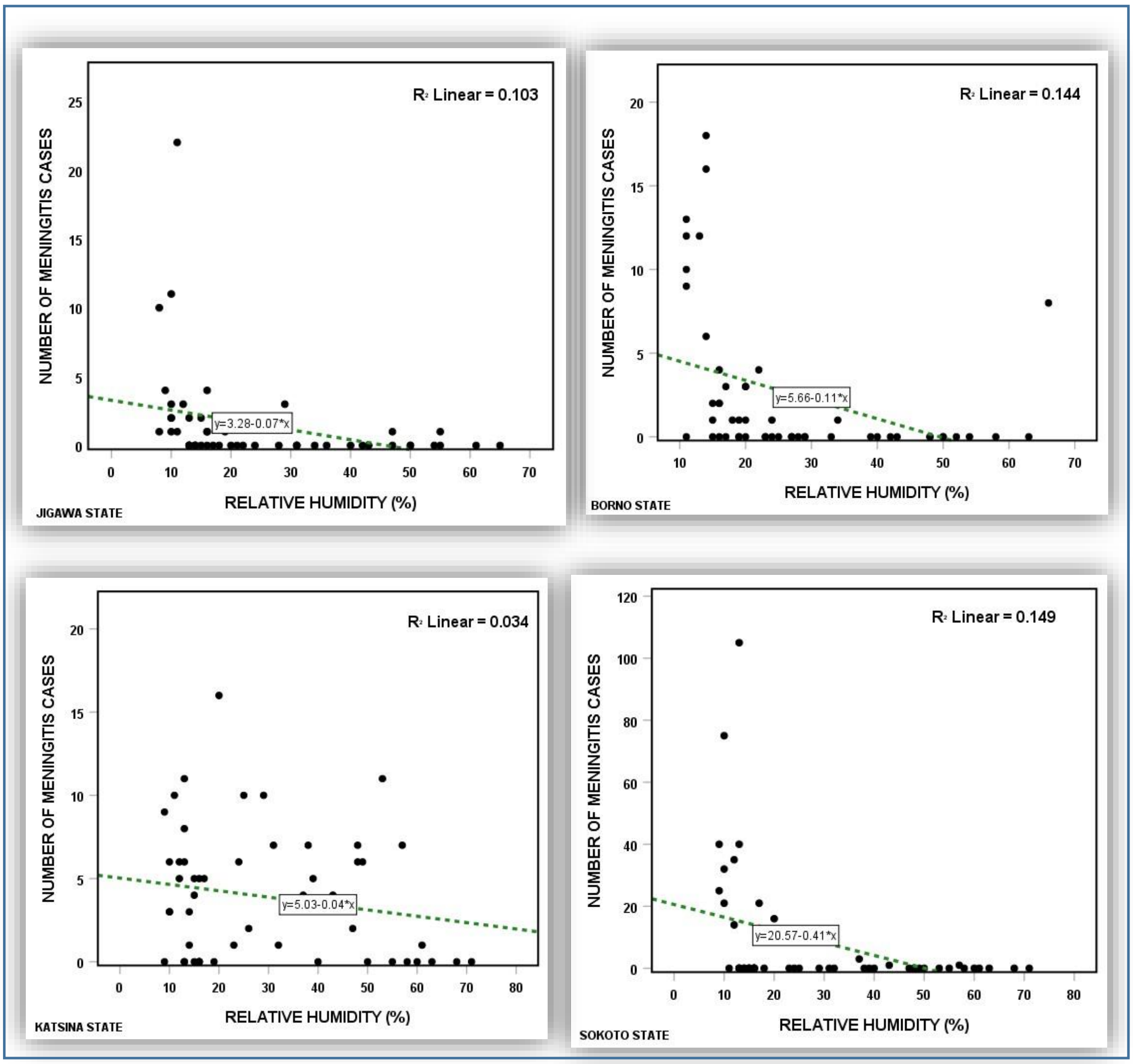

Figure 4.36 Trend in spatial occurrence of meningitis and relative humidity in the Sudano-Sahelian region from 2012 to 2015.

A weak relationship exists between relative humidity and meningitis occurrence with R^2 value of 10% in Jigawa State 14% in Borno State, 3% over Katsina State and 15% in Sokoto State. Meningitis prevailed most at Relative humidity value of less than

20% in the region.

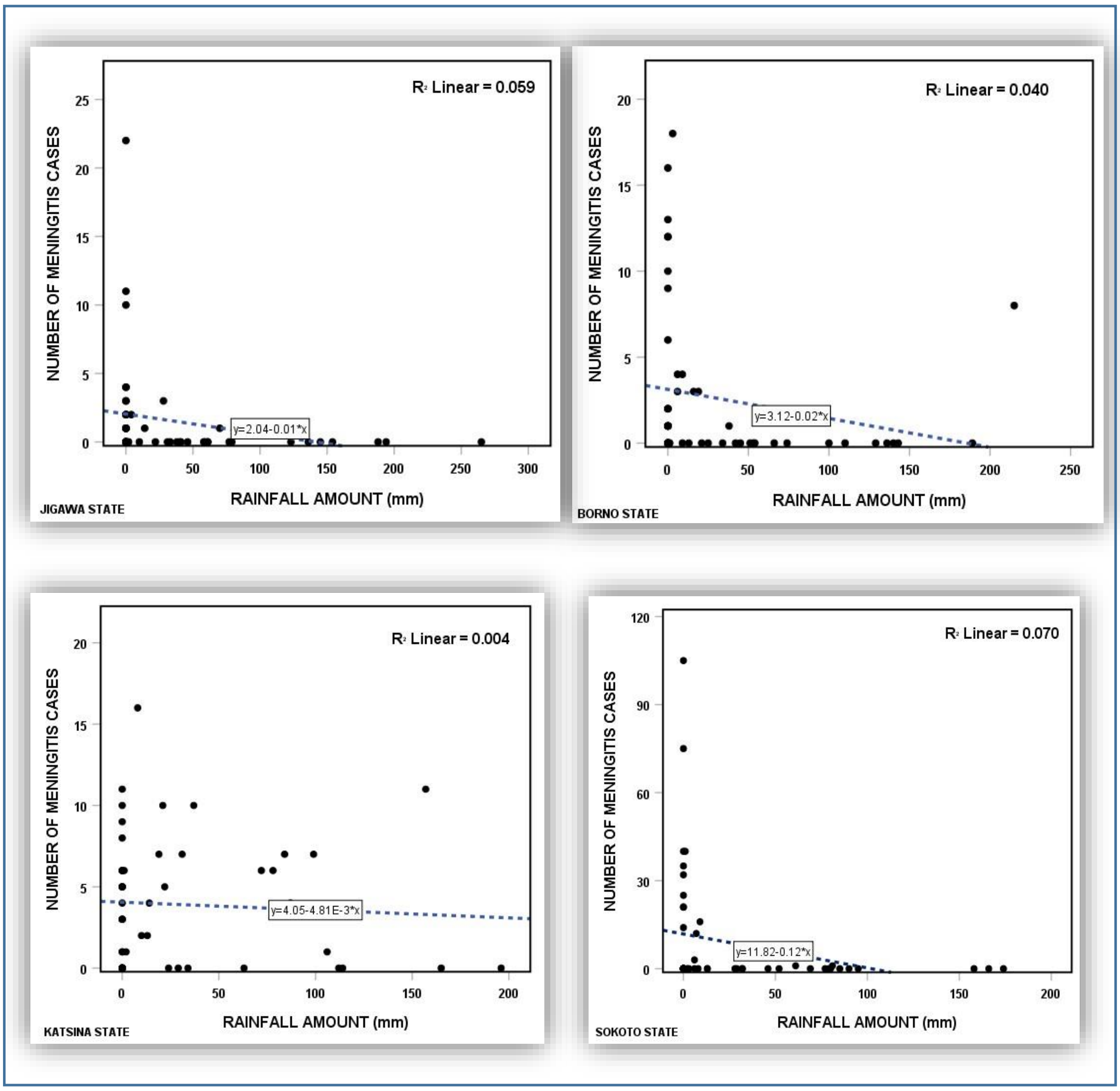

Figure 4.37 Trend in spatial occurrence of meningitis and rainfall amount in the Sudano-Sahelian region from 2012 to 2015.

The relationship existing between CSM and rainfall amount is almost negligible at R^2 value of 5% in Jigawa, 4% in Borno, 7% in Sokoto and less than 1% in Katsina State. Meningitis prevalence is noticed more at rainfall weekly aggregate of less than 50 mm.

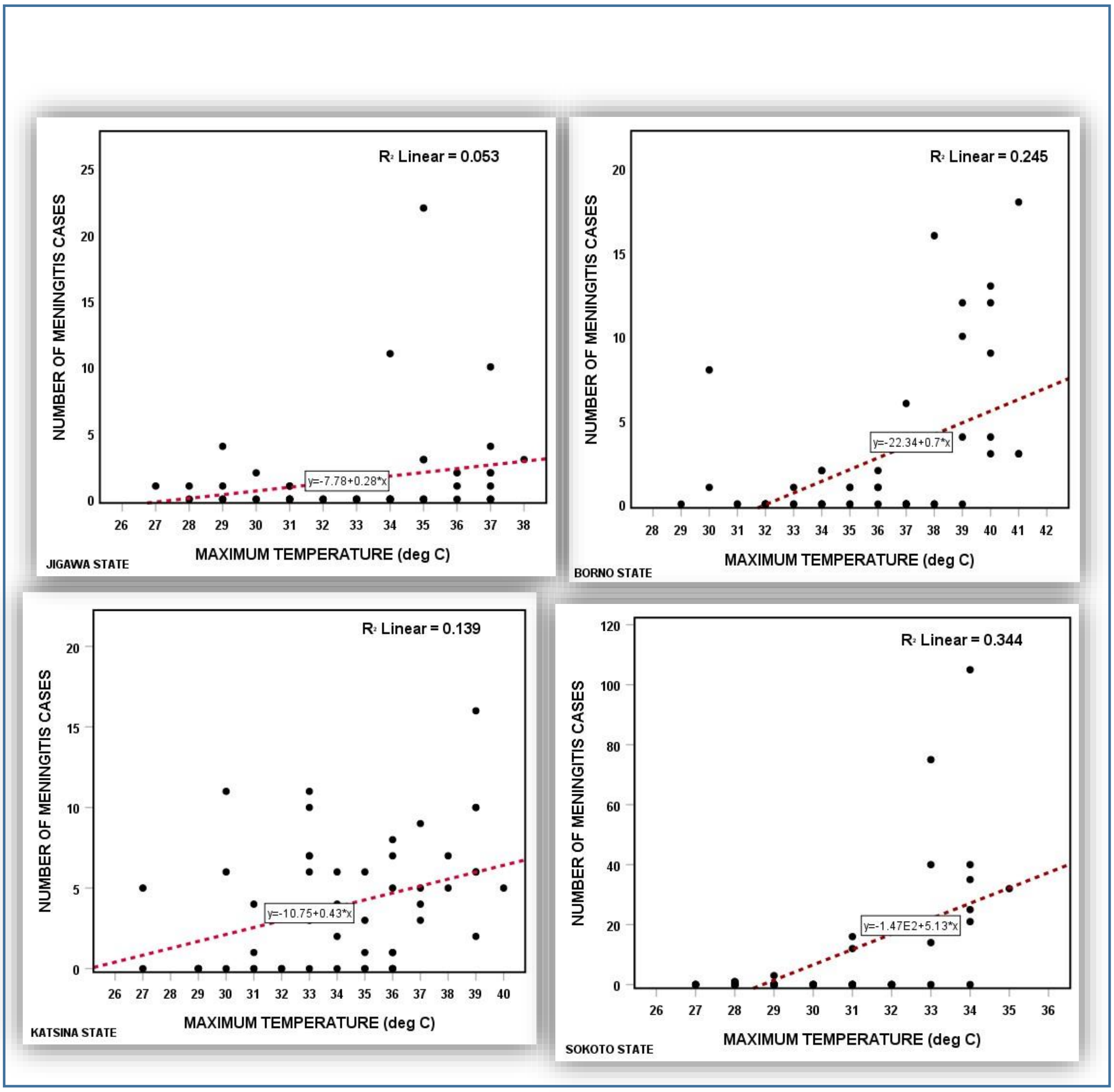

Figure 4.38 Trend in spatial occurrence of meningitis and maximum temperature in the Sudano-Sahelian region from 2012 to 2015.

Weak relationship is witnessed in the region between meningitis prevalence and CSM cases with R^2 values of about 14% in Katsina, 24% in Sokoto State, 5% in Jigawa being the weakest and 34% in Sokoto State which is the strongest impact. Highest number of meningitis cases recorded were when maximum temperature was in the range of 32 ^{0}C – 34 ^{0}C.

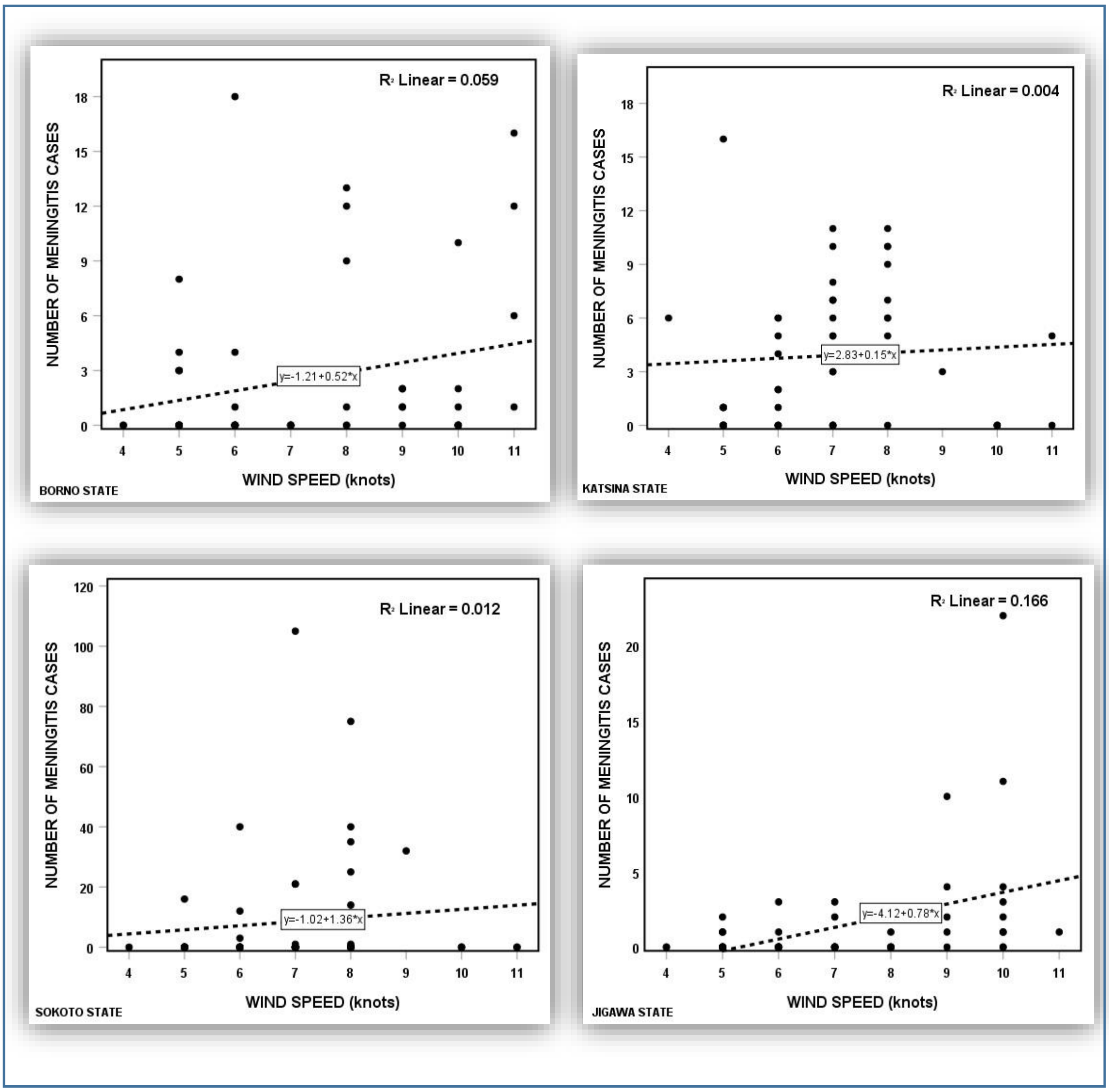

Figure 4.39 Trend in spatial occurrence of meningitis and wind speed in the Sudano-Sahelian region from 2012 to 2015.

The relationship existing between wind speed and meningitis is weak in the region because wind speed accounted for only 5% of meningitis cases in Borno, less than 1% in Katsina which is almost negligible and a little above 1% in Sokoto and Jigawa States. In Borno, CSM cases did not particularly follow any pattern with regards wind speed but over Katsina, Sokoto and Jigawa, CSM cases were most prevalent at wind speed in the range 7 – 10 knots.

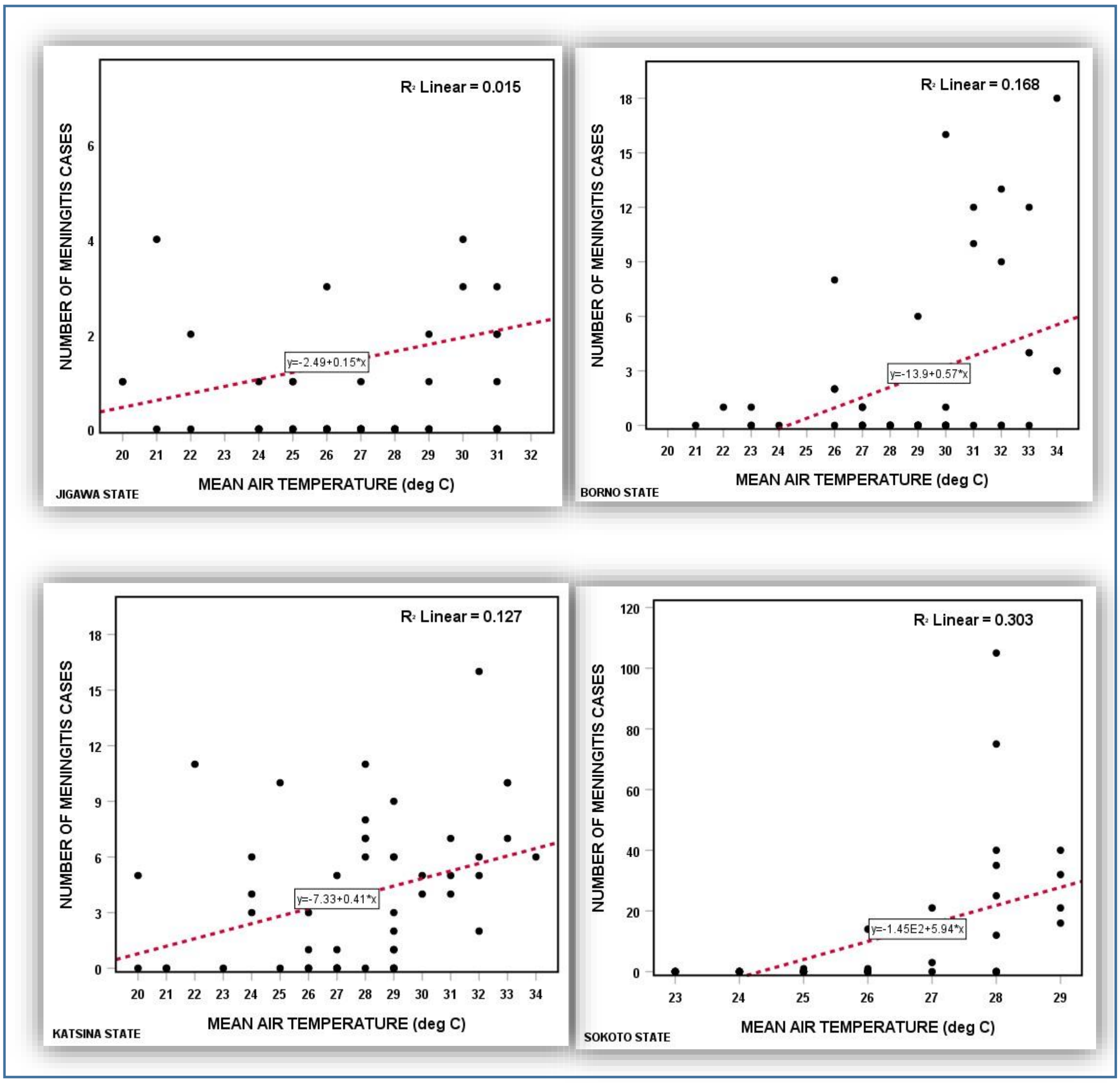

Figure 4.40 Trend in spatial occurrence of meningitis and mean air temperature in the Sudano-Sahelian region from 2012– 2015.

A weak relationship is seen between meningitis cases and mean air temperature in the region from 2012 to 2015 at an R^2 value of about 2% in Jigawa, 16% in Borno, 13% in Katsina and 30% in Sokoto state. Even though CSM cases were recorded at various temperature thresholds, meningitis cases skyrocketed at a mean air temperature between 29 ^{0}C – 32 ^{0}C.

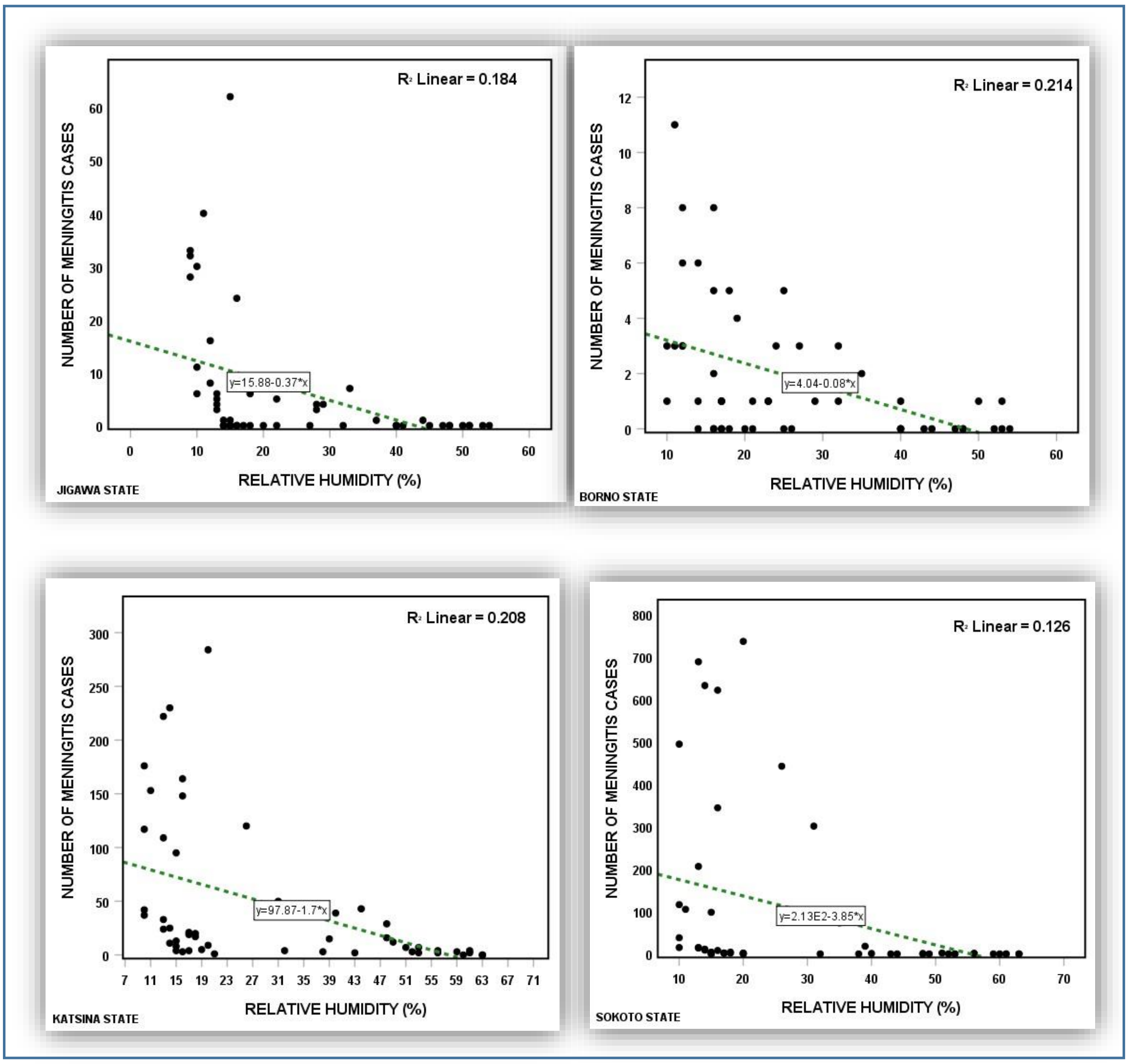

Figure 4.41 Trend in spatial occurrence of meningitis and relative humidity in the Sudano-Sahelian region from 2016 to 2019.

The impact of relative humidity on meningitis in the region from 2016 – 2019 is minimal at 18% of cases accrued to RH in Jigawa, 21% in Borno state, 21% in Katsina and 12% in Sokoto being the least. Howbeit, meningitis cases surged when relative humidity values were below 20% across the region. This indicates that CSM cases respond to low relative humidity threshold as corroborated by Jackou-Boulama et al, in 2005.

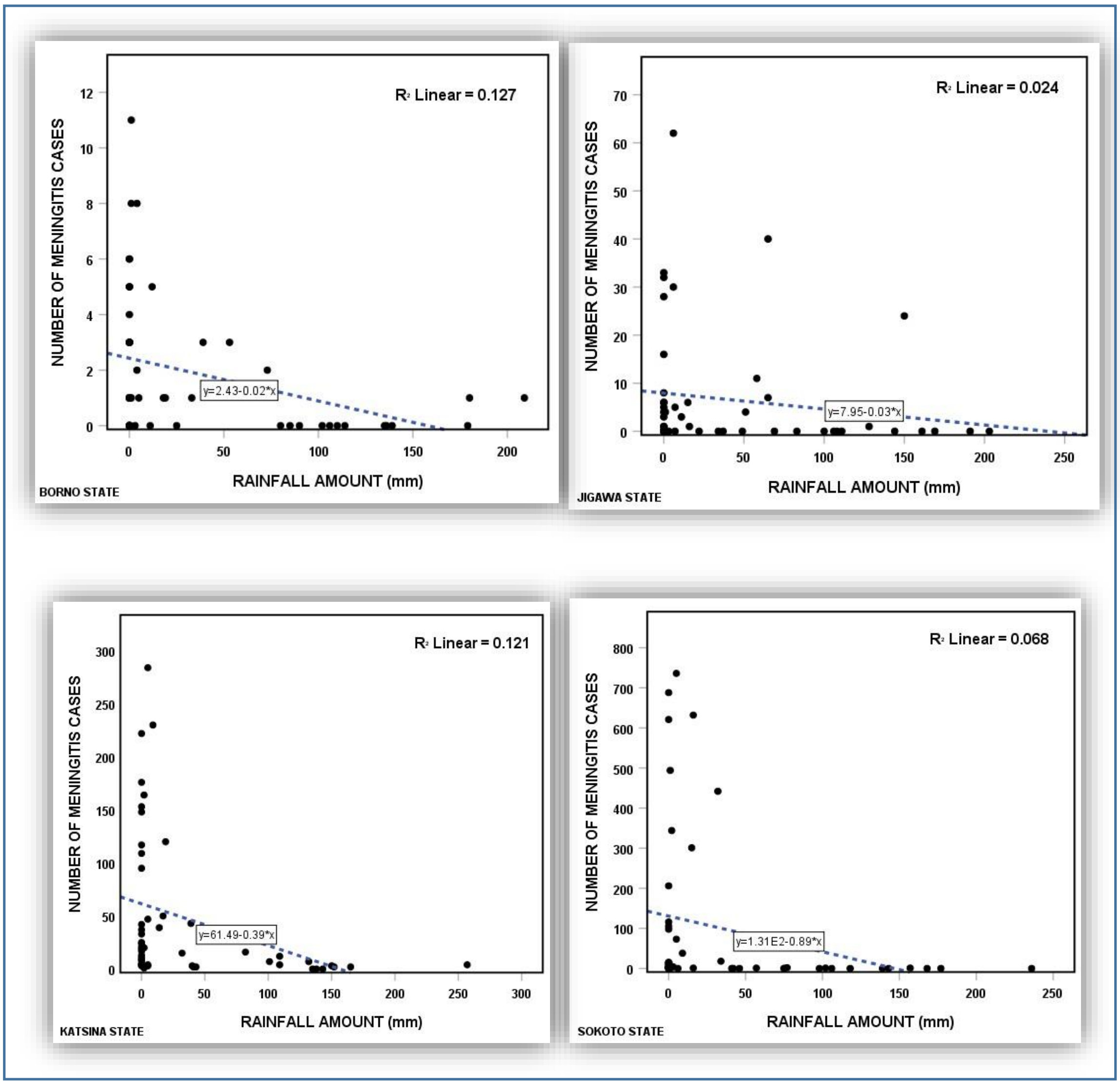

Figure 4.42 Trend in spatial occurrence of meningitis and rainfall amount in the Sudano-Sahelian region from 2016 to 2019.

Weak relationship exists between CSM cases and rainfall in the Sudano – Sahelian region at R^2 = 0.122 in Borno, R^2 = 0.024 in Jigawa, R^2 = 0.121 in Katsina and R^2 = 0.068 in Sokoto state. However, cases in meningitis were recorded more when rainfall was less than 50 mm.

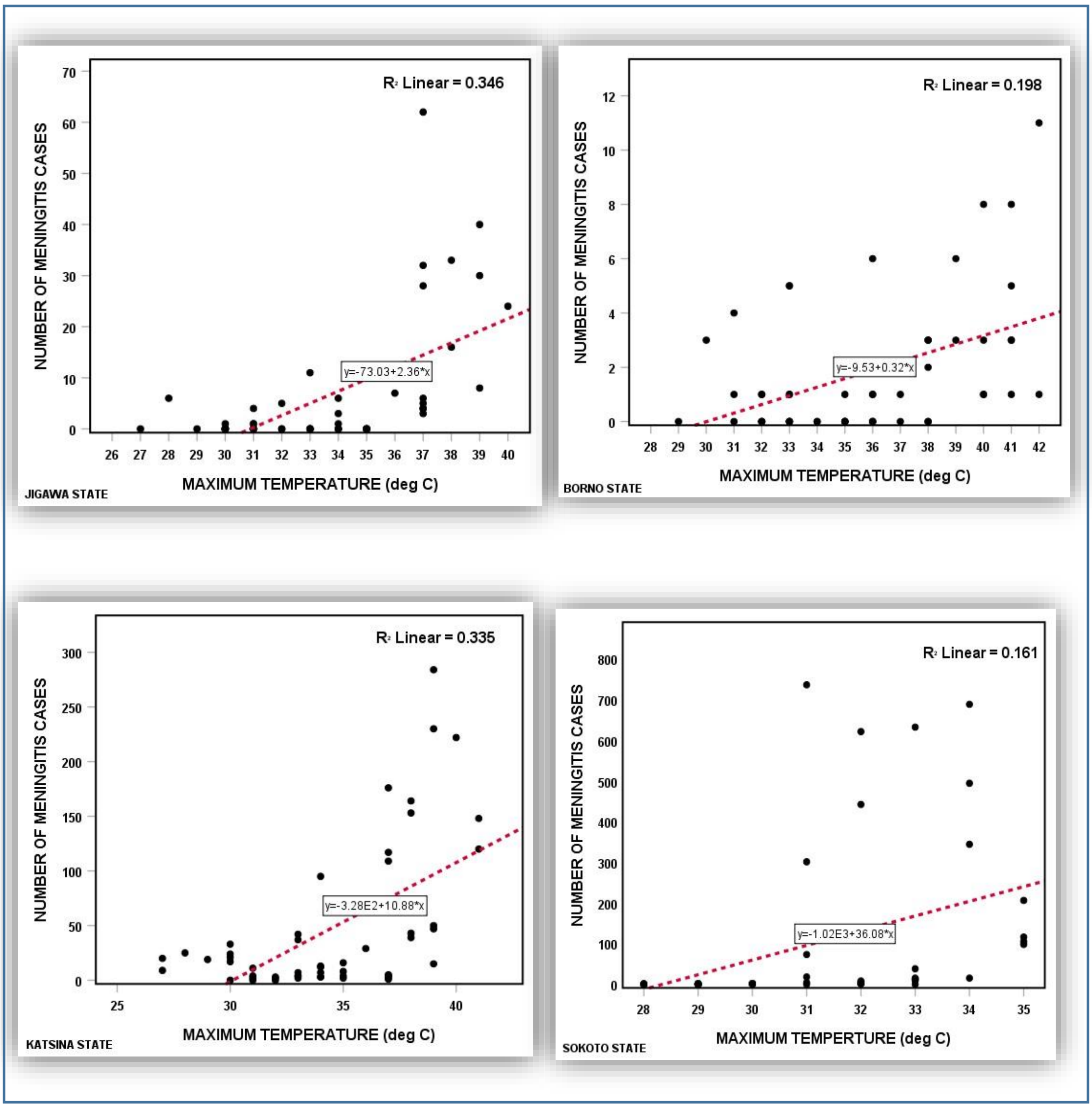

Figure 4.43 Trend in spatial occurrence of meningitis and maximum temperature in the Sudano-Sahelian region from 2016 to 2019.

The influence maximum temperature has on meningitis cases is as depicted by R^2 value of 35% in Jigawa, 20% in Borno state, 34% in Katsina and 15% in Sokoto state. For the occurrence threshold, cases surged when maximum temperature was in the range of 32 ^{0}C – 35 ^{0}C.

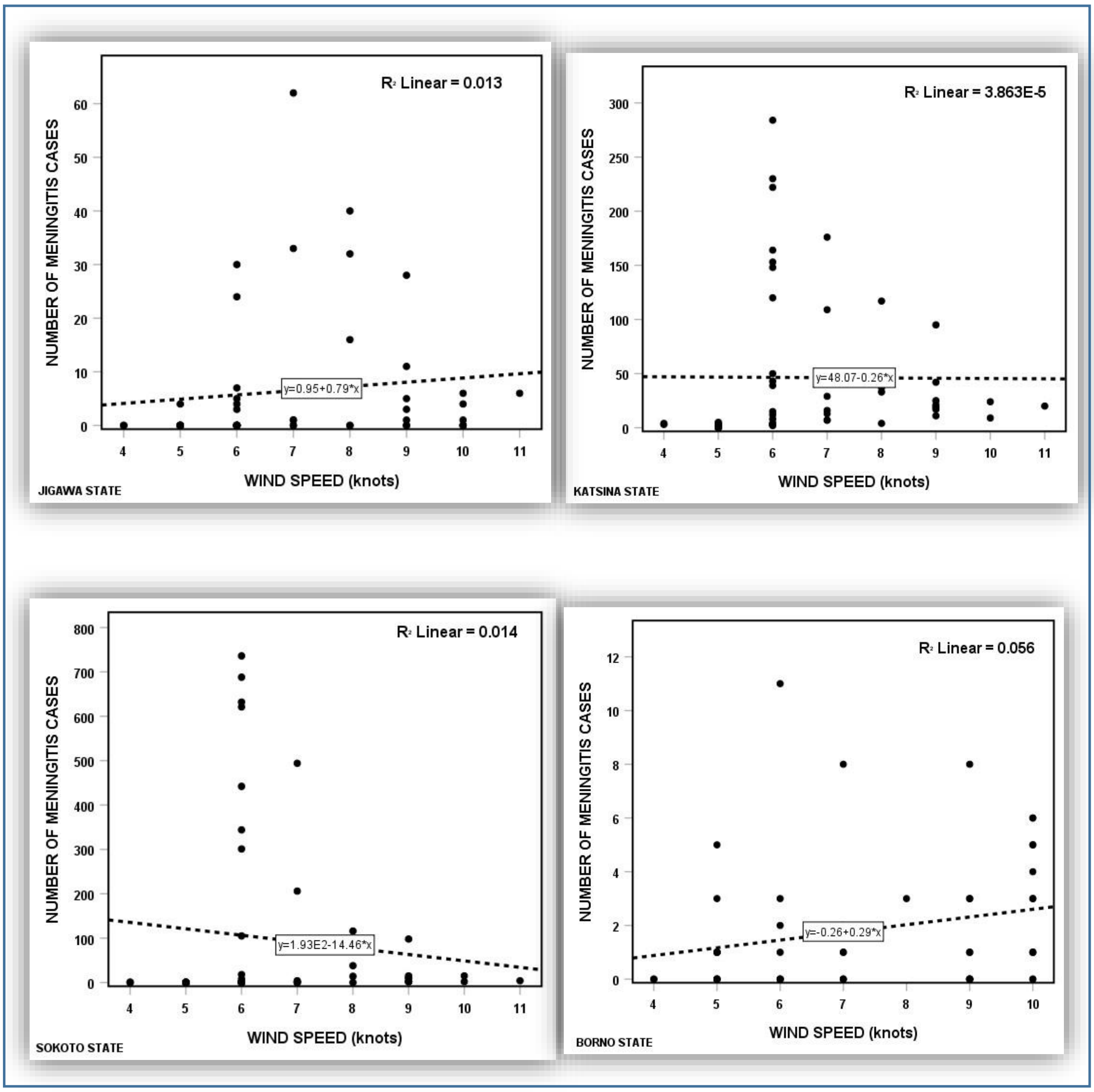

Figure 4.44 Trend in spatial occurrence of meningitis and wind speed in the Sudano-Sahelian region from 2016 to 2019.

Very little impact of wind speed is seen on CSM cases this period because R^2 value of 0.013 over Jigawa, less than 1% in Katsina. 1% and 6% over Sokoto and Borno respectively. Peak cases in the disease were recorded at wind speed of 6 – 8 knots.

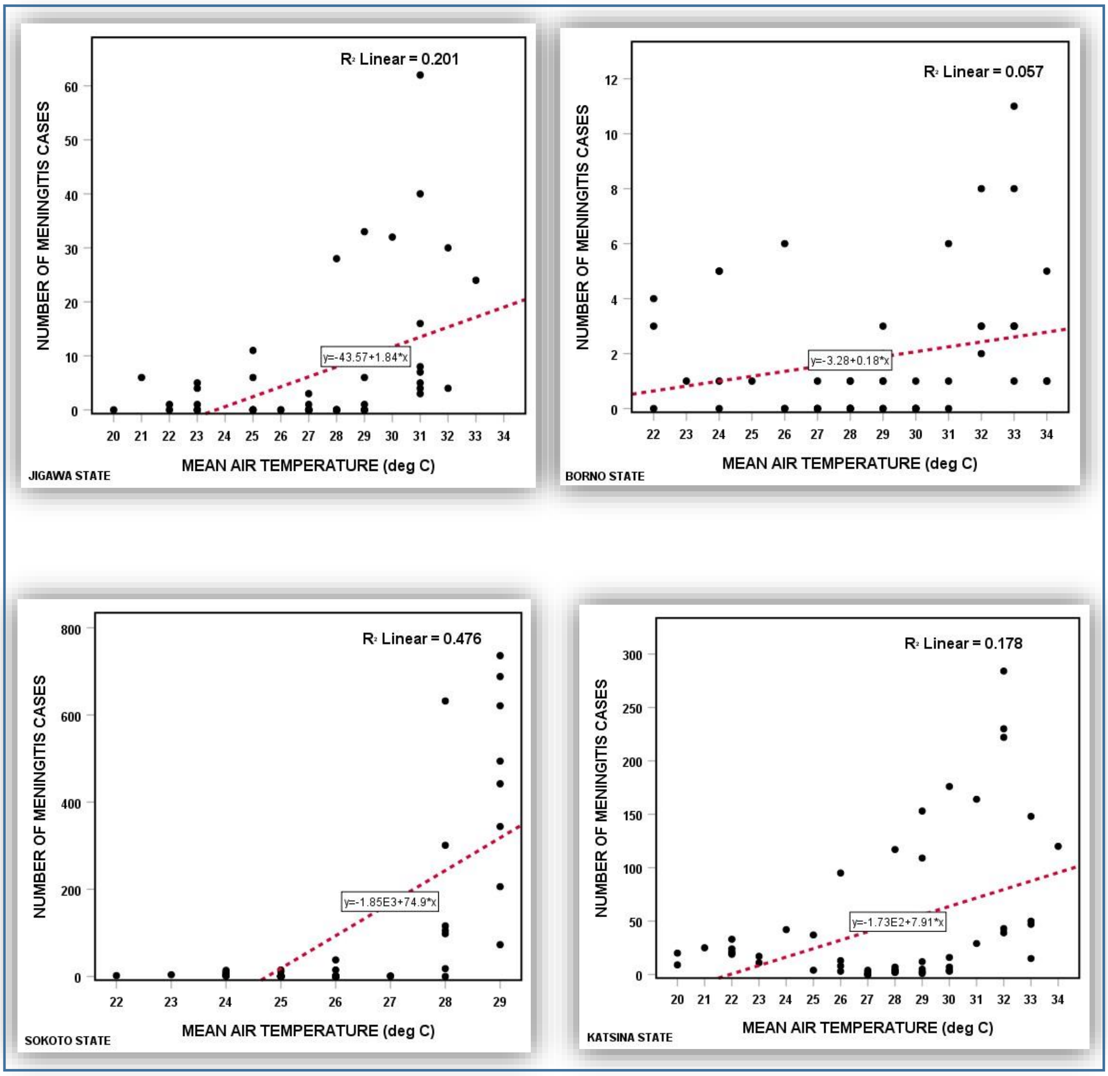

Figure 4.45 Trend in spatial occurrence of meningitis and mean air temperature in the Sudano-Sahelian region from 2016 to 2019.

The relationship between CSM and mean air temperature expounded that mean air temperature influenced about 20% CSM cases in Jigawa, 6% in Borno 48% in Sokoto and 18% in Katsina. Bulk of the meningitis cases in the region were recorded at a temperature threshold of 28 – 34 degrees Celsius which was quite high compared to other states in the region.

4.2.4 Temporal occurrence of meningitis between 2008 – 2011, 2012-2015 and 2016-2019.

A temporal comparison in the occurrence of meningitis in the Sudano-Sahelian, northern and southern Savanna zones are being discussed.

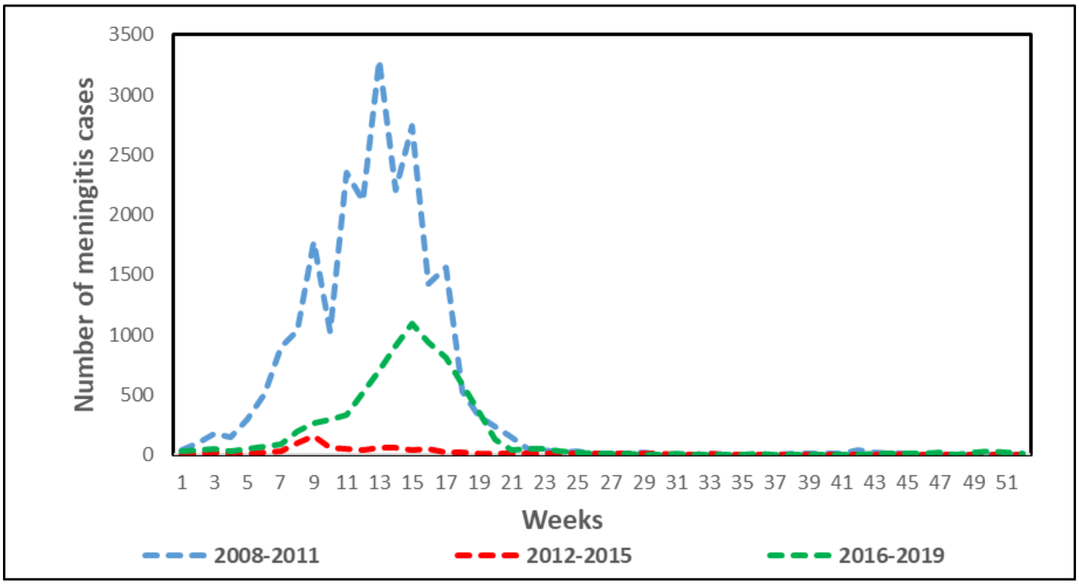

Figure 4.46 Temporal occurrence of meningitis in the Sudano-Sahelian region. On a weekly score, years 2008 to 2011 reported highest incidence of meningitis in the region, it was as high as over 3000 cases. Season with increased cases of meningitis next to 2008-2022 period is years 2016 to 2019 while 2012 to 2015 had the least. For 2008 to 2011 and 2016 to 2019, meningitis cases were at their peak at week 14 while that for the years 2012 to 2015 was at week 9.

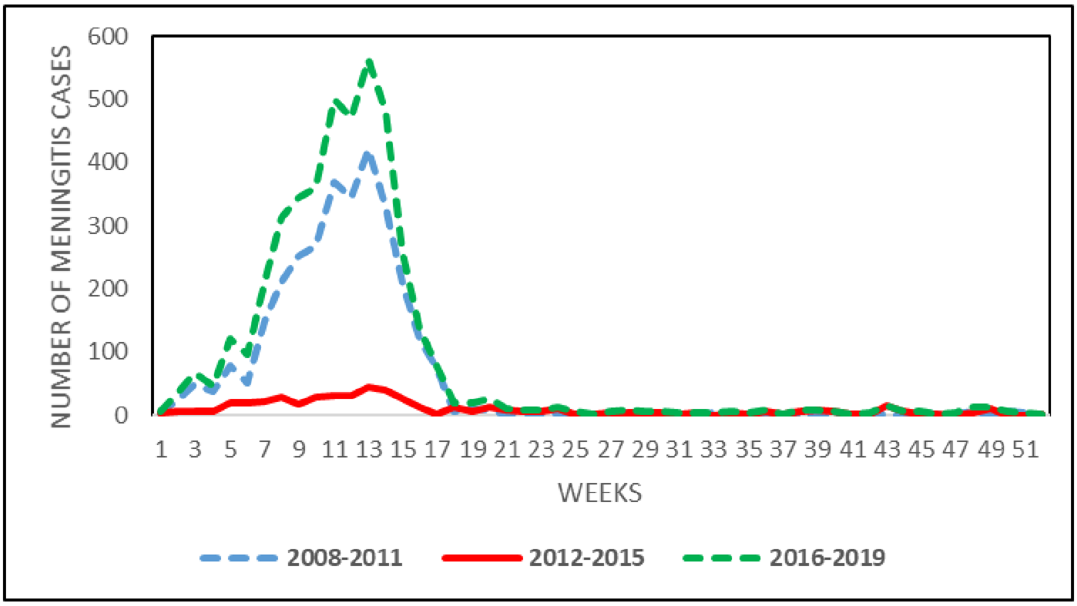

Figure 4.47 Temporal occurrence of meningitis in the Northern Savanna region The 2016 – 2019 period which is a recent time frame recorded CSM cases more than that of 2008 – 2011 period. Years 2012 to 2015 also reported CSM cases but not as high as others. However, weeks 13 reported the highest meningitis incidence across all time periods.

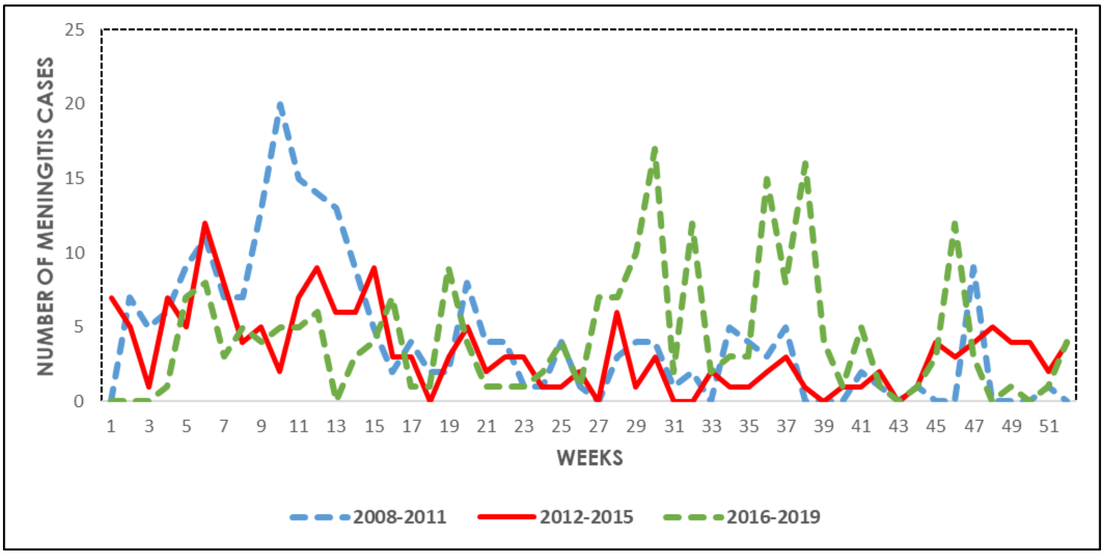

Figure 4.48 Temporal occurrence of meningitis in the Southern Savanna

In the southern Savanna, CSM cases occurred almost all year round compared to other regions, although CSM cases surged between weeks 5 and 12 and weeks 45 and 47 in the period 2008 and 2011. During the period 2016 to 2019, incidence of the disease was high from weeks 26 to 39. Years 2012 to 2015 recorded least CSM cases in the Southern Savanna region.

4.2.5 Spatio-temporal behaviour of meningitis, rainfall, relative humidity, mean air temperature, maximum temperature and wind speed by region from 2008 to 2019.

The behaviour of all variables; meningitis, rainfall, relative humidity, mean air temperature, maximum temperature and wind speed in the climatic zones under study are presented.

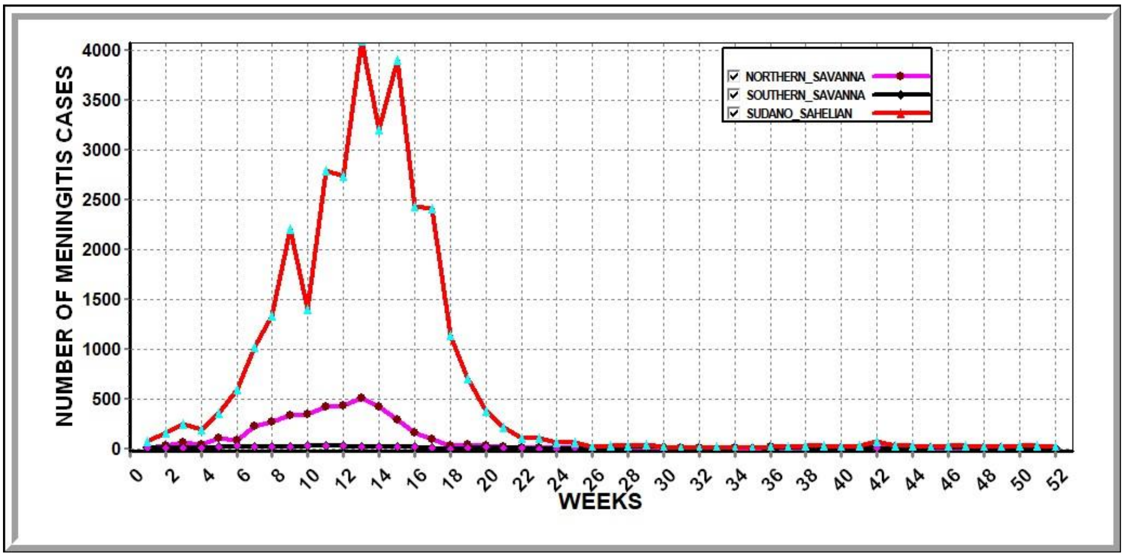

Figure 4.49 weekly meningitis cases over Sudano-Sahelian, Northern and Southern Savanna region from 2008 to 2019

Source: Author's computation, 2020

Figure 4.49 shows the behaviour of meningitis cases over Sudano-Sahelian and Savanna region, 2008 – 2019. The number of meningitis cases assumed similar pattern showing peak values at week 2 to week 24. However, meningitis cases in the Sudano-Sahelian region were much higher than those recorded in other regions. Cases in the northern Savanna were higher than that of southern Savanna but not as high as the Sudano-Sahelian. For northern Savanna, highest meningitis cases recorded were 507 at week 13 while the least was 3 at week 51. In the southern Savanna, the southern Savanna, highest CSM cases was 31 at week 6 and 0 at week 43 while the Sudano-Sahelian region reported CSM cases of 4094 at week 13 at lowest recorded case of 13 at week 31. This suggests that meningitis cases are more prevalent at weeks 10 to 14. This was supported by (Umaru *et al.,* 2015)

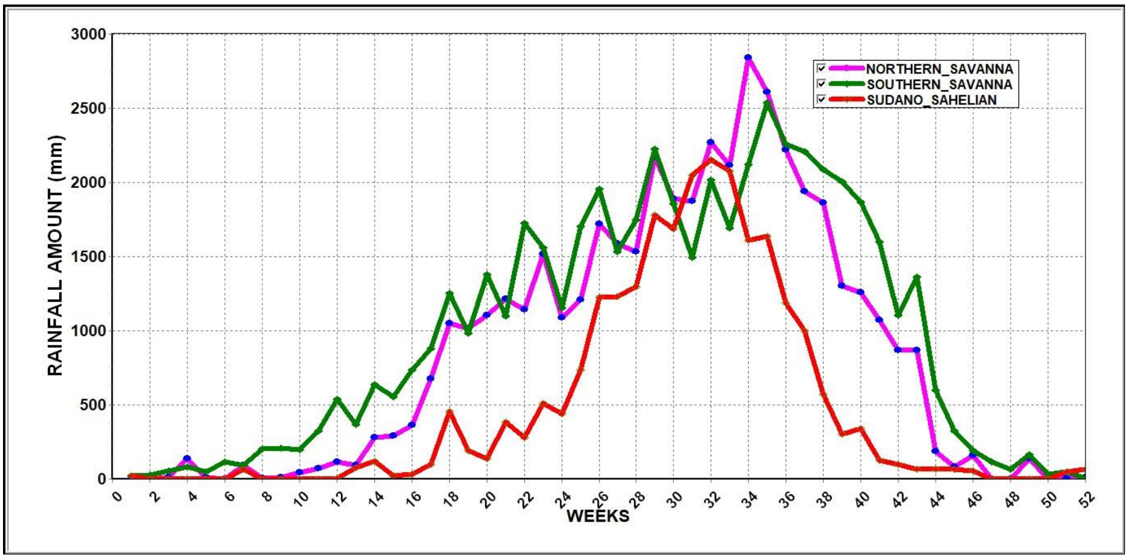

Figure 4.50 Weekly rainfall distribution over Sudano-Sahelian, Northern and Southern Savanna region from 2008 to 2019

Source: Author's computation, 2020.

Figure 4.50 shows the behaviour of rainfall pattern over Sudano-Sahelian and Savanna region, 2008 – 2019. Peak of the rains are recorded between week 32 and 36. Sudano-Sahelian region has its peak at week 32 while southern and northern Savanna have their peak at week 34 at 2839 mm and 2535 mm respectively. For southern Savanna, every week reported rainfall compared to northern Savanna and Sudano-Sahelian region. The first four weeks reported rainfall of less than 50 mm for Southern Savanna, as high as 100mm for northern Savanna because there was an exceptional rainfall of 137 at week four while the Sudano-Sahelian reported rainfall of less than 20 mm in the first four weeks. This rainfall pattern is supported by GarcíaPando *et al*. (2014).

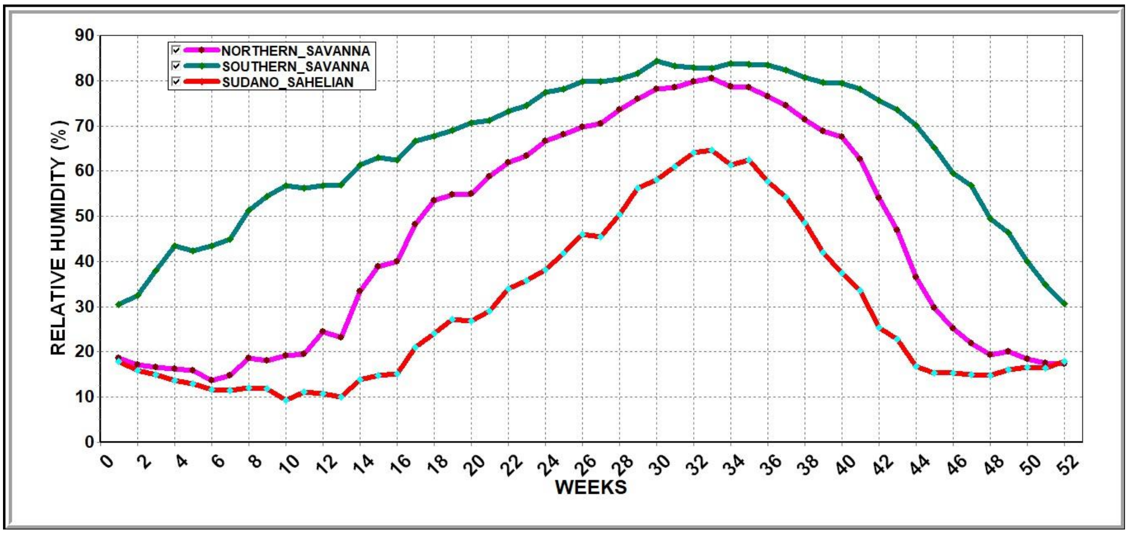

Figure 4.51 Weekly average relative humidity over Sudano-Sahelian, Northern and Southern Savanna region from 2008 to 2019

Source: Author's computation, 2020.

Figure 4.51 shows behaviour of average relative humidity pattern over SudanoSahelian and Savanna region, 2008 – 2019. The weekly relative humidity over the northern Savanna and Sudano-Sahelian region almost had similar pattern showing peak values of 80% at weeks 32, 33 and 65% at week 33 while lowest values were 14% at week 6 and 9% at week 10 respectively. For southern Savanna, peak values of 84% were recorded at weeks 30, 34 and 35 while the lowest relative humidity value was recorded at week 1. Relative humidity values at week 7 over Northern Savanna, Southern Savanna and Sudano-Sahelian region were 14%, 30% and 9% respectively. This denotes that at early weeks where relative humidity values are expected to be very low, the southern Savanna has a considerable amount of moisture of about 30% which is the lowest weekly value.

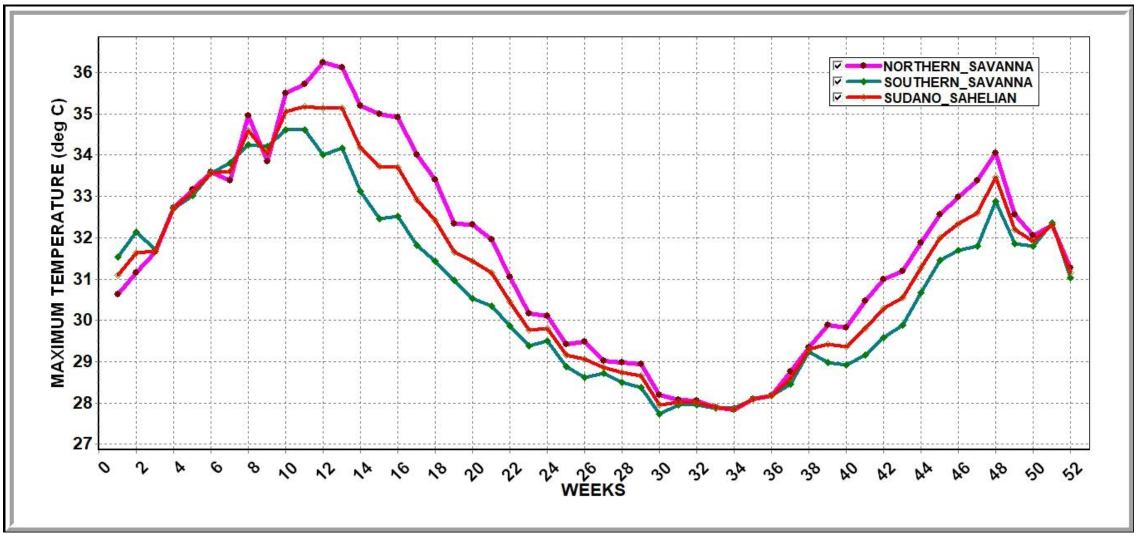

Figure 4.52 Weekly maximum temperature over Sudano-Sahelian, Northern and Southern Savanna region from 2008 to 2019.

Source: Author's computation, 2020.

Figure 4.52 shows the behaviour of maximum temperature pattern over Sudano-Sahelian and Savanna region, 2008 – 2019. Maximum temperature exhibited similar pattern for the three regions.

Lowest temperatures were recorded at week 30 at 28^0C for Sudano-Sahelian and northern Savanna then weeks 29 to 37 for southern Savanna at 28^0C. Temperatures at the 52^{nd} week were higher than that of week one for Sudano-Sahelian, northern and southern Savanna. For week 1 to 4, maximum temperature was in the range of 31 to 33^0C over Sudano Sahel and northern Savanna while for the same period, it was within 32 and 33^0C. The last five weeks reported temperatures in the range of 31^0C and 34^0C for all three regions. This implies that peak temperatures over the regions under study are experienced at weeks 10 to 14 as corroborated by NiMet in 2015.

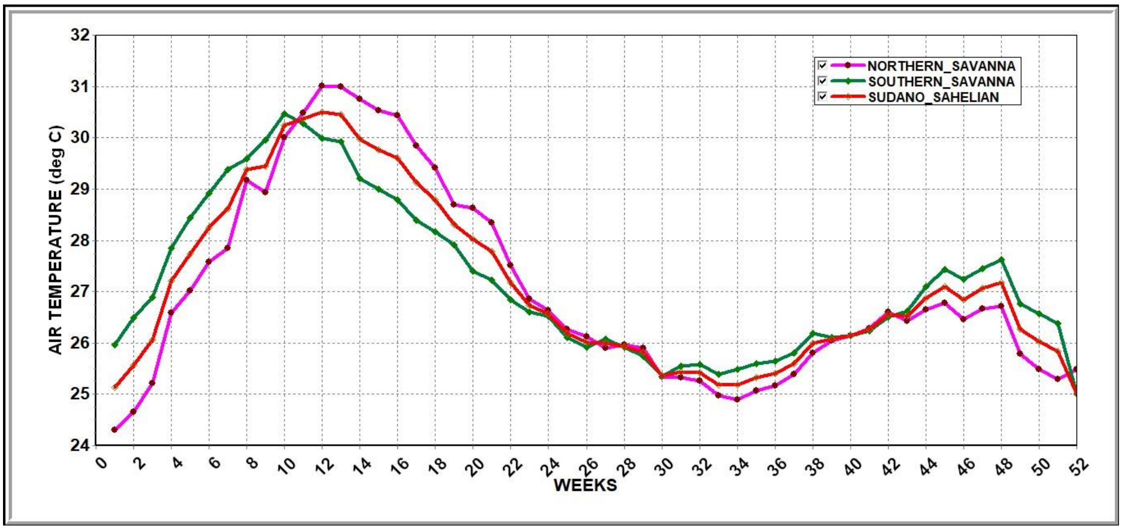

Figure 4.53 Weekly average Mean air temperature over Sudano-Sahelian,

Northern and Southern Savanna region from 2008 to 2019

Source: Author's computation, 2020.

Figure 4.53 shows the behaviour of average mean air temperature pattern over Sudano-Sahelian and Savanna region, 2008 – 2019. This parameter displayed similar pattern for the three regions. Howbeit, the northern Savanna in the first week reported temperature value of 24 ^{0}C, a value lower than other regions. The southern and Sudano-Sahelian recorded 26 ^{0}C and 25 ^{0}C respectively. Temperatures were colder over northern Savanna region and Sudano-Sahelian in the early weeks than the southern Savanna. Two peaks were witnessed for all three regions, the first week was experienced at week 10 for southern Savanna and weeks 12 for both northern Savanna and Sudano-Sahelian region. The second peak was not as high as the first, it was experienced at week 48 for all regions.

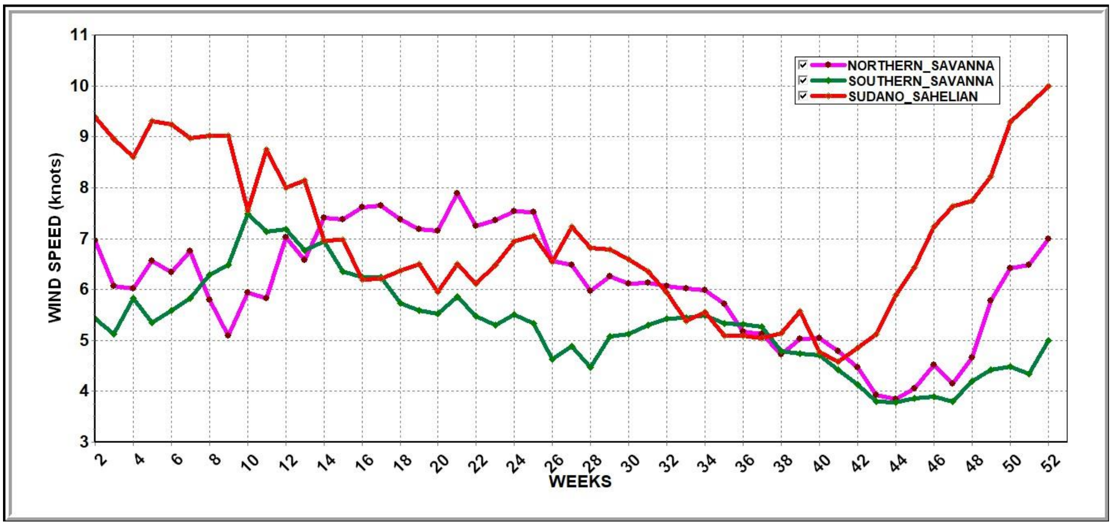

Figure 4.54 Weekly average wind speed over Sudano-Sahelian, Northern and

Southern Savanna region from 2008 to 2019

Source: Author's computation, 2020.

Figure 4.54 shows the behaviour of average wind speed pattern over Sudano-Sahelian and Savanna region, 2008 – 2019. The behaviour of wind speed for each region differed slightly. From week 1 to 4, winds were stronger in the Sudano-Sahelian region than they were in the northern and southern Savanna region. Week one started out at 10 knots over Sudano-Sahelian, 8 in the north and 5 knots in the southern region. From week 16 to 42, there was a decline in speed over the three regions but week 43 to 52, all regions experienced an increase in wind speed. By implication, over the Sudano-Sahelian region, winds were strong at weeks 10 and 12 compared to other regions but stronger week 52 which is same for all regions.

4.2.6 Spatial representation of magnitude of meningitis occurrence as

influenced by rainfall, relative humidity, mean air temperature, maximum temperature and

wind speed over the study area.

The degree of spread of meningitis in the Sudano-Sahelian, northern and southern Savanna zones is expatiated.

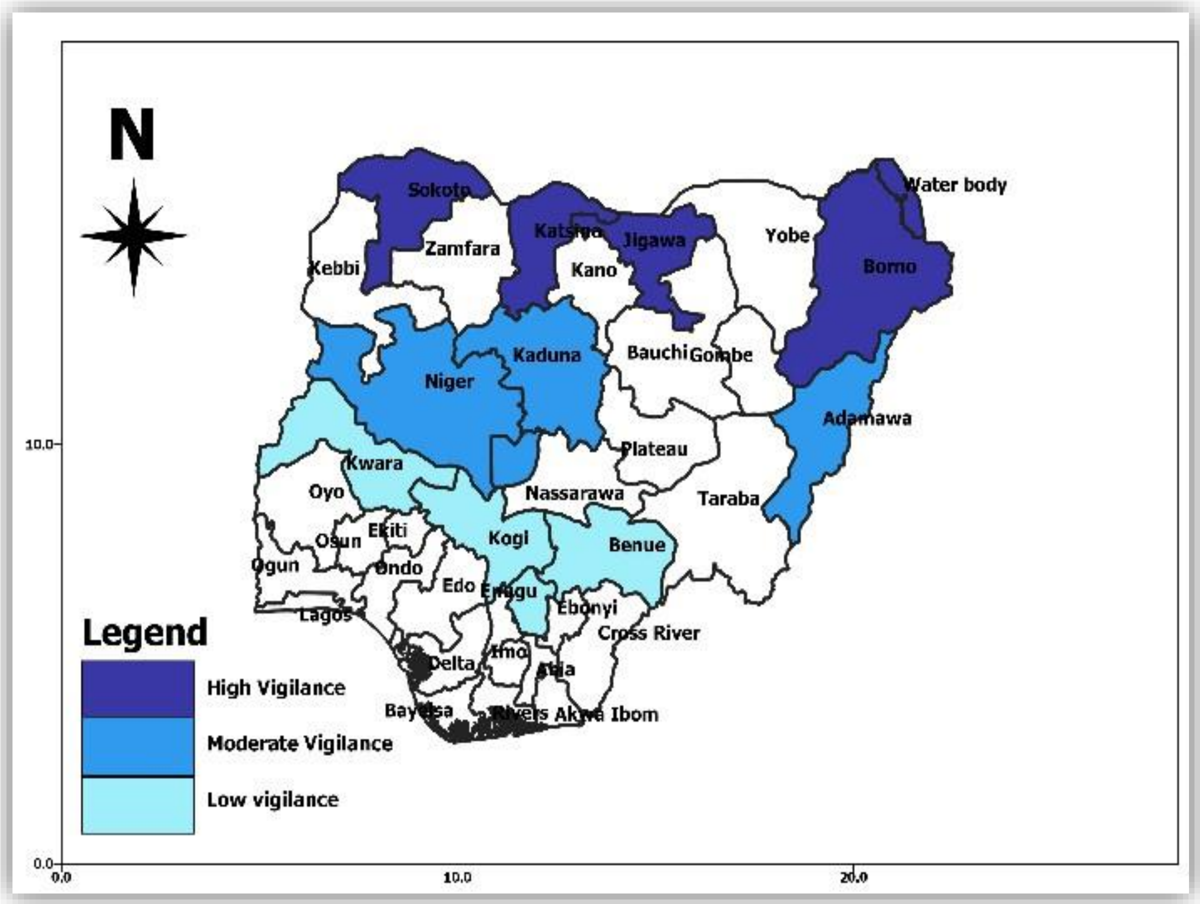

Figure 4.55 magnitude of meningitis occurrence over Sudano-Sahelian, Northern and Southern Savanna zones from 2008 – 2011.

Source: Author's computation, 2020.

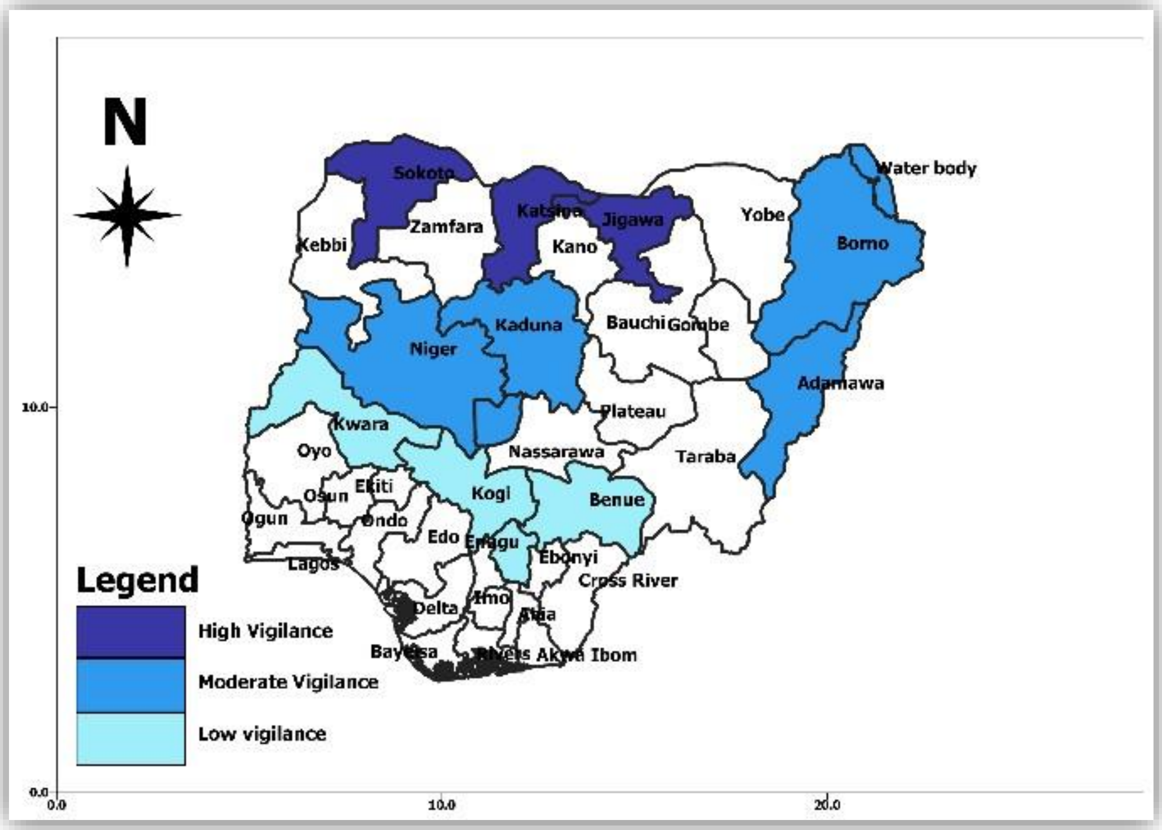

Figure 4.56 magnitude of meningitis occurrence over Sudano-Sahelian, northern and southern Savanna zones from 2012 – 2015.

Source: Author's computation, 2020.

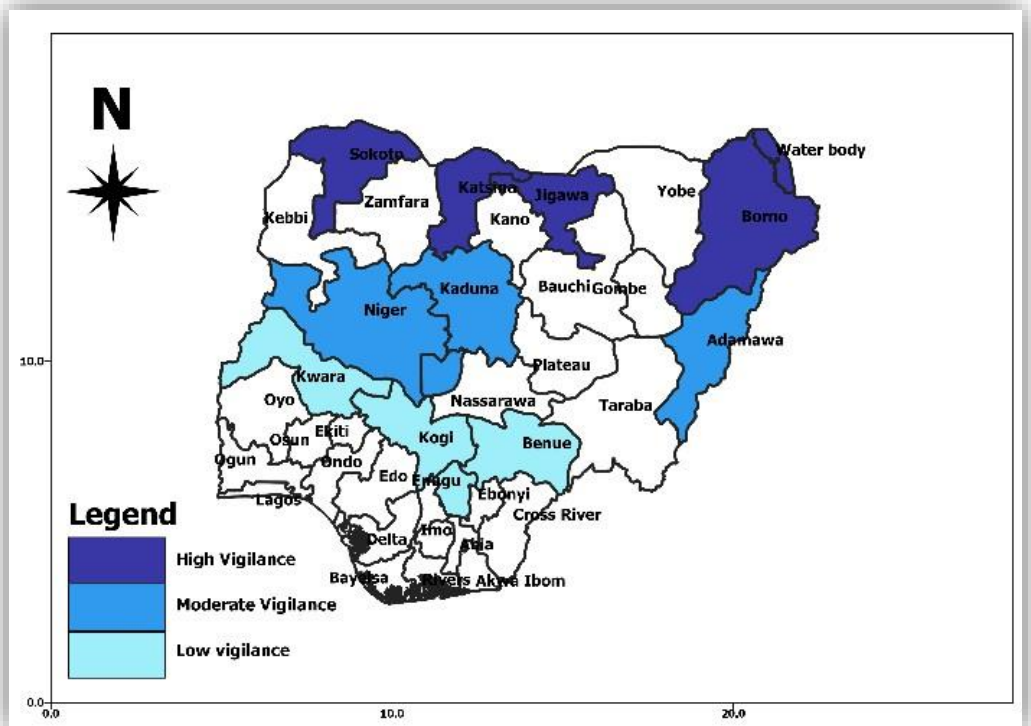

Figure 4.57 magnitude of meningitis occurrence over Sudano-Sahelian, northern and southern Savanna zones from 2016 – 2019.

Source: Author's computation, 2020.

In Figure 4.55 to 4.57 the magnitude of meningitis occurrence over Sudano-Sahelian, Northern and Southern Savanna zones from 2008 to 2011, 2012 to 2015, and 2016 to 2019, is determined by the tested and adopted suitability threshold of African Centre of Meteorological Application for Development (ACMAD) which states that high vigilance, risk, or occurrence of meningitis is expected when relative humidity is less than 20% and rainfall less than 20 mm. Moderate vigilance when relative humidity is between 20% and 40% and rainfall about 40 mm, low vigilance with RH greater than 40% and no vigilance with significant amount of rainfall. Also, temperature is said to be favourable when in the range of 18 ^{0}C and 32 ^{0}C. Coalescing these thresholds, over the three times periods, the Southern Savanna maintained a low risk for CSM and Northern Savanna maintained a moderate risk or occurrence of meningitis cases. Over the Sudano-Sahelian region, high risk for Sokoto, Katsina and Jigawa states was sustained throughout the time period except for Borno state where there was high occurrence of meningitis in the 2016 to 2019 period while during the 2008 to 2011 period, occurrence in CSM cases were moderate with low vigilance for the disease.

4.3 Objective Two

4.3.1 Relationship between climatic variables and meningitis occurrence

The following tables depict the pattern of relationship existing between climatic variables and meningitis particularly in the Northern Savanna region.

Table 4.2 Strength of relationship between climatic variables and meningitis cases over Abuja from 2008 – 2019 on a weekly average.

Abuja	Correlation	P value
Relative Humidity	-0.228	0.104
Rainfall Amount	-0.295	0.034
Maximum Temperature	0.449	0.001
Mean air temperature	0.672	0.000
Wind speed	0.114	0.422

Confidence level (0.05)

Source: Author's computation, 2020.

From the Table 4.2, at a *p* value of ≤ 0.05, relative humidity and wind speed do not have any significant relationship with meningitis which is the dependent variable because of *p* values of 0.10 and 0.42 respectively, as a result, we fail to reject the null hypotheses is rejected implying that there is no significant relation between meningitis and the two climatic variables. Rainfall amount has a significant but weak negative relationship at a *p* value of 0.03 and correlation coefficient of -0.295. Maximum temperature has a significant positive relationship that is weak at (0.449) and mean air temperature also has a significant positive relationship with a correlation coefficient of 0.672. With Positive relationship, it implies that meningitis cases increased with increase in maximum temperature, mean air temperature and wind speed. While for relative humidity and rainfall over Abuja, as these variables increase, CSM cases begin to drop. Since mean air temperature, maximum temperature and rainfall are significant at $p \leq 0.05$, we reject the null hypotheses that States that there is no significant relation between climatic variables and CM occurrence because for these three variables, the relationship is statistically significant.

Table 4.3 Extent of relationship between climatic variables and meningitis cases over Adamawa from 2008 – 2019 on a weekly average.

Adamawa	Correlation	P value
Relative Humidity	-0.486	0.000
Rainfall Amount	-0.395	0.004
Maximum Temperature	0.620	0.000

Mean air temperature	0.586	0.000
Wind speed	0.135	0.339

Confidence level (0.05)

Source: Author's computation, 2020.

As shown in Table 4.3, Meningitis showed significant relationship with the predictor variables which are the climatic variables. However, relative humidity indicates a negative and weak relationship at -0.486, rainfall amount also shows a significant negative weak negative relationship at -0.395, wind speed displays a weak positive relationship with the dependent variable which is meningitis at 0.135. Mean air temperature and maximum temperature also indicate average positive relationship with the dependent variable at 0.586 and 0.620. Although the strength of relationship is slightly stronger with maximum temperature as compared to mean air temperature. By implication, over Adamawa, increase in wind speed, mean air temperature, maximum temperature is directly proportional to increase in meningitis cases while for climatic variables like relative humidity and rainfall, it is inversely proportional with respect to CSM cases. Conversely, the strength of relationship between mean air temperature and meningitis is stronger compared to the strength of relationship with maximum temperature. At a *p* value of ≤ 0.05, we reject the hypotheses for relative humidity, rainfall amount, mean and maximum temperatures because there is significant relationship between the variables and meningitis cases while we fail to reject the null hypotheses for wind speed that says there is no relationship between CSM cases and climate variables.

The extent to which the climatic variables in view are connected with meningitis cases in Benue are expounded upon (Table 4.4)

Table 4.4 Degree of relationship between climatic variables and meningitis cases over Benue from 2008 – 2019 on a weekly average.

Benue	**Correlation**	**P value**
Relative Humidity	-0.178	0.207
Rainfall Amount	-0.133	0.346
Maximum Temperature	0.306	0.028
Mean air temperature	0.282	0.043
Wind speed	0.072	0.611

Confidence level (0.05)

Source: Author's computation, 2020.

From Table 4.4 over Benue state, relative humidity, wind speed and rainfall are insignificant at 0.05 level of significance at values 0.207, 0.611, 0.346 respectively. Although maximum temperature and Mean air temperature for Benue state indicate a weak positive relationship with the meningitis, the relationship is still significant. Since maximum temperature, mean air temperature and mind speed record a positive relationship with CSM cases, it implies increase in CSM cases is influenced by increase in the afore mentioned climatic variables whereas for relative humidity and rainfall, reverse the relationship is inverse. The strength of relationship between mean air temperature and meningitis is stronger compared the relationship existing between meningitis and maximum temperature. At a *p* value of ≤ 0.05, for maximum and mean air temperature, we reject the null hypotheses that says there is no relationship between meningitis and climatic variables while we fail to accept the hypotheses for relative humidity, rainfall amount, and wind speed.

The extent to which the climatic variables in view are connected with meningitis cases in Borno are explained further in Table 4.5.

Table 4.5 Strength of relationship between climatic variables and meningitis cases over Borno state from 2008 – 2019 on a weekly average.

Borno	Correlation	P value
Relative Humidity	-0.506	0.000
Rainfall Amount	-0.356	0.010
Maximum Temperature	0.620	0.000
Mean air temperature	0.433	0.001
Wind speed	0.341	0.013

Confidence level (0.05)

Source: Author's computation, 2020.

From Table 4.5 over Borno state, the relationship between relative humidity and rainfall with meningitis cases is found to be significant at 0.000 and 0.010 respectively but a moderate negative relationship at -0.506 and -0.356 respectively. This implies that increase in weather variables to remarkable decrease in meningitis cases on a weekly scale in the state. Maximum temperature indicates a positive correlation with an average strength of correlation. Mean air temperature, wind speed for Borno indicates a weak positive relationship with the dependent variable. That is to say as maximum temperature, mean air temperature and wind speed increased, meningitis cases increase as well. Nevertheless, the strength of relationship between maximum temperature and meningitis is robust compared to its relationship with maximum temperature.

At a *p* value of ≤ 0.05, the null hypotheses for the region which suggests that there is no significant relationship between meningitis occurrence and weather variable is rejected for all variables because they each p values less than 0.05.

The scope with which the climatic variables in view are connected with meningitis cases in Enugu state are illustrated in Table 4.6.

Table 4.6 Magnitude of relationship between climatic variables and meningitis cases over Enugu from 2008 – 2019 on a weekly average

Enugu	Correlation	P value
Relative Humidity	-0.506	0.000
Rainfall Amount	-0.356	0.010
Maximum Temperature	0.620	0.000
Mean air temperature	0.433	0.001
Wind speed	0.341	0.013

Confidence level (0.05)
Source: Author's computation, 2020.

Table 4.6 shows that there exists significant relationship between all climatic variables and meningitis cases recorded. All variables were statistically significant at $p \leq 0.05$, this implies rejecting the null hypotheses that States there is no significant relationship between meningitis occurrences and climate parameters. However, from correlation coefficient values, between meningitis and relative humidity and rainfall, the relationship is weak and negative at -0.506 and -0.356. Maximum temperature indicates an average positive relationship with the dependent variable, as confirmed by (N'Krumah *et al*., 2014). Mean air temperature, wind speed for Enugu State indicate a weak positive relationship with the dependent variable.

A hike in weekly CSM cases is seen with increase in Maximum temperature, mean air temperature and wind speed while decrease in same is seen with increase in relative humidity and rainfall amount. Nonetheless, the relationship that exists between maximum temperature and meningitis is stronger compared to maximum temperature and CSM.

The degree to which the climatic variables in view are associated with meningitis cases in Jigawa state are expounded in Table 4.7.

Table 4.7. Strength of relationship between climatic variables and meningitis cases over Jigawa from 2008 – 2019 on a weekly average

Jigawa	Correlation	P value
Relative Humidity	-0.409	0.003

Rainfall Amount	-0.289	0.037
Maximum Temperature	0.508	0.000
Mean air temperature	0.358	0.009
Wind speed	0.239	0.087

Confidence level (0.05)

Source: Author's computation, 2020.

From the Table 4.7, all climatic variables except wind speed have significant relationship with meningitis occurrence, this significance stems from the fact that they are all at a $p \leq 0.05$. Hence H_o which states that there is no significant relationship between weather variables and meningitis prevalence is rejected. For wind speed, we fail to reject the H_o because $p \geq 0.05$. Relative Humidity and rainfall amount have a negative correlation with meningitis implying that meningitis cases drop with increase in relative humidity. And also, a weak correlation is presented at -0.409 and -0.289 respectively signifying that the relationship is not strong. Mean air temperature, maximum temperature and wind speed had positive coefficient of correlation over Enugu, implying that increase in these climatic variables influences meningitis cases within the State at varying strength of relationship though, howbeit, the relationship is weak. Maximum temperature has the highest positive correlation, at an average value of 0.508. CSM cases dipped with increase in rainfall amount and relative humidity. Here, the strength of relationship between maximum temperature and meningitis is stronger compared to the disease and maximum temperature.

The extent to which the climatic variables in view are connected with meningitis cases in Kaduna are expounded upon (Table 4.8)

Table 4.8 Magnitude of relationship between climatic variables and meningitis cases over Kaduna from 2008 – 2019 on a weekly average.

Kaduna	**Correlation**	**P value**
Relative Humidity	-0.359	0.009
Rainfall Amount	-0.410	0.003
Maximum Temperature	0.768	0.000
Mean air temperature	0.773	0.000
Wind speed	0.248	0.077

Confidence level (0.05)

Source: Author's computation, 2020.

From Table 4.8, climatic variables like relative humidity, rainfall amount, maximum temperature and mean air temperature are statistically significant at 0.009, 0.003, 0.000, and 0.000 respectively except for wind speed that is short of being significantly correlated with meningitis with an error of 7%. For variables that are statistically significant at $P \leq 0.05$, we reject the H_o that States there is no relationship between meningitis cases and weather parameter because from the result, it is evident that there is a relationship. Relative humidity and rainfall amount have a negative relationship with a weak correlation coefficient of -0.359

and -0.410. Maximum temperature and mean air temperature has a very strong positive correlation with meningitis at 0.768 and 0.773 respectively. Increase in wind speed, mean air temperature and maximum temperature over Kaduna influences a corresponding rise in CSM on a weekly basis. The strength of association between mean air temperature and meningitis is slightly sturdier compared to it and maximum temperature.

The extent to which the climatic variables in view are allied with meningitis cases in Katsina

state are expanded (Table 4.9)

Table 4.9 Strength of relationship between climatic variables and meningitis cases over

Katsina from 2008 – 2019 on a weekly average.

Katsina	Correlation	P value
Relative Humidity	-0.462	0.001
Rainfall Amount	-0.332	0.016
Maximum Temperature	0.509	0.000
Mean air temperature	0.344	0.012
Wind speed	0.086	0.545

Confidence level (0.05)

Source: Author's computation, 2020.

From Table 4.9, all climatic variables except wind speed are significant at $p \leq 0.05$ (5%). By implication, the variables with p values within that range (RH with p value at 0.001, rainfall at 0.01, maximum and mean air temperature at 0.000 and 0.012 respectively) are significant hence for these variables, we reject the null hypotheses that say there is no relationship between meningitis cases and weather variables. Relative humidity, maximum weak strength of relationship but positive correlation with meningitis at 0.509 and 0.344 in that order. Rainfall amount has a weak negative correlation with meningitis. The above implies that over Katsina, meningitis cases increase with corresponding increase in wind speed, mean air temperature, maximum temperature while CSM cases decrease with increase in relative humidity and rainfall. Here, the strength of relationship between maximum temperature and meningitis is stronger compared to mean air temperature and meningitis.

The extent to which the climatic variables in view are connected with meningitis cases in Kogi

state are illustrated (Table 4.10)

Table 4.10 Strength of relationship between climatic variables and meningitis cases over

Kogi from 2008 – 2019 on a weekly average.

Kogi	Correlation	P value

Relative Humidity	0.021	0.884
Rainfall Amount	-0.067	0.639
Maximum Temperature	0.368	0.007
Mean air temperature	0.533	0.000
Wind speed	0.610	0.000

Confidence level (0.05)

Source: Author's computation, 2020.

As seen in Table 4.10, over Kogi state, only maximum temperature, mean air temperature and wind speed are significantly correlated with meningitis. Relative humidity and rainfall amount have insignificant correlation with CSM at *p* values of 0.884 and 0.639 respectively, hence we fail to reject the null hypotheses that States that there is no relationship between CSM cases and weather variables. Maximum temperature and mean air temperature has weak positive correlation with meningitis. Wind speed has a medium positive correlation with the meningitis at 0.610. Increase in wind speed, mean air temperature and maximum temperature, lead to corresponding increase in CSM cases. The strength of association between mean air temperature and meningitis is stronger compared to it and maximum temperature.

The magnitude to which the climatic variables in view are connected with meningitis cases in Kwara state are explained (Table 4.11).

Table 4.11 Relationship scale between climatic variables and meningitis cases over Kwara from 2008 – 2019 on a weekly average.

Kwara	Correlation	P value
Relative Humidity	-0.050	0.726
Rainfall Amount	-0.024	0.867
Maximum Temperature	0.197	0.161
Mean air temperature	0.294	0.034
Wind speed	0.465	0.001

Confidence level (0.05)

Source: Author's computation, 2020.

From Table 4.11 relative humidity, rainfall amount, and maximum temperature have insignificant correlation with meningitis over Kwara state at *p* values greater than

0.05 significant level. With that, we fail to reject the null hypotheses which States that climatic variables and CSM are not related. On the other hand, mean air temperature and wind speed have a weak positive correlation with meningitis, suggesting that increase in the values of these variables favoured increased meningitis cases. Howbeit, they are statistically significant at 0.034 and 0.001 respectively, hence we reject the null hypotheses which says there is no relationship between CSM incidence and climate variables. Suffice it to add that the strength of relationship between mean air temperature and meningitis is stronger compared to meningitis and maximum temperature.

The magnitude to which the climatic variables in view are connected with meningitis cases in

Niger state are explained (Table 4.12).

Table 4.12 Degree of relationship between climatic variables and meningitis cases over Niger from 2008 – 2019 on a weekly average.

Niger	Correlation	P value
Relative Humidity	-0.450	0.001
Rainfall Amount	-0.415	0.002
Maximum Temperature	0.679	0.000
Mean air temperature	0.758	0.000
Wind speed	0.106	0.453

Confidence level (0.05)

Source: Author's computation, 2020.

From Table 4.12, all the climatic variables in Niger State have significant correlation with the meningitis except wind speed which is insignificant at 0.05 level of significance. Since wind speed is at $p \geq 0.05$, we fail to reject the H_o that States there is no significant relationship between meningitis cases and wind speed. Relative humidity and rainfall amount has a negative correlation coefficient of -0.450 and -0.415 respectively. Maximum temperature and mean air temperature both have a strong positive correlation coefficient with meningitis at 0.679 and 0.758 respective. By implication, where there is increase in wind speed, mean air temperature and maximum temperature, CSM cases are spiking as well whereas, the cases are dipping with increase in relative humidity and rainfall amount. So, because relative humidity, rainfall, maximum and mean air temperature are all at $p \leq 0.05$, we reject the null hypotheses for these variables that say there is no significant relationship existing between CSM and weather parameters. In addition, the relationship between mean air temperature and meningitis is stronger compared to that which exists between meningitis and maximum temperature.

The level to which the climatic variables in view are connected with meningitis cases in Sokoto state are explained (Table 4.13).

Table 4.13 Strength of relationship between climatic variables and meningitis cases over Sokoto from 2008 – 2019 on a weekly average.

Sokoto	**Correlation**	**P value**
Relative Humidity	-0.377	0.006
Rainfall Amount	-0.305	0.028
Maximum Temperature	0.553	0.000
Mean air temperature	0.766	0.000
Wind speed	-0.019	0.893

Confidence level (0.05)

Source: Author's computation, 2020.

In Table 4.13, from 2008 to 2019, over Sokoto State, climatic variables like relative humidity, rainfall amount, maximum temperature and mean air temperature are significantly correlated with meningitis cases at $p \leq 0.05$. By inference, the H_o which States that there is no relationship between meningitis occurrence and CSM incidence is rejected. However, relative humidity and rainfall amount have weak and negative correlation with meningitis. That means the relationship is inversely proportional. Maximum temperature on the other hand has a medium to positive correlation while mean air temperature has a high positive correlation with meningitis. The strength of relationship between mean air temperature and meningitis is stronger compared to maximum temperature.

The Strength of relationship between climatic variables and meningitis cases in Sudano-Sahelian are explained (Table 4.14).

Table 4.14 Forte of relationship between climatic variables and meningitis cases over Sudano-Sahelian region from 2008 – 2019 on a weekly average.

Sudano-Sahelian	**Correlation**	**P value**

Relative Humidity	-0.471	0.000
Rainfall Amount	-0.343	0.013
Maximum Temperature	0.697	0.000
Mean air temperature	0.837	0.000
Wind speed	0.193	0.171

Confidence level (0.05)

Source: Author's computation, 2020.

In Table 4.14 from 2008 to 2019, over the Sudano-Sahelian station, relative humidity, rainfall amount, maximum and mean air temperature have significant relationship with $p \leq 0.05$. With this statistically significant values for these parameters, we fail to reject the null hypotheses that says there is no significant relationship between climatic variable and CSM. Wind speed however, has an insignificant correlation at p=0.171, we fail to reject the null hypotheses. Relative humidity and rainfall amount have weak negative relationship with meningitis at -0.471 and -0.343 respectively. While maximum temperature and mean air temperature have a high and positive correlation with meningitis. But, the strength of relationship between mean air temperature and meningitis is stronger compared to it and maximum temperature.

The Strength of relationship between climatic variables and meningitis cases in northern Savanna are elucidated (Table 4.15).

Table 4.15. Strength of relationship between climatic variables and meningitis cases over Northern Savanna from 2008 – 2019 on a weekly average.

Northern Savanna	**Correlation**	**P value**
Relative Humidity	-0.455	0.001
Rainfall Amount	-0.444	0.001
Maximum Temperature	0.734	0.000
Mean air temperature	0.792	0.000

Wind speed	0.210	0.135

Confidence level (0.05)

Source: Author's computation, 2020.

In Table 4.15 from 2008 to 2019, over the northern Savanna region relative humidity, rainfall amount, maximum and mean air temperature have significant p values at $p \leq 0.05$. These statistics implies that we reject the null hypotheses that States that there is no significant relationship between climatic variables and number of meningitis cases because from these results, it is seen that there is a relationship that is significant between rainfall, relative humidity, mean air and maximum temperatures on the occurrence of meningitis. Wind speed however, has an insignificant correlation at $p = 0.135$, hence we fail to reject the fore Stated null hypotheses. Relative humidity and rainfall amount have weak and negative relationship with meningitis. While maximum temperature and mean air temperature has a high positive correlation with the dependent variable at above 0.7. This implies that increase in maximum temperature and mean air temperature favours rise in meningitis cases. While reverse is the case for rainfall and relative humidity. However, the strength of relationship between mean air temperature and meningitis is stronger than the relationship existing between same variable and maximum temperature.

The Strength of relationship between climatic variables and meningitis cases in southern Savanna are interpreted (Table 4.16).

Table 4.16. Extent of relationship between climatic variables and meningitis cases over Southern Savanna from 2008 – 2019 on a weekly average.

Southern Savanna	Correlation	P value
Relative Humidity	-0.159	0.260
Rainfall Amount	-0.197	0.162
Maximum Temperature	0.464	0.001
Mean air temperature	0.548	0.000
Wind speed	0.571	0.000

Confidence level (0.05)

Source: Author's computation, 2020.

From Table 4.16 from 2008 to 2019, over the southern Savanna region, relative humidity, rainfall amount, relative humidity and rainfall amount have insignificant correlation with the meningitis at 0.260 and 0.162 which means $p \geq 0.05$, hence, for these variables, we fail to reject the null hypotheses that States there is no significant relationship between climatic variables and meningitis cases. In contrast, although maximum temperature, mean air temperature and wind speed have a weak positive relationship with meningitis, it is statistically significant, and because they are statistically significant at $p \leq 0.05$. So, we reject the null hypotheses which States that climate variables and CSM cases have no relationship. Also, for these variables that are statistically significant, increase in their values lead to increase CSM cases. Nevertheless, the strength of relationship between mean air temperature and meningitis is stronger as likened to it and maximum temperature.

4.4 Objective Three

4.4.1 Impact of some climatic variables (Mean air temperature, maximum temperature, Rainfall amount, relative humidity and wind speed) on meningitis cases.

The results below depict the impact of the five climatic variables combined on meningitis cases in the area of study. It displays the influence of these climatic variables on meningitis on states and regions of study.

The impact of Mean air temperature, maximum temperature, Rainfall amount, relative humidity and wind speed on meningitis cases by State are displayed and explained.

Explained (Table 4.17).

Table 4.17 Impact of some climatic variables (Mean air temperature, maximum temperature, Rainfall amount, relative humidity and wind speed) on meningitis cases by state.

S/NO	STATE	R^2 Value	R^2 (%)	F TEST
1	Abuja	0.52	52	0.000002
2	Adamawa	0.60	60	0.00000003
3	Benue	0.17	17	0.1
4	Borno	0.69	69	0.0000000001
5	Enugu	0.17	17	0.1
6	Jigawa	0.48	48	0.000001
7	Kaduna	0.708	70	0.00000000004
8	Katsina	0.598	59	0.0000000045
9	Kogi	0.45	45	0.45
10	Kwara	0.27	27	0.01
11	Niger	0.73	73	0.0000000000035
12	Sokoto	0.69	69	0.0000000000085

Source: Author's computation, 2020.

Confidence level (0.05)

Confidence level (0.05)

Source: Author's computation, 2020.

Table 4.17 above presents the regression analysis of States under study. The R^2 which indicates the degree of variation in the dependent variable that is accounted for by the independent variable. The f statistic indicates if the climatic variables entered overall are significant predictors of meningitis.

Abuja has an R^2 value of 0.52 this implies that 52% of the observed variation in meningitis cases is accounted for by climatic variables like relative humidity, rainfall amount, maximum temperatures, mean air temperatures and wind speed. This implies that 48% of CSM cases are counted for by other causes while 52% is accrued to these five climatic factors. This is also significant at 0.05 level of significance.

Adamawa State has an R^2 value of 0.60 this implies that 60% of observed the variation in meningitis cases is accounted for by climatic variables like relative humidity, rainfall amount, maximum temperatures, mean air temperatures and wind speed. By implication, 40% of the meningitis causes are accounted for by other factors while 60% are by these climatic factors. This is also significant at 0.05 level of significance. Borno State has an R^2 value of 0.69 this implies that 69% of the observed variation in meningitis cases in Borno State is accounted for by climatic variables like relative humidity, rainfall amount, maximum temperatures, mean air temperatures and wind speed. Here, 31% of the CSM cases in Borno State is accounted for by other factors while 79% by climatic risk factors. This is also significant at 0.05 level of significance.

Jigawa has an R^2 value of 0.48 this implies that 48% of the observed variation meningitis cases in Jigawa State is accounted for by climatic variables like relative humidity, rainfall amount, maximum temperatures, mean air temperatures and wind speed. Climatic variables account for 48% of the causes of meningitis. However, it is significant at 0.05 level of significance.

For Kaduna state, climatic factors have an R^2 value of 0.708 this denotes that 70.8% of the observed variation in meningitis cases in Kaduna state is accounted for by climatic variables like relative humidity, rainfall amount, maximum temperatures, mean air temperatures and wind speed while the 30.2% is accrued to other factors. However, it is also significant at 0.05 level of significance, and because of this significance, we fail to reject the null hypotheses that States climatic variables do have impact on CSM cases.

Katsina has an R^2 value of 0.598 this indicates that 59.8% of the observed meningitis cases in Katsina State is accounted for by climatic variables like relative humidity, rainfall amount, maximum temperatures, mean air temperatures and wind speed. Other factors account for about 41%. This impact is so significant at 0.05 level of significance. It can be stated that climatic variables have impact on the occurrence of CSM cases so we fail to reject the null hypotheses that claims climatic variables do not have impact on meningitis occurrence.

Kwara has an R^2 value of 0.27 this implies that only 27% of the observed meningitis cases in Kwara State is accounted for by climatic variables like relative humidity, rainfall amount, maximum temperatures, mean air temperatures and wind speed. Greater part of the cases is attributed to other factors, however, this is so significant at 0.05 level of significance. With the level of significance, we reject the null hypotheses that says that climate variables have no impact on CSM cases because from the statistics, it does have impact on meningitis cases.

Niger has an R^2 value of 0.73. This implies that 73% of the observed variation in meningitis cases in Niger State is accounted for by climatic variables like relative humidity, rainfall amount, maximum temperatures, mean air temperatures and wind speed. 27 % of CSM cases in Niger State is attributed to other factors. This impact is so significant at 0.05 level of significance, so in Niger State, we reject the H_o that States that climate variables have no impact on meningitis occurrence.

Sokoto has an R^2 value of 0.69. This implies that 69% of the observed variation in meningitis cases in Sokoto State is accounted for by climatic variables like relative humidity, rainfall amount, maximum temperatures, mean air temperatures and wind speed. Over Sokoto, weather parameters account for greater cause of CSM while 31% is ascribed to other causes. This is also significant at $F \leq 0.05$ level of significance. By implication, we reject the null hypotheses which says climatic variables have no impact on meningitis cases.

Over Kogi, Enugu and Benue States, the findings are statistically insignificant at $F \leq 0.05$ hence we fail to reject the null hypotheses that States that climatic variables have no impact on CSM cases. This suggests that in these states, climate variables do not have any contribution to the occurrence of meningitis, other factors other than weather are responsible for the occurrence of meningitis.

The impact of some climatic variables mean air temperature, maximum temperature, Rainfall amount, relative humidity and wind speed on meningitis cases by region are depicted and explained (Table 4.18)

Table 4.18 Impact of some climatic variables (Mean air temperature, maximum temperature, Rainfall amount, relative humidity and wind speed) on meningitis cases by region.

S/NO	REGION	R_2 Value	R_2 (%)	F TEST
1	Sudano-Sahel	0.77	77	0.000000000000015
2	Northern Savanna	0.79	79	0.000000000000017
3	Southern Savanna	0.44	44	0.000054

Confidence level (0.05)

Source: Author's computation, 2020.

Sudano-Sahelian region has an R^2 value of 0.77. This implies that 77% of the observed variation meningitis cases in Sudano-Sahelian is accounted for by climatic variables like relative humidity, rainfall amount, maximum temperatures, mean air temperatures and wind speed. For the entire region, climatic risk factors account for about 77% of the cases of meningitis recorded in the region. This impact is all so significant at 0.05 level of significance.

Northern Savanna has an R^2 value of 0.79 this implies that 79% of the observed variation in meningitis cases in Northern Savanna region is accounted for by climatic variables like relative humidity, rainfall amount, maximum temperatures, mean air temperatures and wind speed. This region has climatic risk factors account about 79% of CSM cases in the State. This is also significant at 0.05 level of significance.

Southern Savanna has an R^2 value of 0.44. This implies that 44% of the observed variation in meningitis cases in Southern Savanna region is accounted for by climatic variables like relative humidity, rainfall amount, maximum temperatures, mean air temperatures and wind speed. Although the impact of these variables are low, they are however significant at 0.05 level of significance.

Suffice to add that climatic variables in Benue, Enugu and Kogi are not significant predictors of the dependent variable, meningitis. Hence, over these States, we fail to reject the null hypotheses. It can be concluded that climatic variables have no impact of meningitis outbreak. For other States and regions, climatic variables have impact on meningitis outbreak.

At an *F* test value of 0.05, for all regions, findings are statistically significant because the *F* test is less than 0.05. Hence, we reject the null hypotheses which says climatic variables have no impact on meningitis cases.

4.5 Objective four

4.5.1 Model for predicting Cerebro Spinal Meningitis (CSM) outbreak in the study area.

Poisson regression model accepts variables that are only significant at $p = 0.00$ to get variables that will suit the model, step wise regression is employed.

The climatic parameters that have utmost significant for modelling Cerebro Spinal Meningitis (CSM) outbreak over northern Savanna region are being explained (Table 4.19)

Table 4.19. Model for predicting Cerebro Spinal Meningitis (CSM) outbreak over Northern Savanna

Predictors	**β**	**Exponents (β)**	**P values**	**Comment**
Intercepts	-11.2	0.000013	0.000	Significant
Mean air temperature	0.61	1.846	0.000	Significant
Relative humidity	-0.066	0.936	0.000	Significant
Rainfall amount	0.001	1.001	0.000	Significant

Confidence level (0.000)

Source: Author's computation, 2020.

At *p* value of 0.000 over the northern Savanna region, mean air temperature, relative humidity and rainfall amount were significant for the model. The Beta values and their exponents are part of the model fit.

Climatic parameters that are most significant for modelling Cerebro Spinal Meningitis (CSM) outbreak over Sudano-Sahelian region are being explained (Table 4.20)

Table 4.20. Model for predicting Cerebro Spinal Meningitis (CSM) outbreak over Sudano-Sahelian region.

Predictors	β	Exponents (β)	P values	Comment
Intercept	-21.62	0.00000000040	0.000	Significant
Rainfall amount	0.00	1.00	0.000	Significant
Mean air temperature	0.99	2.69	0.000	Significant

Confidence level (0.000)

Source: Author's computation, 2020.

From Table 4.20, after subjecting all five climatic variables to step wise regression, only rainfall amount and mean air temperature were significant at 0.000

Climatic parameters that are most significant for modelling Cerebro Spinal Meningitis (CSM) outbreak over southern Savanna region are being explicated (Table 4.21)

Table 4.21. Model for predicting Cerebro Spinal Meningitis (CSM) outbreak over Southern Savanna

Predictors	β	Exponents (β)	P values	Comment
Intercept	0.444	1.558	0.061	Significant
Wind speed	0.387	1.472	0.000	Significant

Confidence level (0.000)

Source: Author's computation, 2020.

From Table 4.21, all five climatic variables were subjected to step wise regression but just one was significant at 0.000 and that is wind speed.

4.5.2 Northern Savanna

From Tables 4.19, Results from the Poisson log linear regression analysis indicated an overall model significance based on the omnibus test result which indicated a *P* value of 0.000.

Examining each of the model individually based on the parameter estimates, as shown in the table 4.18 mean air temperature, relative humidity, and rainfall are significant predictors of Meningitis for the Northern Savanna.

$$E\ (y_i) = b_0 + b_1x_1 + b_2x_2 + b_3x_3 \qquad (1)$$

where

$E\ (yi)$ = Effect on the mean of meningitis b_0

= Coefficient of the y intercept b_1x_1=

Coefficient of mean air temperature b_2x_2=

Coefficient of relative humidity b_3x_3=

Coefficient of rainfall

For the northern stations our prediction model would be:

$$E\ (y_i) = b_0 + b_1x_1 + b_2x_2 + b_3x_3 \qquad (2)$$

$$E(y) = -11.2 + (0.61x_1) + (-0.066x_2) + (0.001x_3) \qquad (3)$$

Predicting CSM cases using only mean air temperature variable, it will be:

$$E\ (\beta_1) = 1.846 > 1 \qquad (4)$$

$$= 1.846 - 1 = 0.8 \qquad (5)$$

Since 1.846 > 1, increase in meningitis cases are expected with reference to a unit rise in temperature. This implies that the expected count *E(y)* of meningitis will increase 80% (0.8×100) with any increase per unit increase in mean air temperature. Predicting CSM cases using only relative humidity variable, it will be:

$$E(\beta_2) = 0.936 < 1 \qquad (6)$$

$$= 0.936 - 1 = -0.1 \qquad (7)$$

Since 0.936 < 1, decrease in meningitis cases are expected to drop with reference to a unit rise in relative humidity. This implies that the expected count *E(y)* of meningitis will decrease by 10 % (0.1 ×100) per unit increase in relative humidity.

Predicting CSM cases using only rainfall as variable, it will be:

$$E(\beta_3) = 1.001 = 1 \qquad (8)$$

$$1.001-1=0 \qquad (9)$$

Since 1.00 = 1, no change in meningitis cases are expected with any unit rise in temperature. This implies that the expected count *E(y)* of meningitis will not be affected by any increase in rainfall amount.

4.5.3 Sudano-Sahelian

Results from the poison loglinear regression analysis indicated an overall model significance based on the omnibus test result which indicated a p value of 0.000. Examining each of the model individually based on the parameter estimates, as shown in the table above rainfall amount and mean air temperature are significant predictors of Meningitis for the Sudano-Sahelian.

$$E(y_i)) = b_0 + b_1x_1 + b_2x_2 \qquad (10)$$

where

E (yi) = effect on the mean of meningitis b_0

= Coefficient of the y intercept b_1x_1=

Coefficient of rainfall b_2x_2= Coefficient of

mean air temperature

For the Sudano-Sahelian region our prediction model would be

$$E(y) = -21.62 + (0\,x_1) + (0.99x_2) \qquad (11)$$

Predicting CSM cases using rainfall variable, it will be:

$$E(\beta_1) = 1 = 1 \qquad (12)$$

This implies that there would be no change in the expected count *E(y)* of meningitis cases with changes in the Rainfall.

Predicting CSM cases using mean air temperature,

$$E\,(\beta_2) = 2.69 > 1 \qquad (13)$$

$$2.\,69 - 1 = 1.69 \qquad (14)$$

Since 2.69 is greater than 1, this implies that the expected count *E(y)* of meningitis cases will increase by 169 % per unit increase in mean air temperature.

4.5.4 Southern Savanna

Results from the poison loglinear regression analysis indicated an overall model significance based on the omnibus test result which indicated a p value of 0.000. Examining each of the model individually based on the parameter estimates, as shown in the table above only Wind speed is a significant predictor of Meningitis for the

Southern Savanna.

$$E\,(y_i) = b_0 + b_1x_1 + b_2x_2 \qquad (15)$$

where

E (yi) = Effect on the mean of meningitis b_0

= Coefficient of the y intercept b_1x_1=

Coefficient of Mean air temperature b_2x_2=

Coefficient of Wind speed

For the Southern station our prediction model would be

$$E(y) = 0.444 + 0.387x_1. \qquad (16)$$

Predicting CSM cases using only wind speed variable, it will be:

$$E\,(\beta_1) = 1.472 > 1 \qquad (17)$$

$$1.47 - 1 = 0.47 \qquad (18)$$

Since 1.472 is greater than 1, this implies that the expected count *E(y)* of meningitis will increase by 47% per unit increase in wind speed.

CHAPTER FIVE

5.0 SUMMARY AND CONCLUSION

5.1 Summary

The analysis of Spatio- Temporal Effect of Climate Variability on the Occurrence of Meningitis *(Meningococci)* in the Sudano-Sahelian and Guinea Savanna Zones of Nigeria was carried out using records of, rainfall, relative humidity, wind speed, maximum temperature and mean air temperature from online data base of NOAA and meningitis cases from hospital records collated by the Nigeria centre for Disease control and Bureau of statistics for a period of 12 years from 2008 to 2019 and 12 states namely Sokoto, Katsina, Kaduna, Jigawa, Borno, Abuja, Niger, Kwara, Kogi, Adamawa, Benue and Enugu.

These number of years were used because the records of meningitis cases available were just for those number of years. Daily data collected was collected which was aggregated to weekly for the purpose of the research. The exploration of climatic variables and disease from 2008 and 2019 was analysed using person correlation, correlation coefficient and stepwise regression to test for the presence and absence of significant relation between the dependent and independent variables for building of forecast model. The result of the research showed that climate variables have a great impact on the occurrence on meningitis in the zones in this study however, the degree of the impact varies from region to region. Also, climate variable can be used to forecast number of meningitis occurrence in the various zones. However, the variables differ from one zone to the other. The null hypotheses for the two objectives in the study were rejected.

5.2 Conclusion

Weather forecast is a lifesaving tool against meningitis because weather data is used to predict location and scale of impending cases and this prediction helps country level health services to plan emergency responses

Owing to the fact that global warming is becoming a burden, the relationship between climate and meningitis can help forestall any additional burden to already delicate health systems in the affected areas.

Meningitis vigilance maps show areas that are very likely or less likely to experience outbreaks alongside an assessment of whether the outbreaks could result in an epidemic or not. According to the results gotten from this analysis, predicting meningitis epidemic outbreak will aid better response in terms of strengthening of diagnostic, vaccination and management capacities. Also, it will enable climate scientists to appraise their forecasts and also help health professionals and medical services in early response and preparation towards stopping or reducing the outbreak of meningitis.

In conclusion, climatic variables such as relative humidity, rainfall amount, maximum air temperature, mean air temperature and wind speed have a great impact on the occurrence and spread of meningitis over the Sudano-Sahelian, Northern and Southern Savanna zones of the country. In the Sudano-Sahelian region about 77% of the observed variation in meningitis cases was accounted for by afore mentioned climatic variables at a significant level of. 0.05.

In the Northern Savanna zone, these climatic variables accounted for about 79% variation in meningitis cases. This region has climatic risk factors account about 79% of CSM cases in the State. This is also significant at 0.05 level of significance.

The Southern Savanna had an R^2 value of 0.44 which implies that 44% of the observed variation in meningitis cases in Southern Savanna region was accounted for by climatic variables like relative humidity, rainfall amount, maximum temperatures, mean air temperatures and wind speed. Although the impact of these variables are low in the region, they are however significant at 0.05 level of significance. It will suffice to add that climatic variables in Benue, Enugu and Kogi are not significant predictors of meningitis. Hence, over these States, we fail to reject the null hypotheses. It can be concluded that climatic variables have no impact of meningitis outbreak. For other States and regions, climatic variables have impact on meningitis outbreak. At an *F* test value of 0.05, for all regions, findings are statistically significant because the *F* test is less than 0.05. Hence, we reject the null hypotheses which says climatic variables have no impact on meningitis cases.

On modelling meningitis outbreak, different climatic variables are significant for the different zones in consideration. For northern Savanna, only three variable, mean air temperature, relative humidity and rainfall amount can be used to predict meningitis outbreak using the formula. In the Sudano-Sahelian region, the two variables used to predict meningitis outbreak are rainfall amount and mean air temperature while in the Southern Savanna zone, only wind speed can be inputted into the formula to adequately predict meningitis outbreak because it was the only variable that was statistically significant at 0.000

5.3 Recommendations

People should be enlightened about climate change, climate variables and the consequent effect on health and possibly how to mitigate its effect on man.

One of the objectives of this research was to attempt to generate a model for predicting meningitis outbreak in the study area using climatic variables which was achieved. This model gives a template that can assist in predicting meningitis outbreak. It can also be used in developing meningitis outbreak matrix for weather parameters. The model can also support decisions taken by health organizations as it relates to meningitis outbreak. Hence, it is advised that it be adopted because it has helped simplify the reality of meningitis outbreak in relation to weather parameters. It is imperative that relevant health agencies and all and sundry should take weather and climate forecast as priority as it can go a long a long way in helping to make adequate preparations before the outbreak of the disease by providing vaccinations. Collaboration between health service providers and climate scientists should be encouraged because this will aid in better understanding of the disease and how it affects lives which will in turn help in rendering apt services by same and will also intimate health workers on potential outbreaks. The public should be encouraged to understand weather seasons and the attendant consequence of each, especially as it relates to meningitis.

Since being able to predict an epidemic outbreak suggests that there is a possibility of better response of vaccination, strengthening of diagnostic and hospital management capacities, these findings should be taken and applied with every iota of significance. Also, relevant organizations are encouraged to liaise with the Nigerian meteorological Agency that is saddled with the responsibility of providing weather and climate information for update on the changes in these weather parameters as they occur. Keeping tab on these changes can go a long way in curbing the devastating effect of meningitis since in the study area, about 70% of the cases are attributed to weather.

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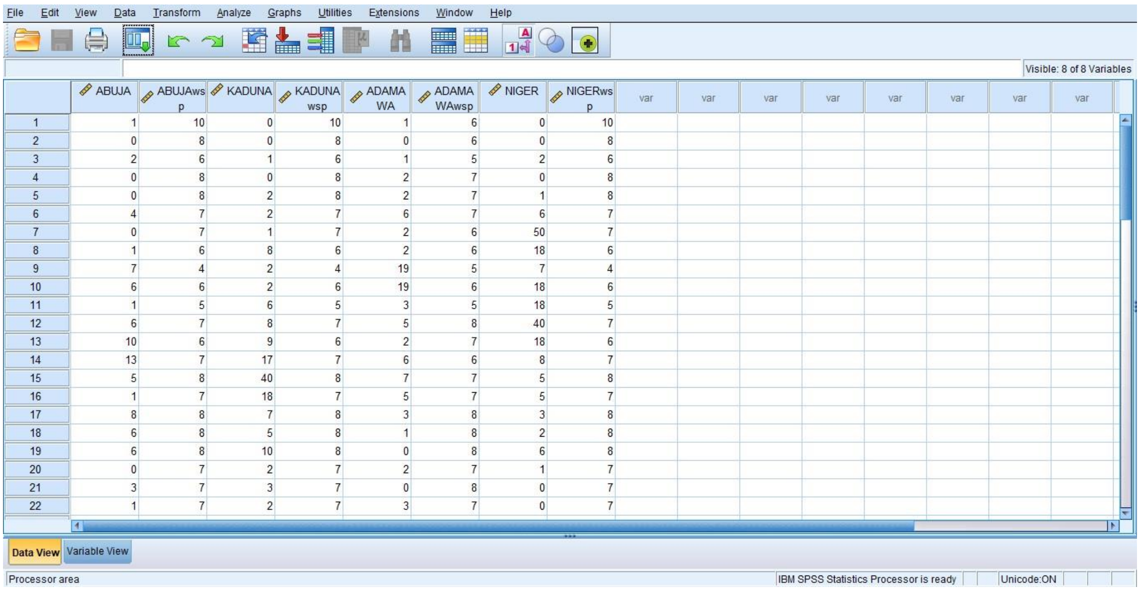
APPENDIX



	ABUJA	ABUJAwsp	KADUNA	KADUNAwsp	ADAMAWA	ADAMAWAwsp	NIGER	NIGERwsp
1	1	10	0	10	1	6	0	10
2	0	8	0	8	0	6	0	8
3	2	6	1	6	1	5	2	6
4	0	8	0	8	2	7	0	8
5	0	8	2	8	2	7	1	8
6	4	7	2	7	6	7	6	7
7	0	7	1	7	2	6	50	7
8	1	6	8	6	2	6	18	6
9	7	4	2	4	19	5	7	4
10	6	6	2	6	19	6	18	6
11	1	5	6	5	3	5	18	5
12	6	7	8	7	5	8	40	7
13	10	6	9	6	2	7	18	6
14	13	7	17	7	6	6	8	7
15	5	8	40	8	7	7	5	8
16	1	7	18	7	5	7	5	7
17	8	8	7	8	3	8	3	8
18	6	8	5	8	1	8	2	8
19	6	8	10	8	0	8	6	8
20	0	7	2	7	2	7	1	7
21	3	7	3	7	0	8	0	7
22	1	7	2	7	3	7	0	7

Figure 4.58 Data analysis for the northern Savanna region

From Figure 4.58, data containing weekly meningitis over the northern Savanna region for states like Abuja, Kaduna, Adamawa, and Niger are displayed.

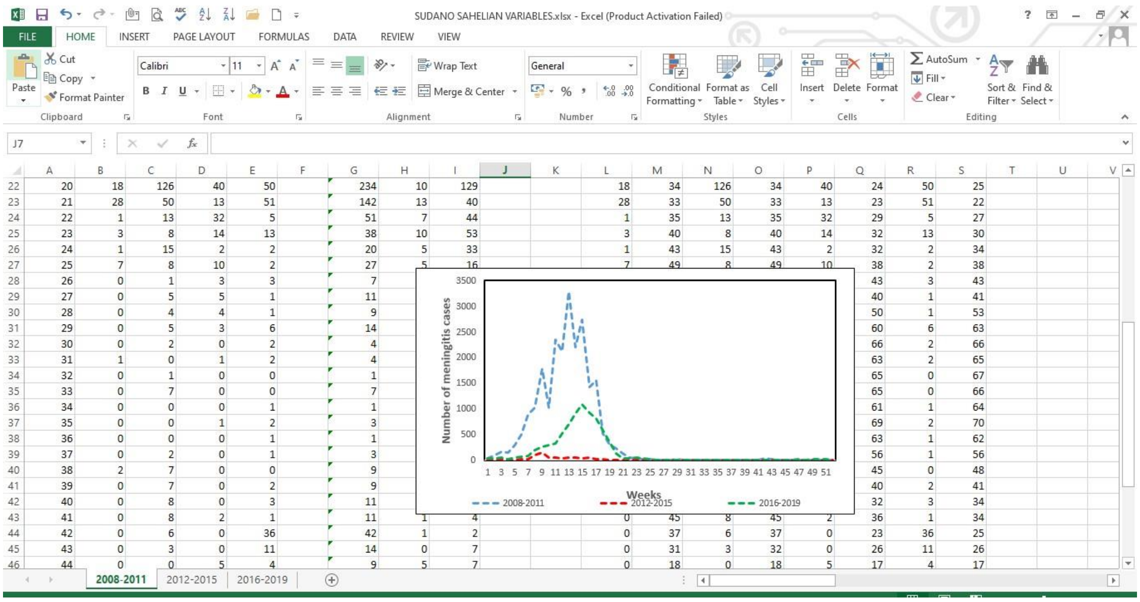


Figure 4.59 Graph plot of Sudano-Sahelian region

Plots of Meningitis cases for three time periods displayed on a Spreadsheet