STATE LEVEL INVESTIGATION OF THE INTERPLAY OF ENVIRONMENTAL AND SOCIOECONOMIC DRIVERS OF CHOLERA RISK IN NIGERIA

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ABSTRACT

Cholera is one of the global infectious diseases, but it's commonly linked with low latitude and particularly developing countries. In 2010, the highest proportion of cases in Africa was reported by Nigeria. In many areas of the globe, studies have been conducted which explore the relationship between either climate or socioeconomic conditions and cholera. This study explores both of these relationships in Nigeria at individual states level. Multiple linear regressions was used to explore this relationship on an inter-annual scale between cholera cases and deaths, climate and socioeconomic conditions for the 36 states and FCT. The result reveals that in almost all states inter-annual relationships were found between cholera, climate and socioeconomic conditions; the strongest meteorological relationships were largely found in the southern part of the country and the largest contribution from socioeconomic conditions largely in the north. Models with the combination of both climate and socioeconomic variables were found to explain disease variability better in both the Incidence Rate and Case Fatality Rate. As a national average, they explain 52.67% of the inter-annual variability in the IR and 60.29% of the inter-annual variability in the CFR. It is concluded therefore that despite their individual relationships, both climate and socioeconomic variables have a critical role to play in governing inter-annual variability in cholera and both must be included in an effective early warning system. Finally the study establishes that in order the menace of the disease, authorities in charge need to improve the quality of drinking water, healthcare delivery, poverty alleviation, and education. Also, embarking on widespread vaccination campaigns will do well, especially when epidemic of the disease is perceived.

Key words: Cholera, Environmental, Inter-annual Variability, Socioeconomic, Nigeria

INTRODUCTION

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

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

Since the seventh pandemic, the reported number of cholera cases is on the increase (Marin et al., 2013). According to WHO over 50 countries are currently cholera endemic (WHO, 2012b). Annually there are an estimated 3–5 million cases and over 100,000 deaths due to cholera (WHO, 2012a) with most of the cases reported from Africa and Asia (Harris et al., 2012). In Africa, cholera cases and deaths are reported to be increasing both in severity and number, most especially in countries like Nigeria (Marin et al., 2013). Statistics of WHO reported cholera cases suggest that Africa is the 'new home' for cholera (Gaffga et al., 2007). The endemic nature of cholera (Lipp et al., 2002) makes it one of the major public health threats in these countries (Emch et al., 2008), where the environmental and food hygiene tradition remains grossly insufficient. Over 90 percent of both 221,226 cases and 4,999 deaths of cholera cases reported to WHO in 2009 were from Africa. In 2010 and 2011, Nigeria alone reported over 46,700 (1840) and 23,000 (700) cases and deaths from cholera respectively.

Cholera has a notable seasonality (Pascual et al., 2002) that is influenced by environmental factors (Rajendran et al., 2011), although these seasonal characteristics may vary with location. The annual variability (Koelle, 2009) of the disease may also be related both to variability in climate and diminishing levels of population immunity developed from preceding epidemics. The influence of climate on the cholera dynamic has been well established in Asia (Bouma and Pascual., 2001), South America (e.g., Speelmon et al., 2000), and in Africa (Constantin de Magnay et al., 2012). The link between temperature increase and the amplification of cholera incidence have been well reported (Colwell, 2002). Also, cholera outbreaks are characterized by strong seasonality corresponding with heavy rainfall and warm temperatures (Reyburn et al., 2011). Islam et al. (2009) reported significance of temperature and sunshine hours to cholera outbreaks both in summer and winter seasons in Matlab, Bangladesh, while rainfall and associated river levels were found to have influence on cholera patterns in Bangladesh (Akanda et al., 2009).

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

Researches have indicated that many other socioeconomic variables also have the potential to influence spatial and temporal variability of outbreaks. Mari et al., (2012) found that the movement of infected individuals, who might show no symptoms, can be an important mechanism of the spread of the disease, especially in urban environments. Statistically significant negative relationships have been found between cholera, the Human Development Index (HDI) and female literacy in Latin America by Ackers et al. (1998). In Tanzania it has been found that literacy rate, water source and sanitation levels were each significantly related with the number of cholera cases independently of climatic variables (Traerup et al., 2010). It has been stated that young and old people are most vulnerable to contracting cholera and therefore the proportion of elderly or young people in a community may determine how fast the disease spreads or if it is able to spread to other areas (Chou et al., 2010).

Given the previous information, it would appear that cholera is not only related to the natural environment but also the built environment (Ali et al., 2002a). Consequently, meteorological variables alone do not have complete capability to influence the temporal and spatial variability in cholera incidence rates. Again, this crucial relationship between socioeconomic conditions and cholera in Nigeria is currently lacking research.

The transmission of cholera in Nigeria might be facilitated by numerous factors such as lack of access to safe drinking water, unhygienic environment, environmental disasters, literacy levels, population congestion, and internal conflicts which lead to populations being displaced to Internally Displaced Persons (IDP) camps. Provision of safe drinking water remains a serious issue of concern: this leads people, even in cities, to buy water from street vendors, which have a high risk of being contaminated. Typical areas at risk might include populations living in urban and peri-urban slums. These areas are mostly densely populated by people on low incomes, and basic infrastructure is not readily available. Despite the availability of the oral cholera vaccines, anecdotal evidence shows that this effective control method is not yet commonly used in Nigeria. The main control method is treatment through rehydration with oral salts after infection.

Despite the large burden of the disease in Nigeria, only (Leckebusch and Abdussalam, 2015) have attempted to study the disease considering both the impact of climate variability and socioeconomic conditions on a regional scale. This paper is the first to analyze the role of both climate and socioeconomic factors at state level in Nigeria. As a result, this study aims to understand the interplay between climatic variables, socioeconomic variables and cholera in Nigeria on an inter-annual basis at state levels. It will be necessary to study this relationship at the smallest possible scale, as socioeconomic variables may vary on a scale as small as household level as a result of state level legislation or urbanization (Penrose et al., 2010; Ali et al., 2002a). By understanding as much about these relationships as possible it is hoped that the national problem might be minimized (Bouma and Pascual, 2001).

MATERIALS AND METHODS

Epidemiological data

Annual records of cholera cases and deaths were obtained from the Epidemiology Division at the Centre for Disease Control of the Federal Ministry of Health, Abuja. Data is accumulated to state level, of which there are 36 states and the Federal Capital Territory (FCT) between 1997 and 2014. Although national data exists over a longer time series, state level data will allow an exploration of relationships which have the potential to vary over a smaller area.

Meteorological data

Meteorological station data was not available in all states (for this study) for the appropriate time period, and so an alternative source of data was used. ERA-Interim is a reanalysis product which produces gridded, modelled quantities of meteorological variables on a global scale between 1979 and the present day. Data is produced on a reduced Gaussian grid at a T225 spatial resolution at present which is representative of around 79km spacing (Dee et al., 2011). All states are uniquely associated with at least one grid cell, with the exception of Abia, it is not expected that associating this small state with information from one of two nearby grid cells will cause substantial errors in the analysis.

ERA-Interim data is freely available to download from the European Centre for Medium-Range Weather Forecasts (ECMWF) at http://data-portal.ecmwf.int/data/d/interim_full_daily. Surface data was selected as this is considered to have the most direct impact on the survival and abundance of Vibrio cholera. Four times daily values of temperature along with daily accumulated precipitation fields were downloaded. Relative humidity was also computed and downloaded from the website using 2m dew point and surface pressure fields. There are no missing values included in ERA-Interim, however all data was visually checked to ensure that values are physically meaningful and realistic.

In order to ensure that the simulated quantities provided by ERA-Interim are representative of reality, some meteorological station data has been obtained to validate it with. Observations data from 10 stations in different states across Nigeria were obtained from Nigerian Meteorological Agency (NIMET). Monthly average values of daily maximum temperatures (tmax), daily minimum temperatures (tmin), monthly sums of daily accumulated precipitation, and average humidity have been obtained for the overlapping study period.

Socioeconomic data

Socioeconomic data was obtained from the Nigerian National Bureau of Statistics (NBS) for the time spanning the study period. Variables have been chosen based on previous research and if they are available at both an appropriate spatial and temporal resolution. Data obtained includes percentages of population having access to pipe borne water, adult literacy, and absolute poverty. State's population census (2006) was obtained from the Nigerian Population Commission (NPC), Abuja, Nigeria. Annual population estimate for each state was calculated forward and backward in time using Nigerian population growth rate index provided by World Bank (2014). Population density for each of the 36 states and FCT were computed by dividing each state's population with its aerial cover.

Small amounts of missing data are present in all of the socioeconomic data with the exception of population density. Only 4.1% of data in both the adult literacy and absolute poverty time series are missing.

Data validation and transformation

From the global ERA-Interim product, data representative of Nigeria between 1997 and 2014 was extracted using Climate Data Operator (CDO) commands. Monthly averages of daily maximum temperature (tmax), daily minimum temperature (tmin), monthly sums of daily accumulated precipitation, and monthly average of relative humidity from the grid cells were extracted. Each grid cell was assigned to a state using a state specific code. Where more than one cell was assigned to a state, an average monthly value was taken. For the 10 states where meteorological station data exists, time series were generated from an average of the four closest grid cells to the station for use in validation.

Firstly, the monthly time series were validated in order to demonstrate that the seasonal cycle in ERA-Interim is realistic. For each of the ten states station's data, the long term (1997-2014) average for each month of the year was calculated, subtracting this from the actual monthly value produced a filter time series with the seasonal cycle removed. Validating these time series demonstrates how realistic the inter-annual variability in ERA-Interim is.

Finally, annual averages of the climate data were computed in order for the relationship with cholera on an inter-annual basis to be explored. Simple annual averages were calculated; however, in order to preserve the variability in the data which cholera is likely to be related to, rainy season average precipitation, and humidity (an average for the rainy season only, May to September) were also calculated. Rainy season average tmax/tmin will explore whether temperature variability in the rainy season has a relationship with cholera, whilst seasonal average tmax and tmin are averages calculated over March to June only when temperatures are often higher. A validation of these annual values allowed an assessment of the representation of inter-annual variability in ERA-Interim.

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

Model development

Multiple Linear Regression (MLR) is a powerful statistic which uses the equation of a straight line (equation one) to predict the outcome in a dependent variable from a linear combination of independent predictor variables. This statistic will not only allow an exploration of the relationships which exist between cholera, climate and socioeconomic conditions but also explores the predictive power of these relationships (Field, 2005).

$$Y_i = b_0 + b_1X_1 + b_2X_2 + \ldots\ldots b_nX_n) + \varepsilon_i$$

Where Y_i is the outcome in the dependent variable, b_0 is a constant, b_1 is the coefficient associated with the first predictor variable (X_i) and so on and ε_i is the term which calculates the difference between the observed and predicted value of Y_i.

The R^2 value produced by MLR indicates how much variability in the outcome variable is explained by the predictor variables, while the coefficients indicate the strength and direction of the relationship between the dependent and each independent variable. For each MLR model a significance level is calculated, indicating how likely the R^2 value is to be produced by chance alone. An appropriate significance level is subjective and varies across studies, popular values include 0.01, 0.05 and 0.10 (Rogerson, 2001). In accordance with this, models found to be significant at less than the 0.1 level will be accepted as statistically significant in this study.

Models were subsequently developed in the following stages:

Stage 1: Simple (one independent variable) linear regression was conducted. For each state, both the IR and the CFR were input (separately) as the outcome variable using each of the climate variables individually as the independent variables. The intent here is to explore the relationship cholera has with each climate variable.

Stage 2: a combination of climate variables were used as predictor variables in a MLR model, again, whilst using first the IR and secondly the CFR as the outcome variable in each state. These models allow an investigation of the potential power that climate can have in explaining variability in either the IR or the CFR.

Stage one and two were then repeated with respect to socioeconomic variables.

Stage 3: MLR model was developed in each state which included a combination of climate variables and socioeconomic variables as the predictors and individually the IR and the CFR as the outcome variable.

An assumption of MLR is that none of the predictor variables have high multi-collinearity (defined as a correlation coefficient of 0.8 or greater (Field, 2005)). If high multi-collinearity was detected, a correlation was performed in order to determine the most suitable predictor variable by choosing the variable which had the highest correlation coefficient with the appropriate dependent variable whilst remaining independent of all other predictor variables.

Finally the relative difference between the final stage of statistical modelling and the MLR which included a combination of climate variables only was calculated. This calculation allows an understanding of the proportion of the variability in the final MLR model which is explained by socioeconomic data only. This will give an indication of the states where either climate or socioeconomic data can make the largest contribution to explaining variability in the IR or the CFR. IBM SPSS 20 statistical packages was used for the regression analysis.

RESULTS AND DISCUSSION

From the validation process carried out of the ERA-Interim data used in this study, the strongest maximum temperature associations are found between the unfiltered monthly time series , with the highest correlation coefficient found ($r = 0.964$). Weaker associations are found between the filtered monthly time series with the highest ($r = 0.834$). Annual values have the lowest correlation coefficients, with a range of $r =0.229$ to $r = 0.762$. For tmin, the highest coefficient calculated between both the monthly time series and the filtered time series ranges ($r = 0.767$ to $r = 0.934$). Again the lowest coefficients are found between the annual time series, the strongest association is ($r = 0.62$). All values are statistically significant ($p< 0.01$).

Consistently strong associations in the results from monthly sum precipitation is found in the validation process, with a maximum coefficient of $r = 0.919$. All the ten values are statistically significant. With respect to the filtered monthly time series, positive associations are statistically significant but much weaker.

To summarise, the association across the range of meteorological variables is stronger if the seasonal cycle is present in the time series, whilst associations decrease with respect to the filtered and annual time series. Associations are weakest when considering inter-annual variability in precipitation.

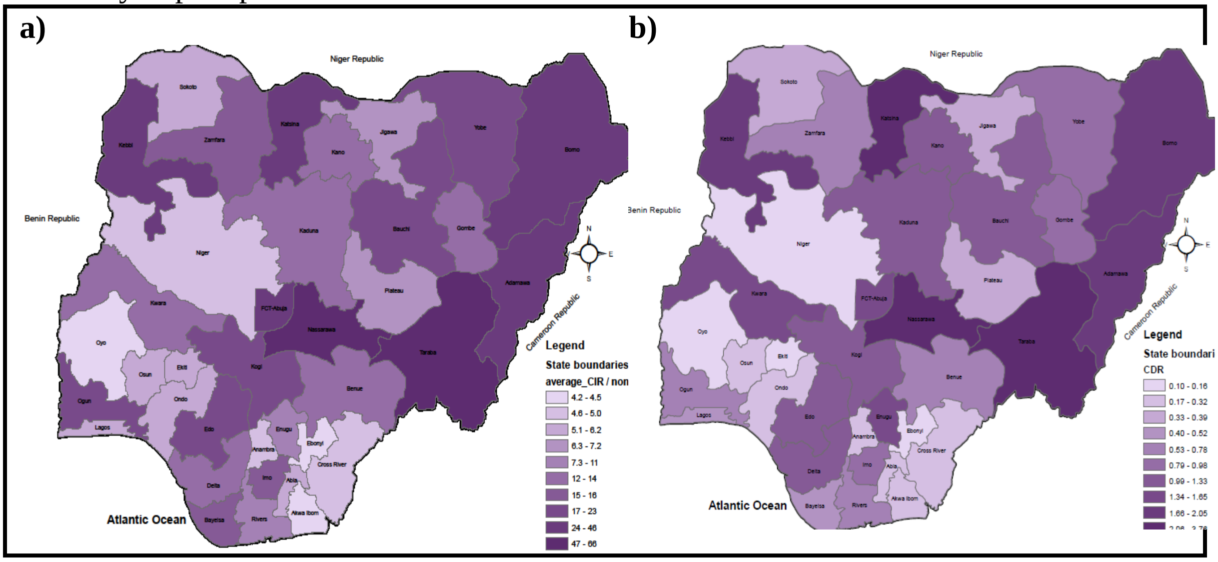

Figure 1: a) Mean incidence rate, and b) Mean case fertility rate of cholera per state between 1997 and 2014

Source: Authors' analysis

Figures 1a and b demonstrate the spatial variability in the mean case fertility rate and incidence rate respectively between 1997 and 2014. Generally higher incidence and death rates are found in the north east of the country.

Table1 presents the regression coefficient (b) calculated during the first stage of statistical modelling. The coefficients for the state where the relationship between the IR, CFR and each individual climate variable is strongest and statistically significant are presented. All temperature and precipitation variables have a positive relationship with the IR. The relationship between minimum temperature, precipitation and the CFR is positive, conversely the CFR exhibits a negative relationship with maximum temperatures.

Table 1: Results from a linear regression model using either the IR or the CFR as the independent variable

Predictors	IR (R^2 %)	CFR (R^2 %)
Annual average tmax	6.52	10.52
Rainy season average tmax	8.54	16.15
Seasonal average tmax	8.88	10.64
Annual average tmin	7.28	7.05
Rainy seasonal average tmin	7.10	11.32
Seasonal average tmin	7.83	4.69
Annual total precipitation	6.55	11.95
Rainy season average precipitation	6.06	10.27
Rainy season average humidity	4.34	6.54
Annual average humidity	5.32	7.12

Source: Authors' analysis

Seasonal average tmax explains the highest proportion of variability in the IR, whilst the most important predictor for the CFR is rainy season average tmax. Annual average tmax explains the lowest proportion of inter-annual variability in the IR, whilst the least important variable in explaining inter-annual variations in the CFR is seasonal average tmin.

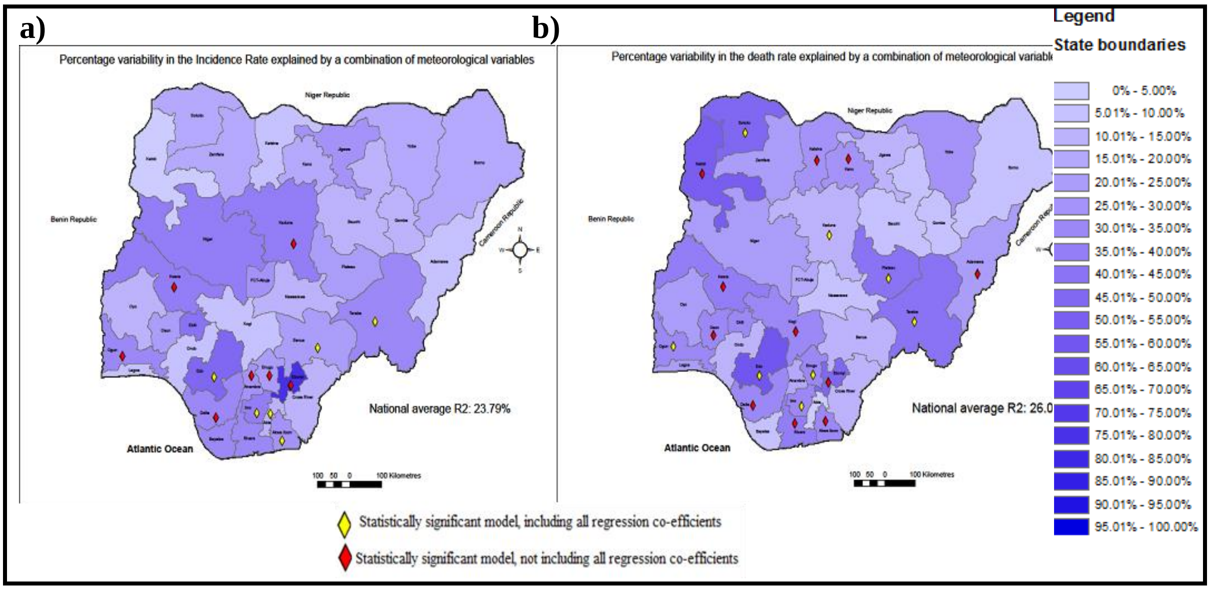

Figure 2: Results of a simple linear regression model for each state including a) IR, and b) CFR as the dependent variable and the combination of meteorological variables.

Source: Authors' analysis

Figures 2a and b demonstrate the results from the second stage of statistical modelling where a combination of climate predictors found to explain the highest proportion of variability in the dependent variable, whilst remaining independent of each other, are included in the MLR models.

Regardless of the dependent variable, the national average relationship between cholera and climate is always stronger if a combination of climate variables is used as opposed to a single variable. Considering the IR, climate variability appears to be most effective at explaining the relationship in the south of the country. However, strong and significant relationships are more widespread if the CFR is used as the dependent variable. Climate variability is able to explain a higher proportion of the inter-annual variability in the CFR with respect to the IR.

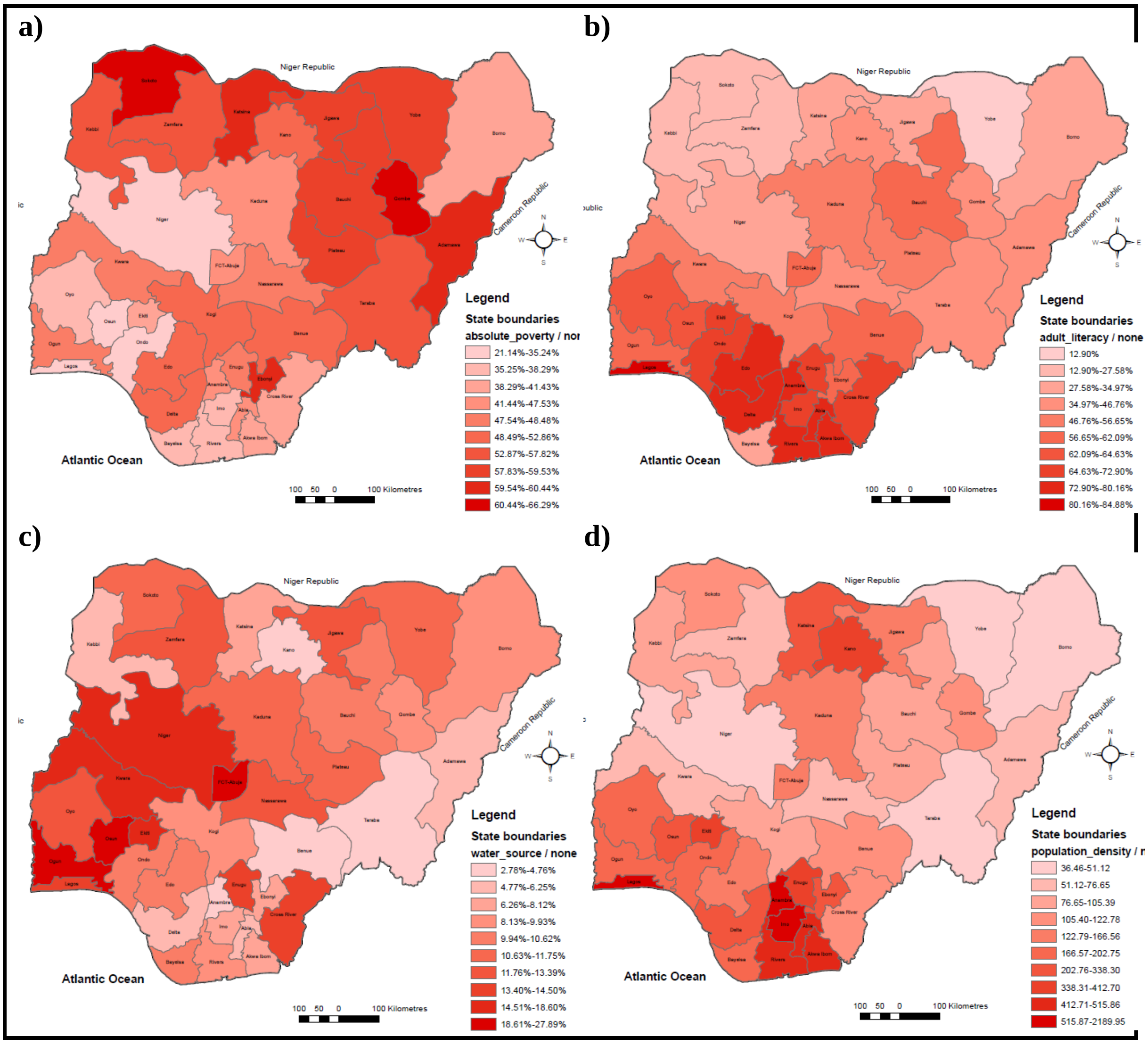

Figure 3: Plots illustrating the mean spatial variability of socioeconomic conditions over the respective time series for each variable: a) absolute poverty, b) adult literacy, c) water source, d) population density

Source: Authors' analysis

Figure 3 illustrates the mean value for each of the four obtained socioeconomic variables across all states from the length of each respective variables time series. Highest poverty levels are found in the northwest and northeast of the country in addition, these are the areas where lowest levels of adult literacy are found. Generally access to pipe borne water is low, with areas of the highest access found in the west of the country. Lastly, the highest population densities are often found in the south of the country. The national average relationship has been calculated and is shown in Table 2.

Table 2: Results from a linear regression model using either the IR or the CFR as the independent variable

Predictors	IR (R^2 %)	CFR (R^2 %)
Water source	17.19	15.02
Absolute poverty	6.11	7.81
Population density	6.83	10.04
Adult literacy	5.14	11.51

Source: Authors' analysis

Regardless of the dependent variable, individually, water source explains the greatest variability in the cholera time series as a national average. Adult literacy is the least important predictor with respect to inter-annual variability in the IR, whilst population density explains the lowest proportion of variability in the CFR. With the exception of water source, socioeconomic variables explain more variability in the CFR than the IR. For example, adult literacy explains 3 times more variability in the CFR than the IR.

The results from the second stage of statistical modelling are shown in figures 4a and b, where a combination of socioeconomic predictors which are found to explain the highest proportion of variability in the dependent variable, whilst remaining independent of each other, were included in the MLR models. Strong relationships are observed to be reasonably widespread across the country with respect to previously demonstrated relationships with climate.

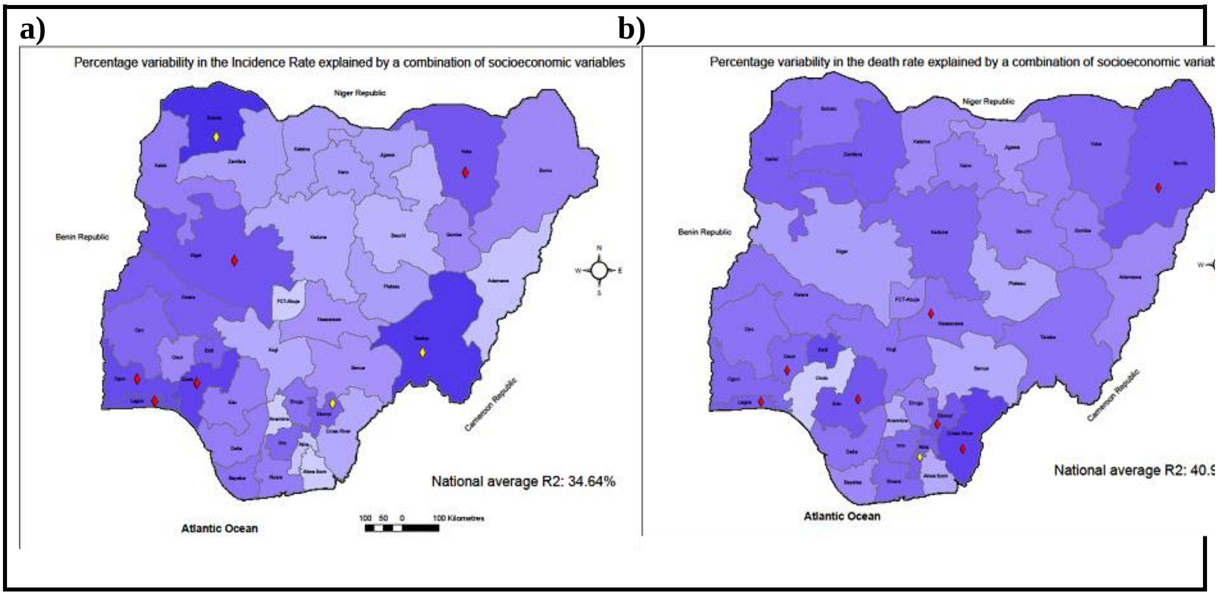

Figure 4: Results of a multiple linear regression model for each state including a) IR, and b) CFR as the dependent variable and the combination of socioeconomic variables.

Source: Authors' analysis

A higher proportion of variability is consistently explained if a combination of socioeconomic variables is included in the MLR as opposed to the single variable included in the simple linear regression model. Additionally, figures 2a and b (climate MLR models), explain less inter-annual variability than figures 4a and b (socioeconomic MLR models).

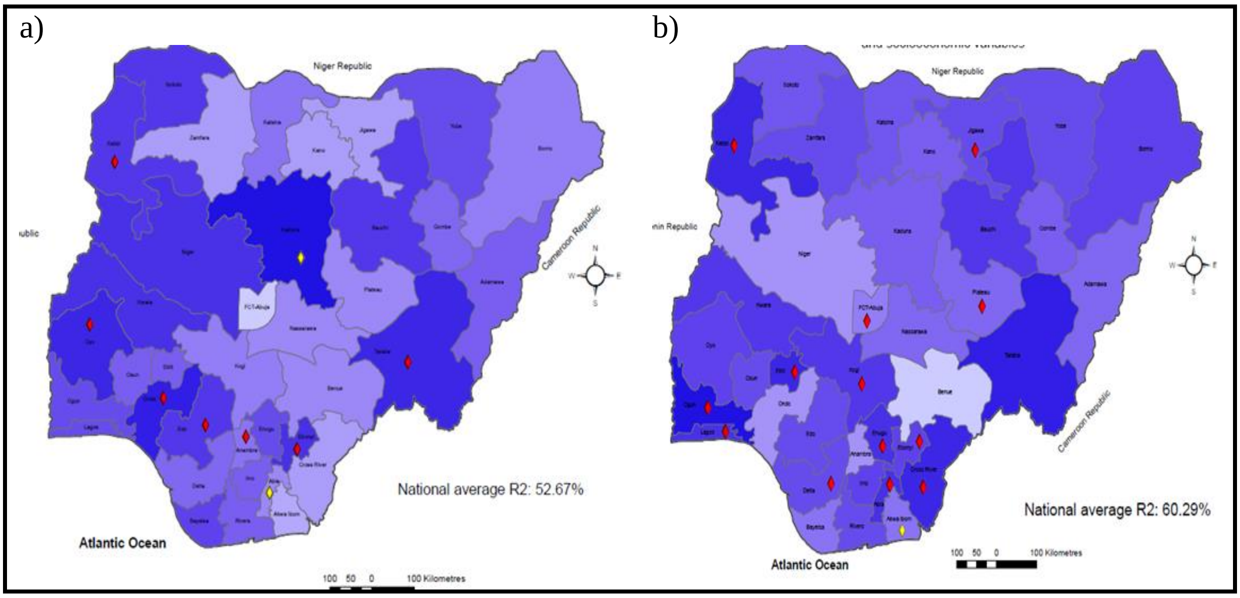

Figure 5: Results from a MLR model for each state containing a combination of both meteorological and a combination of socioeconomic variables.

Source: Authors' analysis

Figures 5a and b illustrate the results from the final stage of statistical modelling. The first noticeable result from these plots is that although there is a clustering of statistically significant results around the south of the country, when the CFR is considered (Figure 5b), relationships in the north and in particular the north east are consistently higher than if the IR is considered. Importantly, the MLR model is able to explain an extra 7.62% of the inter-annual variability in the CFR as opposed to the IR.

Figures 6a and b aim to assist in the understanding of the contribution which socioeconomic variables can make in explaining inter-annual variability in cholera, by illustrating the relative difference in explained variability (R^2) between the MLR results presented in figures 5a and b (both climate and socioeconomic variables) and the MLR results presented in figures 2a and b (climate variables only). The relative contribution which socioeconomic variables can make to the total proportion of explained inter-annual variability in the IR is not completely distinct, although tentatively the north of the country appears to include more states where the relative contribution is highest. With respect to the CFR it would appear that socioeconomic variables are able to make the highest contribution in the north east of the country with some exceptions such as Cross River and Abia. In both instances socioeconomic conditions are shown to have the potential in many states to explain a large proportion of variability.

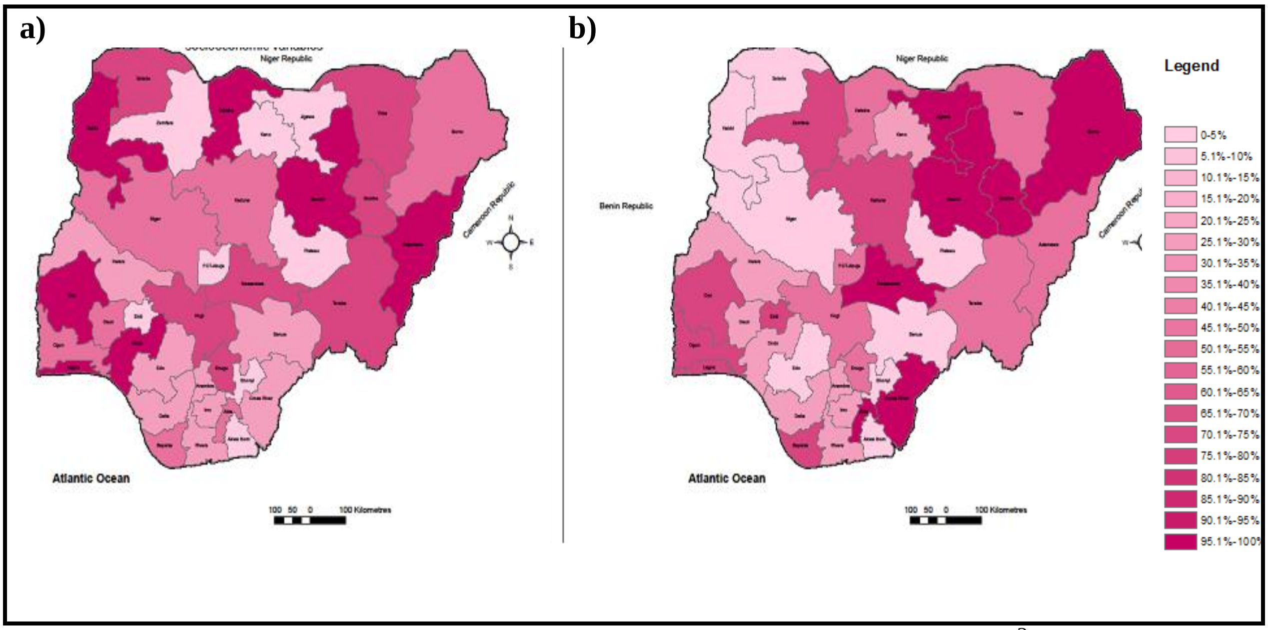

Figure 6: Plots illustrating the relative difference in explained variability (R^2) between the MLR results of both climate and socioeconomic variables for a) IR, and b) CFR
Source: Authors' analysis

Relationships between cholera and climate

The positive relationship observed between the IR and the CFR, temperature and precipitation has been mirrored by many studies. This study has found that inter-annual variability in climate is often able to explain higher proportions of variability in the IR and the CFR closer to the coast. The relationship between Vibrio *Cholerae* and the temperature of the aquatic environment is very well documented (Bouma and Pascual, 2001), with inter-annual Sea Surface Temperature (SST) variability such as that associated with Elnino-Southern Oscillation (ENSO) or the Indian Ocean Dipole (IOD) being found to have a relationship with cholera in various areas of the globe (Bouma and Pascual, 2001). It is hypothesized that the effect which land temperatures have on the temperature of brackish waters near the coast may be the cause of the stronger relationship in this area found by this study, this conclusion was drawn from a study conducted in Ghana (Constantin de Magny et al., 2007).

Similarly, precipitation is well documented to have a positive relationship with cholera globally (Hashizume et al., 2011). This link was previously explained to be as a result of flooding allowing a greater proportion of the population access to the bacterium (Hashizume et al., 2007). Flooding of brackish waters close to the coast where a higher concentration of the bacterium will be found is expected to be a far greater influence in causing cholera than flooding of freshwater environments which may have a far lower concentration of the bacterium, this may explain the reason for the stronger relationship close to the coast. Inter-annual variability in rainfall in Nigeria may be attributed to several sources, such as the link between the intertropical convergence zone and ENSO in low latitudes of the Atlantic Ocean (Constantin de Magny et al., 2007). A detailed investigation into the causes of inter-annual precipitation variability in Nigeria shows the inter tropical discontinuity to play a significant role in the north of the country while SST in the Gulf of Guinea may be a dominant cause of variability on this timescale in the south (Odenkule, 2010).

Although the previous findings are supported by existing literature, some findings appear to be new. Firstly, it is found that the CFR has a negative association with all three of the annual maximum temperature averages, suggesting that the relationship between fatal cholera cases and temperature is potentially more sensitive than the relationship between the IR and temperature. Secondly, a distinction has been made between the IR and the CFR as it has been found that in Nigeria, climate variability has a higher ability to explain whether individuals will die from cholera than whether they will catch cholera.

Cholera and socioeconomic conditions

The positive relationship observed between cholera, absolute poverty and population density is in accordance with previously reviewed literature (Shahid, 2009). Poverty is linked to environmental degradation and low levels of sanitation which can cause the disease to be prolific (Talavera and Perez, 2009). Higher population densities allow the disease to spread quickly possibly via fecal contamination (Ali et al., 2002b). The results show that adult literacy has a negative relationship with cholera indicating that as more adults become literate cases of and deaths from cholera decrease, this relationship is mirrored in studies conducted in Tanzania, Latin America and Bangladesh (Traerup et al., 2010). Those with a higher level of education are thought to make more sensible choices with regard to seeking professional treatment for the disease before fatality occurs in addition to being more aware of how to avoid contracting the disease (Ali et al., 2002a).

Finally water source was the most important predictor of the inter-annual variability in both deaths and cases (considering both climate and socioeconomic variables) and was negatively associated with the incidence and death rate, indicating that as more people have access to safer water source, less individuals contract and consequently die from the disease. If the bacterium is not removed from the water which is consumed by the population (i.e. non pipe borne water), then those who consume the water are at a higher risk of developing and potentially dying from the illness (Talavera and Perez, 2009).

In this study, socioeconomic variables tend to contribute to the total explained variability by both climate and socioeconomic factors by the largest amount in the north of the country and especially in the north east if the CFR is considered. Broadly speaking the north of the country has lower levels of access to treated water, lower levels of adult literacy and higher levels of poverty. Existing literature details that there are areas within countries where high cholera rates may be attributed to poor socioeconomic status (Ali et al., 2002b). It is thought that this area of lower socioeconomic status which exists to the north of the country is the reason why incidence and death rates are higher in this area and as a result why socioeconomic variables are able to explain a greater proportion of inter-annual variability in these areas.

Cholera, climate and socioeconomic conditions

This study not only quantified the individual relationship between climate, socioeconomic conditions and cholera but also combined these relationships within two MLR models in order to attempt to explain the maximum amount of inter-annual variability in cholera. Again it was found that the chosen variables are able to explain a greater proportion of variability in the CFR than the IR. As a national average, they explain 52.67% of the inter-annual variability in the IR and 60.29% of the inter-annual variability in the CFR. It is concluded therefore that despite their individual relationships, both climate and socioeconomic variables have a critical role to play in governing inter-annual variability in cholera and both must be included in an effective early warning system.

In one of the northeastern state (Taraba), the MLR model which was developed in this state using a combination of both climate and socioeconomic variables is statistically significant, explaining 80.3% of the inter-annual variability in the cholera incidence rate. Because the inter-annual variability in the IR within Taraba is very similar to the national average IR variability, this shows that the relationships explained by this study have the potential to predict the national inter-annual variability in the cholera incidence rate by using a MLR model developed in a state such as Taraba considerably well. This result gives hope for the development of early warning system in cholera with a sufficiently long lead time in Nigeria, which is the ultimate motivation for this study.

CONCLUSION

This study has explored the relationships which exist between climate, socioeconomic factors with both incidence and death rates of cholera in each individual of the 36 states of Nigeria and the FCT. It has been shown that increases in temperature and rainfall on an inter-annual scale appear to increase cases of cholera, the reasons for such relationships have been supported by existing literature, although increases in minimum temperatures and precipitation lead to an increase in deaths from cholera, a decrease in maximum temperatures leads to an increase in deaths from cholera which appears to be a new finding.

Higher levels of adult literacy and access to a treated water source lead to lower cases and deaths from cholera, while higher poverty and higher population densities lead to more cholera cases and deaths. Socioeconomic variables appear to explain the highest amount of inter-annual variability in cholera in the north of the country, where socioeconomic conditions are often poor. Socioeconomic variables are able to explain a higher proportion of inter-annual variability in both the IR and the CFR than climate variability alone despite studies conducted elsewhere expecting this not to be the case. However, the greatest proportion of inter annual variability is explained if a combination of both climate and socioeconomic variables are used in a MLR model.

This study has clearly established the role of climate and socioeconomic influences on cholera case in Nigeria. In order to reduce or eliminate the disease in the country, authorities must improve the provision of safe drinking water, healthcare delivery, poverty alleviation, and enlighten the populace on how to avoid contracting the disease. This study has observed that, despite the availability of WHO approved effective vaccines (*Shancol* and *Dukoral*), these vaccines have not been used in Nigeria. In this regard, the government should embark on widespread vaccination campaigns, most especially in population with high risk of contracting the disease, such as in emergency camps. In addition, and effective early warning system should be put in place to help in predicting epidemics.

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