

EXAMINE SEASONAL VARIATIONS OF DISEASE INCIDENCE IN THE FEDERAL CAPITAL TERRITORY (FCT), NIGERIA

KAMA HOSEA GOBAK¹, ALHASSAN IKO DAVID ², IDUSERI O. EMILY³, IYAKWO AUDU ANDY⁴ AND NANEN D. HEMBE⁵

^{1,3}Department of Environmental Science, National Open University of Nigeria (NOUN). ^{2,4}Nigerian Building and Road Research Institute. ⁵Department of Geography, Nasarawa State University Keffi-Nigeria.

Corresponding Author: hkama@noun.edu.ng

Abstract

This study examines the impact of seasonal climatic elements on the incidence of malaria, measles, meningitis, and pneumonia within the Federal Capital Territory (FCT), Nigeria. Data were collected from 767 health facilities using secondary sources, including hospital records and health departments, across the six area councils of the FCT. Statistical analysis was conducted using the Statistical Package for Social Sciences (SPSS) version 25 and Microsoft Excel, the study employing descriptive and inferential statistics, including chi-square and multiple regression tests, to assess the relationship between climatic variables and disease incidence. The study found significant seasonal variations in disease incidence with Malaria peaked during the rainy season with 32.41% higher

Introduction

It is evident that pathogens thrive more under humid weather conditions than they do during dry seasons (World Health Organisation (WHO), 2015). Because evidence suggests that climatic conditions influence activities of man and his environment, most advanced countries focus research and development efforts towards trend analysis and prediction of new disease pathogens that could result to health emergencies and fatalities. These predictions by health care providers are key to preservation of mankind from elimination via

incidences than average, Measles exhibited no significant variation across seasons, with a marginal increase of 3.52% during warm months, Meningitis showed a significant increase of 6.40% during warm seasons and Pneumonia had minimal seasonal variations, with no statistically significant differences. The study revealed that climatic factors such as rainfall, temperature, and relative humidity significantly influence the incidence of malaria and meningitis in the FCT. Malaria incidence was notably higher during the rainy season, while meningitis outbreaks were more prevalent during warmer months. No significant seasonal variation was observed for measles and pneumonia. It's also Concluded that Seasonal weather patterns in the FCT have a marked impact on disease transmission, particularly for malaria and meningitis. Understanding these seasonal variations is crucial for public health planning, allowing for targeted interventions during periods of high disease transmission. The study recommends enhanced disease surveillance systems, particularly during the rainy season for malaria and warmer months for meningitis, incorporating climatic variables into public health forecasting tools to predict and prevent disease outbreaks, and improving public health awareness and preventive measures during critical seasons to mitigate disease incidence.

Keywords: Seasonal Variations, Disease, Incidence, Climatic, Federal Capital Territory

Infections (Indhumathi and Sathesh, 2020). The health effects of such impacts tend to reveal shifts in geographic and seasonal patterns affecting human infectious diseases and frequency and severity of disease outbreaks (Altizer et al., 2013). Poor environmental sanitation as practices as well as poor water supply has been associated with high-rise transmission of diseases (Alhassan, Kama, and Alhassan, 2023).

Changes in weather and season have an influence on transmission of diseases and people's health and well-being (WHO, 2005). Most vector borne diseases exhibit a distinct seasonal pattern, which clearly suggests their weather sensitivity. Rainfall, temperature, relative humidity, wind, cloud cover, and sunshine in many ways affect both the vectors and the pathogens they transmit. For example, high temperatures can increase or reduce survival rate, depending on the vector, its behaviour and many other factors (Gubler-Jonathan et al., 2001). Thus, the

probability of transmission may or may not be increased by higher temperatures. Extremely high air temperatures contribute directly to deaths from cardiovascular and respiratory diseases, particularly among elderly people. In the heat wave of summer 2003 in Europe for instance, more than 70 000 deaths were recorded (Robine-Michel et al., 2008). High temperatures also raise the levels of ozone and other pollutants in the air that exacerbate cardiovascular and respiratory disease. Rising temperatures and variable precipitation are likely to decrease the production of staple foods in many of the poorest regions with the potential to increase prevalence of malnutrition and under nutrition, found to cause about 3.1 million deaths every year (WHO, 2019).

Frequent and uncertain changes in seasons and climatic elements seem to be the primary cause of high morbidity and mortality globally; this uncertainty reflects the difficulty in predicting and addressing the effects on human health and survival (Prüss-Ustün, Annette and Havelaar, 2001). The spatial and temporal distribution of climate- sensitive elements leads to outbreak of infectious and parasitic diseases (WHO, 2004), that cause millions of deaths annually including preventable diseases (WHO, 2008). A study by Kama et al. (2019) conforms that climate of the study area is characterized by two well defined seasons. These are the wet season and the dry season. The existence of these two seasons determines the regimes of both ground water and surface water (Kama et al., 2019).

The study area experiences a mix of high and low temperatures throughout the year; the relative humidity is about 65% and it increases during the rainy season. Rainfall collects into drainages, swamps, lakes and ponds which serve as breeding grounds for mosquitoes and other disease transmitting vectors. The periods of low temperature in the study area provides some level of comfort to residents but triggers respiratory tract infections and diseases that thrive in cold weather such as pneumonia, while warm periods in the study area aggravate the outbreak of diseases that are sensitive to high temperature such as meningitis and measles

LITERATURE REVIEW

Seasonality of Infection Disease Occurrence

Although the seasonality of infectious disease occurrence may be startling in its regularity, it is reasonable to ask what public health benefit can be expected if

resources are devoted to the study of seasonality. In recent years, the emergence of novel respiratory pathogens such as the SARS associated coronavirus, concern about the mechanisms that could drive pandemic influenza transmission, and a desire for improved tools for forecasting of infectious disease occurrence in the context of global climate change have all contributed to a resurgence in interest in the seasonality of infectious diseases. At least four potential benefits may accrue from the study of the seasonality of infectious disease occurrence:

- (a) Improved understanding of host and pathogen biology and ecology
- (b) Enhanced accuracy of surveillance systems,
- (c) Improved ability to predict epidemics and pandemics, and
- (d) Better understanding of the long-term implications of global climate change for infectious disease control. (Fisman, 2007)

In Akure, Ondo State, Nigeria, it was observed that there was a significant monthly variation in measles occurrence and weather variables. Temperature had the same general pattern of variation with measles, decreasing from January to August and increasing thereafter to December. An opposite pattern was observed with relationship to relative humidity and rainfall, suggesting a negative relationship (Akinbobola and Omotosho, 2010).

Over Hong Kong, China and Maricopa, Arizona USA, it was shown that including the climatic variables as input series result in models with better performance than the univariate model where the influenza cases depend only on its past values and error signal. Including environmental variables generally increases the prediction capability for the occurrence of seasonal influenza. It was found that the accumulated rainfall, land surface temperature and relative humidity are significant predictors for influenza in Hong Kong. The higher temperatures tend to occur at the end of the dry season (February-March) and the lowest temperature in the middle of the dry season (December – January) generally corresponding to the spring and autumn equinoxes (Kama et al., 2019).

Temperature and relative humidity are often associated with influenza epidemics such as in Tokyo, Japan and especially in temperate regions where influenza peak coincides with winter. Influenza incidences are positively associated with the mean air temperature. The results are in agreement with the findings that dry and cold condition enhances influenza transmission. (Soebiyanto, Adimi, and Kiang, 2010) Seasonal infections of humans range from

childhood diseases such as measles, diphtheria and chicken pox to faecal-oral infections, such as cholera and rotavirus, vector-borne diseases including malaria and even sexually transmitted gonorrhoea.

Early identification of an infectious disease outbreak is an important first step towards implementing effective disease interventions and reducing resulting mortality and morbidity in human populations. In the majority of cases, however, epidemics are generally well under way before authorities are notified and able to control the epidemic or mitigate its effects (WHO, 2004). Both geographical and seasonal distributions of many infectious diseases are linked to climate, therefore the possibility of using seasonal climate forecasts as predictive indicators in disease early warning systems (EWS) has long been a focus of interest. During the 1990s, however, a number of factors led to increased activity in this field: significant advances in data availability, epidemiological modelling and information technology, and the implementation of successful EWS outside the health sector. In addition, convincing evidence that anthropogenic influences are causing the world's climate to change has provided an added incentive to improve understanding of climate-disease interactions. Projections indicate an approximate average global warming of 2-5 °C within the twenty-first century (IPCC, 2001), accompanied by an increase in the frequency of extreme and anomalous weather events such as heat-waves, floods and droughts (McMichael, 2001). It has been widely speculated that these projected changes may have significant impacts on the timing and severity of infectious disease outbreaks.

Host Immune Function

Seasonal change in host immune competence, and hence susceptibility to infection or to symptomatic disease following an infection, has been proposed as a cause of seasonal variation in the incidence of some infectious disease of humans. Several potential mechanisms for annual variation in immune competence have been suggested including photoperiod effects and physiological stress. Perhaps the best-supported role for seasonal changes in human immune competence is the decline in mucosal integrity during the rainy season in Africa, and the associated increase in cases of bacterial meningitis. This is likely to be due to an increased risk of invasive disease among infected individuals, rather than increased transmission, since bacterial transmission continues during the rainy season (Grassly and Fraser, 2006).

Abundance of Vectors and Non-Human Hosts.

Seasonal changes in vector abundance, including mosquitoes, ticks, snails, fleas and flies are well documented causes of seasonality for vector borne infections. For example, seasonal variations in mosquito abundance in response to annual variation in temperature and rainfall can cause strong seasonal patterns of disease incidence in malaria epidemic regions.

Kenya highlands. Similarly, seasonal peaks in the incidence of diarrhoeal disease in Pakistan correlate with a high density of houseflies, and maybe suppressed by effective fly control.

(Grassly and Fraser, 2006) Although various genetic strains of measles are known to exist, recovery from infection from one strain leads to a life time immunity to re-infection from all others. This combination of long-lasting immunity and a high infection rate results in measles being a predominantly childhood disease and intimately connects the infection dynamics and the birth process. The short timescale of this progression to immunity leads to relatively violent epidemic cycles, followed by deep troughs in measles abundance. In essence a simple oscillator, the dynamics are strongly influenced by seasonal variation (forcing) of the transmission rate. In the best documented case in the U.K., forcing depends on the seasonal aggregation of children in primary schools, thus the pattern of mixing with age is also potentially important, though much can be learned from simple non-age-structured models. In the context of many less developed countries, more general seasonal drivers than schooling, such as the agricultural cycle and associated droughts and famine, are likely to play a more significant role. (Conlan and Grenfell, 2007).

METHODOLOGY**Study Area**

The Federal Capital Territory (FCT), Abuja, serves as the capital city and seat of government for Nigeria. It is centrally located between 8° 27'–9° 20' N latitude and 7° 25'–7° 45' E longitude, covering a land area of 8,000 sq. km. FCT is bordered by Abuja (East), Kaduna (North), Niger (West), and Kogi (South) states, and sits at an elevation of 476 meters above sea level (Oluwafemi & Oluwayinka, 2020; Owolabi, Ogunsajo, Bodunde, & Olubode, 2020). The specific study area falls between Latitude 8° 56' 48" N and 9° 1' 48" N and Longitude 7° 17' 00" E and 7° 22' 12" E.

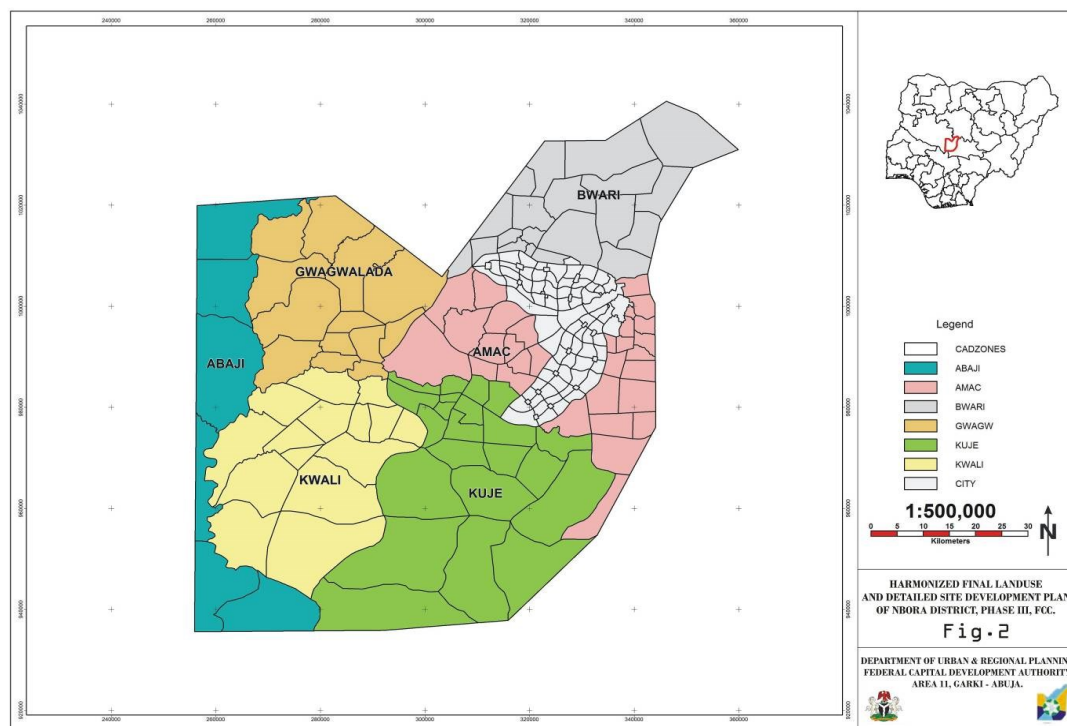


Figure 1: FCT showing Area Council

Source: NSUK Lab

Climate

Abuja Municipal Area Council experiences a tropical climate, characterized by distinct wet and dry seasons (Balogun, 2001). The wet season runs from April to October, with daytime temperatures ranging from 28°C to 30°C and nighttime temperatures between 22°C and 23°C (Sawyer et al., 2017a). During the dry season, daytime temperatures can rise to 38°C, while nighttime temperatures may drop to 12°C. Annual rainfall varies between 1100 mm and 1600 mm, influenced by the Jos Plateau. Relative humidity averages 30% in the dry season and 70% during the wet season (Chimereze et al., 2016). Wind speeds range from 3.0 to 4.6 knots in June/July, and 1.5 to 3.7 knots in December/January, with prevailing winds coming from the south-southwest and north-northeast, respectively (Sawyer et al., 2017b).

Soil and Vegetation

The soil in Abuja Municipal Area Council shows considerable variability, comprising sand, silt, clay, and gravel. Alluvial soils, prevalent in the valleys,

particularly around the River Usuma, are rich in decomposed organic matter and are generally moist and poorly drained, making them suitable for farming (Ebisintei et al., 2015; Sawyerr et al., 2017b). The area falls within Nigeria's Guinea Savanna Vegetation Zone, dominated by species such as *Antirisan africana*, *Anthocleistanoblis*, *Ceiba pentandra*, *Cola gigantea*, *Celtis* spp., *Chtorophora excels*, *Piptadenia africanum*, *Lophira alata*, *Terminalia ivorensis*, *Triplochiton scleroxylon*, and *Dracaena arborea* (Magaji and Mallo, 2020). The dominant vegetation consists of three savanna types.

Sources of Data

This study primarily relied on secondary data collected from hospitals. Additional secondary data sources included journals, books, articles, newsletters, internet resources, magazines, as well as published and unpublished materials. The specific data required encompassed information such as: Medical records for both inpatients and outpatients treated for malaria, measles, meningitis, and pneumonia in hospitals within the Federal Capital Territory. These records were obtained from the Health Departments of each Area Council, covering both Government and Private Health Facilities, as well as from the National Hospital and University of Abuja Teaching Hospital, Gwagwalada.

Technique, Sample Size and Population

The target population consisted of approximately 767 health facilities spread across the six area councils, encompassing the tertiary, secondary, and primary health sectors for both government-owned and private hospitals. A multiple strata or hierarchical random sampling technique was employed. This involved stratifying the Federal Capital Territory based on its six area councils and purposively selecting both government and private hospitals from each council. Only hospitals that submitted their monthly records and met the criteria set during the reconnaissance stage, providing available records of cases for malaria, measles, pneumonia, and meningitis, were included. This also extended to the health departments within the area councils, the National Hospital, and the University of Abuja Teaching Hospital, Gwagwalada.

Methods of Data Collection

An application for access to medical records was submitted to the Ethical Committees of all hospitals selected for the study. Each application was

accompanied by a proposal outlining the study's purpose, along with the necessary documentation for clearance by the hospital management. The data collection process spanned several months and involved intensive collaboration with the relevant units and departments at each data collection point. Some challenges arose with processing the disease incidence data due to incomplete data sets from certain hospitals, which were only able to provide monthly records instead of daily records.

Method of Data Analysis

The collected data were processed through a range of procedures and analytical techniques. The disease data were inputted and analysed using the Statistical Package for Social Sciences (SPSS) version 25 and Microsoft Excel 2016. Both descriptive and inferential statistics were employed in the analysis. Maps were utilized to summarize the data visually, while descriptive statistics such as percentages, proportions, total values, and averages were used to describe the dataset. Seasonal variations in the incidence of diseases were analysed using chi-square and multiple regression tests.

RESULTS AND DISCUSSIONS

Seasonal Variations in Disease Incidence in FCT

To examine the health implications of climatic elements on malaria, measles; meningitis, and pneumonia in FCT be mitigated; Chi-square and adjusted residual methods were used to determine variations in the incidence of disease by seasons or periods of high or low impact on public health. It also helps to know the direction or nature of the relationship between these diseases and climatic elements in order to clearly understand their implications. The seasons were divided into 3 logs; Warm (February, March, April and May), Rainy (June, July, August and September) and Cold (October, November, December and January) respectively.

Seasonal Variations in Malaria Incidence in FCT

Tables 4.6 indicated that the warm, rainy and cold months of the year have high incidences of malaria. The rainy season is clearly the peak period which has a positive adjusted residual of 32.406. The Chi-Squared probability value shows that the variation between the seasons is significant as the calculated value is less

than the level of significance at 0.05%. In the cases of malaria, therefore, it is expected that the rainy seasons should be examined more closely.

The results of the residuals indicated that the warm and rainy months are clearly responsible for the variations. Both values exceeded 2. The cold month's average number of incidences is much like the mean number of reported cases for the study period. However, the warm season has much lower incidences, while the rainy season has much higher number of reported incidences of malaria than the mean.

The rainy seasons (13354.37) and cold seasons (12104.03) have higher number of reported incidence than the warm seasons (11373.02). The adjusted residuals also showed that the rainy season is important but that the warm and cold season have a negative adjusted residual.

The results of the Chi-Squared test showed that there is a significant variation in the number of reported cases of malaria by seasons (Table 4.6). The calculated probability value is much lower than the level of significance at 0.05%. The adjusted residuals also confirm that rainy seasons are particularly important in this variation. The season have adjusted residuals that exceed 2, which is the normal distribution score (Z at 0.005 is 1.96, which is usually approximated at 2). The rainy season average is the highest and the warm season's average is the lowest. The cold season has an average that is close to the seasonal average, consequently the residual value is not significant (-30.84). Because the value is lower than the seasonal average, the residual has a negative sign to indicate that. However, maximum temperature, rainfall and relative humidity showed individual significance of the variables at 0.05% alpha level impact on number of cases of malaria in the study area (Table 4.2). These are all associated with rainy and cold seasons. During the rainy season, relative humidity is usually high and temperatures may also be lower than the warm season. Evidently, the warm seasons may not favour mosquitoes much because of the heat and dry nature of the climate that is detrimental to their survival. This also agreed with Kama, Marcus, Hembe and Yisa, (2024) reported that malaria is particularly sensitive to rainfall and humidity, with peak incidences occurring during the rainy season. Generally, maximum temperature may not be as favourable to mosquito breeding than minimum temperature, however, may fall within their threshold of favourable climate conditions and allow them to thrive. These may account for the seasonal variation in the incidence of malaria (Hajison et al., 2017).

Table 4.6 Seasonal Variations in Malaria Incidence

Seasons	Mean Seasonal Malaria Incidence	Adjusted Residuals
Warm	11373.02	-30.84
Rainy	13354.37	32.406
Cold	12104.03	-15.62
Average incidence	12277.14	
Chi-Squared Probability at α 0.05:	3.07162E-36	

Source: Fieldwork, 2021

Seasonal Variations in Measles Incidence in FCT

Table 4.7 showed that Chi-Squared test for measles had no variation in reported cases of the disease between seasons. Warm seasons (143.8) have a marginally higher average number of reported cases but it is not significantly different from what has been reported for rainy seasons (128.66) and cold seasons (134). The Chi-Squared probability (0.452155) value is therefore higher than the level of significance at 0.05%. However, the adjusted residuals for cold had a negative value (-1.55) and the normal distribution score Z at 0.005 is 1.96, which is usually approximated at 2.

In this case, no significant variation is found but the adjusted residuals are computed to confirm this. Warm and rainy season adjusted residuals for the observations are larger than 2, which indicates that the observations are within similar brackets of the mean values.

The average seasonal distribution for measles is low; however seasonal variations are not significant. The calculated probability Chi-Squared value (0.452155) is greater than the 0.05% probability level of significance. The warm season appears to have a higher-than-average number of incidences per season, while the rainy and cold seasons have fewer averages per season.

The adjusted residual values are therefore not necessary because there is no significant variation in the number of measles incidence according to seasons. The results shows that the warm season may have higher number of values as seen in Table 4.7 and high temperatures may be significant in explaining the distribution, but overall, it is not significantly different than for other seasons.

Table 4.7 Seasonal Variations in Measles Incidence

Seasons	Mean Seasonal Measles Incidence	Adjusted Residuals
Warm	148.8	3.516
Rainy	128.66	2.741

Cold	134	-1.55
Average incidence	137.153	
Chi-Squared Probability at α 0.05:	0.452155	

Source: Fieldwork, 2021

Seasonal Variations in Meningitis Incidence in FCT

Table 4.9 showed that incidences of meningitis occurred more frequently during the warm seasons (192.2667) and cold seasons (143.6) with mean seasonal cases of incidences, but it is lowest during rainy season. Meningitis on the other hand had the highest reported cases during the hot and dry seasons with the highest reported mean cases of 55.8. Meningitis incidences were observed more in March, with a low mean incidence of 28.0 cases in August (figure 4.7).

The chi-squared probability is significant at 0.05% with positive adjusted residuals warm value of (6.40) and negative values from rainy seasons (-5.51) and (-3.00) respectively.

The positive trend in temperature will mean an increase in the cases of meningitis in the study area. The findings of this study corroborate findings by Kama, (2022) that that high temperature in the study area leads to high outbreak of CSM. That is, increasing in temperature trigger more incidence cases of meningitis in the study area.

Table 4.8 Seasonal Variations in Meningitis Incidence

Seasons	Mean Seasonal Meningitis Incidence	Adjusted Residuals
Warm	192.2667	6.40
Rainy	122.2	-5.51
Cold	143.6	-3.00
Average incidence	152.6889	
Chi-Squared Probability at α 0.05:	0.0002152	

Source: Fieldwork, 2021

Seasonal Variations in Pneumonia Incidence in FCT

Table 4.9 showed the Chi-Squared test result which indicates that there is no significant variation in the seasonal distribution of pneumonia incidence in FCT. The calculated probability value is greater than the level of significance (0.05%). The seasonal average (663.8) and the probability value (0.3429021) showed that there are no significant variations between the seasons. The adjusted residuals

had a negative calculated value for both warm seasons (-1.13) and cold seasons (-3.97), since there are no significant variations found between the seasons (Table 4.9).

This finding agrees with a study by Amuakwa-Mensah, Marbuah and Mubanga, (2016) reported more directly considered the situation in the tropics and concluded that there is evidence to indicate that there are no significant variations in the distribution of pneumonia cases between seasons. It is easy to assume that because pneumonia is generally associated with the cold periods, the cold harmattan season should be the peak period of the epidemic. It may be noted that because people are generally aware of such general correlations, they take more precautions during the cold season and therefore prevent pneumonia attacks. FCT experience relatively high temperatures which may not be conducive for the occurrence of large cases of pneumonia, usually associated with colder conditions. Among all the five climatic elements namely sunshine, maximum temperature, minimum temperature, rainfall and relative humidity only rainfall is significant at 0.0245 with adjusted R-square of 46.10% (figure 4.8).

Table 4.9 Seasonal Variations in Pneumonia Incidence

Seasons	Mean Seasonal Pneumonia Incidence	Adjusted Residuals
Warm	660.8667	-1.13
Rainy	691	5.433
Cold	638.7333	-3.97
Average incidence	663.8	
Chi-Squared Probability at α 0.05:	0.342902165	

Source: Fieldwork, 2021

Conclusion

The study reveals that climatic elements significantly influence the incidence of certain diseases in the Federal Capital Territory (FCT), Nigeria. Malaria showed a strong seasonal pattern, peaking during the rainy season, while meningitis was more prevalent during warmer months. No significant seasonal variation was observed for measles and pneumonia, although slight fluctuations were noted. These findings underscore the importance of understanding how climate affects disease transmission, as the health of the population is closely tied to seasonal changes. The study highlights the need for public health strategies that address

the relationship between climatic conditions and disease outbreaks to ensure timely interventions and reduce morbidity and mortality.

Recommendations

- **Enhanced Disease Surveillance:** Public health authorities should strengthen disease surveillance during critical periods, particularly the rainy season for malaria and warmer months for meningitis. This will enable early detection and prompt response to outbreaks.
- **Integration of Climatic Data in Health Planning:** It is crucial to incorporate climatic data, such as temperature, rainfall, and humidity, into health forecasting models to predict disease outbreaks more accurately. This would improve preparedness and response strategies.
- **Public Health Education:** Increase awareness campaigns, particularly in rural areas, on the impact of seasonal changes on health, emphasizing the importance of preventive measures during high-risk seasons for diseases like malaria and meningitis.
- **Environmental Management:** Implementing environmental management strategies, such as improved sanitation and water drainage systems, can help reduce breeding grounds for disease vectors like mosquitoes, thereby minimizing the risk of malaria during the rainy season.
- **Health Infrastructure and Resources:** Ensure that hospitals and health facilities are adequately equipped with the necessary resources and personnel, especially during seasons when disease incidence is expected to rise, to handle potential surges in patient numbers.

REFERENCES

- (2006) Nipah virus-associated encephalitis
 (2006) Nipah virus-associated encephalitis
 (2006) Nipah virus-associated encephalitis
 (Centers for Disease Control and
 (Centers for Disease Control and
 (Centers for Disease Control and
 12, 235-240.
 12, 235-240.
 12, 235-240.
 Alhassan I. D., Kama H. G., and Alhassan J. J., (2023). An Assessment on the Utilisation of Sanitation Facilities in the Attainment of Sustainable Development Goal in Tertiary Institutions of Plateau State, Nigeria. *Journal of African Sustainability Development (JASD)*, 2(2), 122-137.
 Akinbobola A. & Omotosho, J.B. (2010). Meteorological Factors and measles occurrence in Akure, Ondo state, Nigeria, *Journal of Meteorology and Related Sciences*, 4(1), 35-47.
 Balogun, A. A. (2001). Tropical Climate: Wet and Dry Seasons. *Journal of Climate Studies*, 15(3), 45-53.

- Conlan A.J.K. and B.T.Grenfell, (2007); Seasonality and the persistence and invasion of Cholera incidence and El Nino-related higher ambient temperature. *Jama-Journal of the American Medical Association*, 283(23), 3072-3074.
- Chimereze, C. E., Osarenmwinda, O., & Igwe, A. (2016). Climate Analysis and Impacts in Abuja Municipal Area Council. *Journal of Climate and Environmental Research*, 8(2), 120-135.
- Ebisintei, O. E., Iyakoregha, A. S., & Ukpebor, E. F. (2015). Soil Composition and Agricultural Suitability of the Abuja River Basin. *Journal of Environmental Science and Agriculture*, 11(5), 77-88.
- Fisman D., (2007). Seasonality of Infectious diseases, Annual Review of Public Health, Canada, 28,127-143
- Grassly N.C. & Fraser, C. (2006); Seasonal Infectious disease Epidemiology, PMC, PubMed.
- Gubler DJ, et al. (2001) Climate variability and change in the United States: Potential impacts on vector- and rodent-borne diseases. *Environmental Health Perspectives*, 109: 223-233.
- Hajison, P.L., Mwakikunga, B.W., Mathanga, D.P. et al. (2017) Seasonal variation of malaria cases in children aged less than 5 years old following weather change in Zomba district, Malawi. *Malar J* **16**, 264.
- Indhumathi, K., & Sathesh Kumar, K. (2021). A review on prediction of seasonal diseases based on climate change using big data. *Materials today. Proceedings*, 37, 2648-2652.
- IPCC. (2001) Climate change 2001: impacts, adaptation and vulnerability. Contribution of working group II to the third assessment report of the Intergovernmental Panel on Climate Change (IPCC). McCarthy JJ, et al., eds. Cambridge: Cambridge University Press.
- Kama H. G., MARCUS N. D., NANEN D. HEMBE., and ABRAHAM G. YISA, (2024). Assessing the Incidence Trend of Malaria, Measles, Meningitis, and Pneumonia in the FCT, Nigeria. *Journal of Health, Metabolism and Nutrition Studies (JHMNS)*, Berkeley Research and Publications International. 5 (3), 15-32.
- Kama H. G., Alhassan I. David., And Hadiza A. A. (2024). Examining Farmers Perception and Responses to Climate Change on Crop Production in Akwanga Local Government Area of Nasarawa State, Nigeria. *International Journal of Environmental Research & Earth Science (IJERES)*. Published by Cambridge Research and Publications. 4 (4) 73-82.
- Kama, H. G., (2022). Assessment of the Relationship between Cerebrospinal Meningitis Outbreaks and Climatic Elements in Jos North Local Government Area, Plateau State, Nigeria. *International Journal of Built Environment and Earth Science, TIMBOU-AFRICA Academic Publications International Journal*, 8 (4), 34-45.
- Kama H. G, Olukaejire SJ and Gumau BG, (2019). Impact of Slum Development on Environment in Masaka, Karu Local Government Area of Nasarawa State, Nigeria. *International Journal of Environmental Design and Construction Management (IJECDM)*, Cambridge Research and Publications International. 17 (4), 38-47.
- Magaji, Y. & Mallo, S. (2020). Vegetation Patterns and Dynamics in the Guinea Savanna Zone of Nigeria. *Nigerian Journal of Ecology and Environmental Science*, 12(4), 98-109.
- McMichael AJ. (2001) Human frontiers, environments and disease. Past patterns, uncertain futures. Cambridge: Cambridge University Press.
- Oluwafemi, O. & Oluwayinka, A. (2020). Geographical Coordinates and Elevation of Abuja, Nigeria: Implications for Urban Development. *International Journal of Urban and Regional Studies*, 14(1), 22-35.
- Owolabi, I., Ogunsajo, A., Bodunde, T., & Olubode, O. (2020). Elevation and Climatic Conditions in the FCT, Nigeria. *Journal of Geographical and Environmental Science*, 10(3), 56-70.
- Prüss-Ustün, Annette & Havelaar, Arie. (2001). The Global Burden of Disease study and applications in water, sanitation and hygiene. Water Quality: Guidelines, Standards and Health.
- Robine J.M, Cheung SL, Le Roy S, Van Oyen H, Griffiths C, & Michel JP. (2008). Potential impact of climate change on schistosomiasis transmission in China. 331(2):171-8.
- Sawyer, J., Igwenagu, C., Akinbobola, S., & Obiora, E. (2017a). Climate Characteristics of Abuja Municipal Area Council. *Nigerian Journal of Meteorological Science*, 19(2), 84-93.
- Sawyer, J., Igwenagu, C., Akinbobola, S., & Obiora, E. (2017b). Wind Speed Variability and its Effect on Rainfall in Abuja. *Nigerian Meteorological Journal*, 18(4), 100-109.
- Soebiyanto, R. P., Adimi, F., & Kiang, R. K. (2010). Modeling and predicting seasonal influenza transmission in warm regions using climatological parameters. *PloS one*, 5(3), e9450.
- World Health Organisation (2015). Achieving the malaria MDG target: reversing the incidence of malaria 2000-2015. Geneva: World Health Organisation and United Nations Children's Fund.
- World Health Organization (2008). Climate Change and Allergic Diseases. Report of a WHO Task group, Geneva WHO Unpublished Document. WHO/PEP/90.10.

World Health Organization. (2004). Using climate to predict infectious disease outbreaks: A review, Communicable Diseases Surveillance and Response Protection of the Human Environment, Geneva, 2004.

World Health Organization. (2019), Weekly Epidemiological Report, Geneva.