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Potential Future Risk of Cholera Due to Climate Change in Northern Nigeria

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Abstract

Cholera is one of the infectious diseases that remains a major health burden in West-Africa and especially in Nigeria. Several studies have raised concern that climate change may exacerbate the risk of the disease in the future. Projecting the future risk of this disease is essential, especially for regions where the projected climate change impacts, and infectious disease risk, are both large. Projections were made by forcing an empirical model of cholera with monthly simulations of four meteorological variables from an ensemble of ten statistically downscaled global climate model projections for Representative Concentration Pathways 2.6, 6.0 and 8.5 scenarios. Result indicates statistically significant increases in cases during April-September for RCPs 6.0 and 8.5 in both near (2020-2035) and far (2060-2075) future. The months with the largest increases coincide with the months (May and June) in which maximum temperature increases are also large. Cases only showed potential increases in the wettest months of July and August in the far future projections for RCPs 6.5 (8.3 and 7.9%) and 8.0 (17 and 21%) respectively.

Key words: Climate change; Cholera; Projections; Nigeria

Introduction

Assessing the potential impact of climate change on infectious diseases that are established to be climate sensitive is crucial (Grasso et al., 2012), specifically for regions where changes to disease distribution and seasonality are deemed to pose greater health challenges (WHO, 2013), especially in developing countries with low coping capacity (Shuman, 2011). Northern Nigeria is one of the regions identified as are areas identified as hotspot of climate change (Diffenbaugh and Giorgi, 2012), and are highly likely to be most affected due to the vulnerability of the populations (Suk & Sumenza, 2011).

Determining the future risk of infectious disease involves a number of uncertainties, this is because many factors that influence are these diseases (both climatic and non-climatic) might change in the future. For example, the administration of an effective cholera vaccines for all the serogroups that are responsible for epidemic at appropriate time may greatly reduce the disease burden in the future. Also, improved sanitary condition, education, and poverty reduction may reduce the risk of contracting cholera in the future. Despite these uncertainties, this study is imperative because it indicate the potential impact of climate change on future diseases risk in the absence of interventions such as widespread vaccination campaigns, improved healthcare delivery. In turn, estimates of the potential future of infectious diseases burden will inform authorities as they develop mitigation and adaption strategies, particularly to protect the vulnerable populations expected to be disproportionately impacted (Mendelsohn et al., 2006).

In this study, an improved empirical statistical model for cholera that were developed and validated in (Leckebusch & Abdussalam, 2015) were applied to assess the potential impact of future climate change on cholera incidence in northern Nigeria. Four statistically downscaled variables from Atmosphere-ocean Global Climate Models (AOGCMs) projections that participated in Coupled Model Intercomparison Experiment Phase (CMIP5) (Tylor et al., 2015) were used as explanatory variables.

Despite the large burden of infectious disease in Africa, only very few studies have been carried out in terms of future estimation of these diseases (e.g., Abdussalam et al., 2014; Alexander et al., 2013). Most of these studies have reported future increases in cases due to climate change on diseases, specifically, Alexander et al. (2013) reported an increase in diarrheal diseases primarily due to temperature in Botswana. This paper is the first to assess the future impact of climate change on cholera in northern Nigeria.

Table 1: List of climate models and their modelling centres

SN	Model Name		Modelling Centre/Institution
1	BCC-CSM1.1	BCC	Beijing Climate Center, China Meteorological Administration
2	CESM1-CAM5	NSF-DOE-NCAR	National Center for Atmospheric Research
3	CSIROMk3.6.0	CSIRO-QCCCE	Commonwealth Scientific and Industrial Research Organization in collaboration with the Queensland Climate Change Centre of Excellence.
4	GISS-E2-R	NASA GISS	NASA Goddard Institute for Space Studies
5	HadGEM2-ES	MOHC	Met Office Hadley Centre
6	IPSL-CM5ALR	IPSL	Institute Pierre-Simon Laplace
7	MIROC5	MIROC	Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology
8	MIROC-ESM	MIROC	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies
9	MRI-CGCM3	MRI	Meteorological Research Institute
10	NorESM1-M	NCC	Norwegian Climate Centre

Materials and Methods

1. Cholera Disease Models

Empirical model for cholera was used for projecting the future potential cases of the disease in northern Nigeria. This statistical model was developed and validated in (Leckebusch & Abdussalam, 2015) using Generalized Additive Models (GAMs) approach which can better account for the seasonally-varying influence of additional climatic and non-climatic influences that may influence the disease (the model has been improved with updated disease data for the purpose of this study). GAM has been used for projection studies (e.g., Astrom et al., 2012). These models were developed based on monthly aggregate of clinically-diagnosed cases of cholera from three selected hospitals (Kano, Sokoto and Gusau), and monthly weather variables from nearby meteorological stations. Validation results suggests the ability of the models to predict independent observations not used in model fitting (Leckebusch & Abdussalam, 2015).

In this study, model specifically designed for climate change studies in which previous cases were not included during model fitting were applied. Predicted cases have a cross-validation correlation 0.69 ($p<0.05$) and a skill score of 0.61 with 1990-2015 observed cases for cholera, meaning the root-mean square error of the predicted cases yielded a 61% improvement over assuming the long term mean of cases is the value in each year (i.e., "persistence") for all models. This model was used to project potential cases risk for two 21st century time slices, 2020-2035 and 2060-2075, by forcing them with an ensemble of downscaled future climate simulations.

2. Climate Projections and Statistical Downscaling Technique

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

Model fields were obtained from the Earth System Grid - Program for Climate Model Diagnosis and Intercomparison (ESG-PCMDI) gateway at Lawrence Livermore National Laboratory, http://pcmdi3.llnl.gov/esgcet/home.htm. Model scenarios used in this study include the historical simulation and three future projections. The historical simulation was forced by observed natural and anthropogenic atmospheric composition changes spanning 1861-2005 in all of the models; it is used to provide a baseline against which to assess climate change in the three future projections. The future projections are determined by the values of their RCPs. This study uses three scenarios namely; RCP2.6, RCP6.0 and RCP8.5 scenarios for 2006-2100 (Moss et al., 2010). Compared to the Special Report on Emissions scenarios (SRES) that informed the climate projections for the previous CMIP experiment (CMIP3), The CO_2 concentration in RCP2.6 is below B1, in RCP6.0 is slightly above A1B, and in RCP8.5 exceeds A2. Therefore, a broad range of potential GHG trajectories for the 21st century is represented by the three chosen scenarios. Generally, multiple ensemble members are available for each CMIP5 scenario for the given model. This study uses only one ensemble member (the first) from each CMIP5 model and scenario. The variables used include near surface maximum and minimum temperature, precipitation, and relative humidity. A comparison of the annual cycle of the historical AOGCM simulations versus observations of the climatic variables used in this study were evaluated.

The climate projection outputs were statistically downscaled to each of the three cities used in developing the disease models (Kano, Sokoto and Gusau). A variety of statistical downscaling techniques of varying complexity are available (e.g., Gutiérrez et al., 2012; Wilby and Dawson, 2012). In this study, a relatively simple but robust perturbation downscaling techniques was employed through the following stages: Firstly the climate projection outputs were bilinearly interpolated to the coordinates of each of the three cities; next is computing the AOGCM climate change signal for each of the four variables for a specified future RCP period (e.g., 2020-2035) relative to the AOGCM historical period that overlaps with the observational record (1990-2005); and lastly adding the computed change signal (which includes changes in the mean and the variance) to the 1990-2005 observational record to compute the downscaled future climate in 2020-2035 or 2060-2075 for a given variable and city.

The perturbation method is expressed as follows:

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

Where $X_{f_{m,y}}$ is the downscaled future value of variable X for a given month, m, and year, y. Downscaled variables include maximum temperature, minimum temperature, rainfall, and relative humidity. $\bar{X}_{p,obs_m}$ is the mean present-day observed climate for a given month averaged across all years of the historical period (1990-2005), as calculated from the airport weather station in each city. $\bar{X}_{f,gcm_m}$ and $\bar{X}_{p,gcm_m}$ are the mean future (e.g., 2020-2035 or 2060-2075) and present-day (1990-2005) averages, respectively, for a given month in the AOGCM. $X_{p,obs_{m,y}}$ is the observed climate for a given year and month. $\bar{\sigma}_{f,gcm_m}$ and $\bar{\sigma}_{p,gcm_m}$ are the mean future and present-day standard deviations from the monthly mean over the period, respectively, for a given month in the AOGCM. Therefore, the above equation is in essence a Reynolds averaging approach: the monthly mean AOGCM change signal (bracketed term 2) is added to the present-day observed monthly mean (bracketed term 1), then the observed perturbation for each year and month is added back to the mean change signal (bracketed term 3). First, however, the perturbation term is multiplied by the fractional change in the standard deviation (bracketed term 4) prior to adding it back to the mean, in order to account for changes in the variability of a given variable in the future. This is done so on a fractional basis to account for the fact that variability in a AOGCM may be dampened or enhanced compared to the observed variability due to the coarse spatial resolution and physical assumptions of the AOGCM. Adjusting the observed perturbation on a fractional (rather than absolute) basis accounts for such differences. Likewise, the change in the mean of variable X, expressed in bracketed term 2, is modified slightly when downscaling rainfall to be expressed as a fractional change. This is done because AOGCMs often underestimate the magnitude of rainfall

In order to test the significance difference between the observed present-day climatic variables and cholera cases versus their respective future projections, student's t-tests statistical technique was employed. Changes are expressed as percentages in the text, the uncertainty is given as the 95% confidence interval bounding the projected mean change.

Results

1. Downscaled Climate Projections

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

From the results obtained, the models captured the seasonal cycle of all the variables, as measured by the ensemble mean values. For maximum temperature during the hottest months (February – April), the ensemble mean of the models is nearly perfect, and there is a 1.5-2-degree cold bias during April and May. The models exhibit a larger standard deviation and range than the observations because there are more data points used for the statistics: for the observations, there are 16 data points for each month (because there are 16 years of data for 1990-2005). For the models, there are 10 times as many data points, since there are 10 models. In summary, the models are able to capture the seasonal cycle and magnitude of the key meteorological variables that impact cholera, albeit with some small biases. This indicates the models are resolving key atmospheric processes, which in turn suggests that the models' climate change projections for 2020-2035 and 2060-2075 may have reasonable fidelity. Also, testing the diseases models with the ensemble simulations reveals the same annual cycle for the recent control period of cholera (1990-2005).

An aggregate annual cycle for the three targeted cities of the observed present day maximum temperature and rainfall in comparison with the RCP6.0 simulations for 2020-2035 and 2060-2075 is shown in Figure 1. In both the two-time slices used in this study, maximum temperature has shown a statistically significant increase almost across all months, with the months of March – July showing the highest warming. Maximum temperature increases of about 0.5-1^{o}C in the near future projections, while in the far future the increase ranges from 1-3^{o}C. Similar trends were observed with minimum temperature. In the case of rainfall, a statistically non-significant increase in the months June-July-August (JJA) in both time slices was

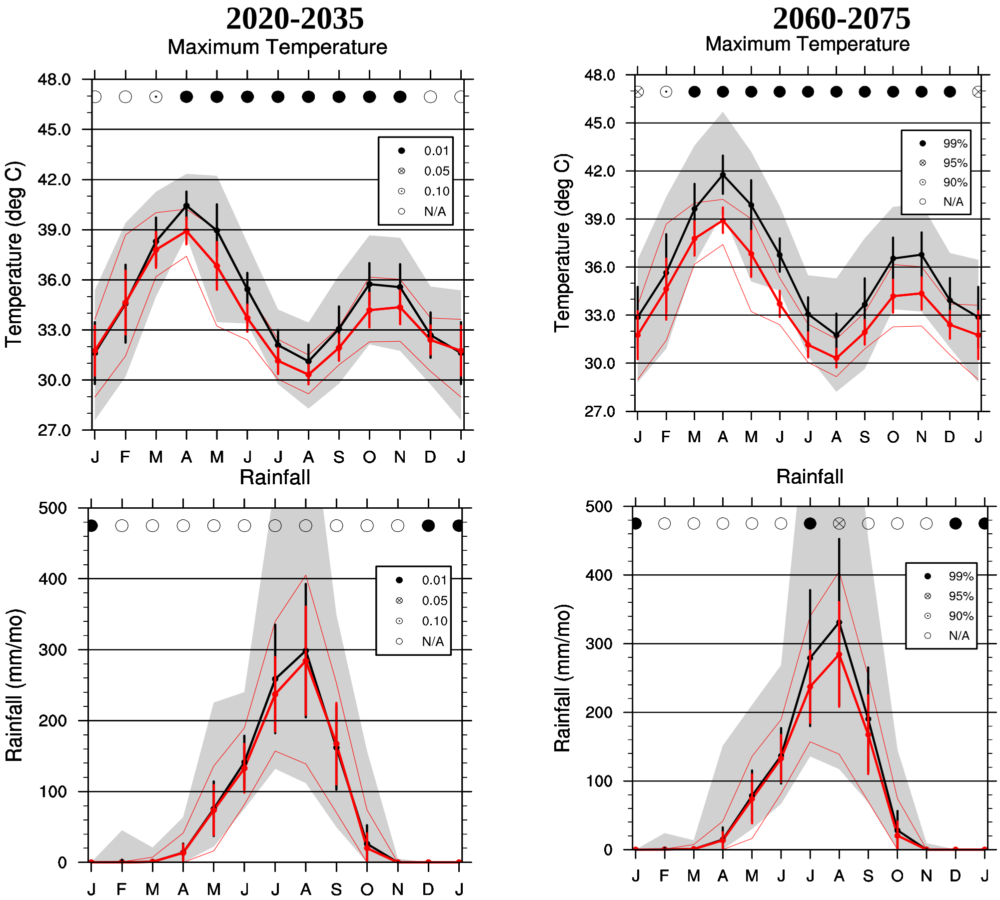

Figure 1: An aggregate annual cycle for the three targeted cities of the observed present day maximum temperature and rainfall in comparison with the RCP6.0 simulations for 2020-2035 and 2060-2075. The thick and thin red lines represent the mean and range of observed monthly values, respectively. The thick black line and gray shaded areas represent the mean and range of the AOGCM simulations, respectively. The vertical lines represent +/- 1 standard deviation from the means for the observations and AOGCM projections, respectively. The dots on top represent the significance level ($p<0.01$, $p<0.05$, $p<0.10$, or N/A for no significance) of the future changes versus the observations, as indicated in the legend.

observed, this is in agreement with the findings of (Vizy et al., 2013). The projections reveal only little but significant changes in humidity in both the near and far future most especially in the dry months (December – February).

2. Cholera Projections

Result from cholera projections indicate statistically significant increases in cases during most months (approximately April through September), most especially in the far future, for RCPs 6.0 and 8.5 (Figure 2). Changes are largest and have the strongest statistical significance ($p<0.05$) towards the end of the dry season and the beginning of the rainy season, with increases over the present-day case rate (25 cases per 100,000 of population in the month of June) to rates ranging from 27 to 29 and 30 to 35 in the near (2020-2025) and far future (2060-2075) respectively, depending on the RCP. The months with the largest increases coincide with the months (May and June) in which maximum temperature increases are also large. Cases only showed potential increases in the wettest months of July and August in the far future projections for RCPs 6.5 (8.3 and 7.9%) and 8.0 (17 and 21%) respectively. This finding corroborates that of a related study of diarrheal diseases in Botswana by Alexander et al. (2013) where diarrheal disease incidences was suggested to increase with hot conditions and decline likely in the wet season. There is little difference among projected cholera case rates among the three scenarios for 2020-2035, for example in May and June increases ranges from 13-16% and 10- 16% respectively, but larger differences among the scenarios occur for 2060-2075 after the RCP emissions scenarios diverge (Moss et al., 2010), with May increases of about 20%, 27%, and 40% for RCP 2.6, 6.0, and 8.5 respectively.

Discussion

The potential impact that climate change might cause in the dynamics of some infectious diseases begs for the need to assess these changes in the future, particularly for vulnerable regions that are projected to be affected most. This is in order to keep authorities in charge informed so as to prepare for the potential challenges ahead. Even though many promising developments may reduce the future risk for infectious diseases transmission despite enhanced risk due to climate change, there may also be increased challenges for preventing and controlling disease outbreaks (Ebi et al., 2013).

Cholera is a disease that remain a health burden in the region under investigation, and its sensitivity to climate is raising concern about their future dynamics. In this study the potential impact of future climate change on the risk of cholera cases was assessed by forcing validated empirical model of the disease developed specifically for the region. In order to assess uncertainties in the projections, multi model ensemble from ten monthly AOGCMs simulations from CMIP5 were used (e.g., Giorgi, 2005).

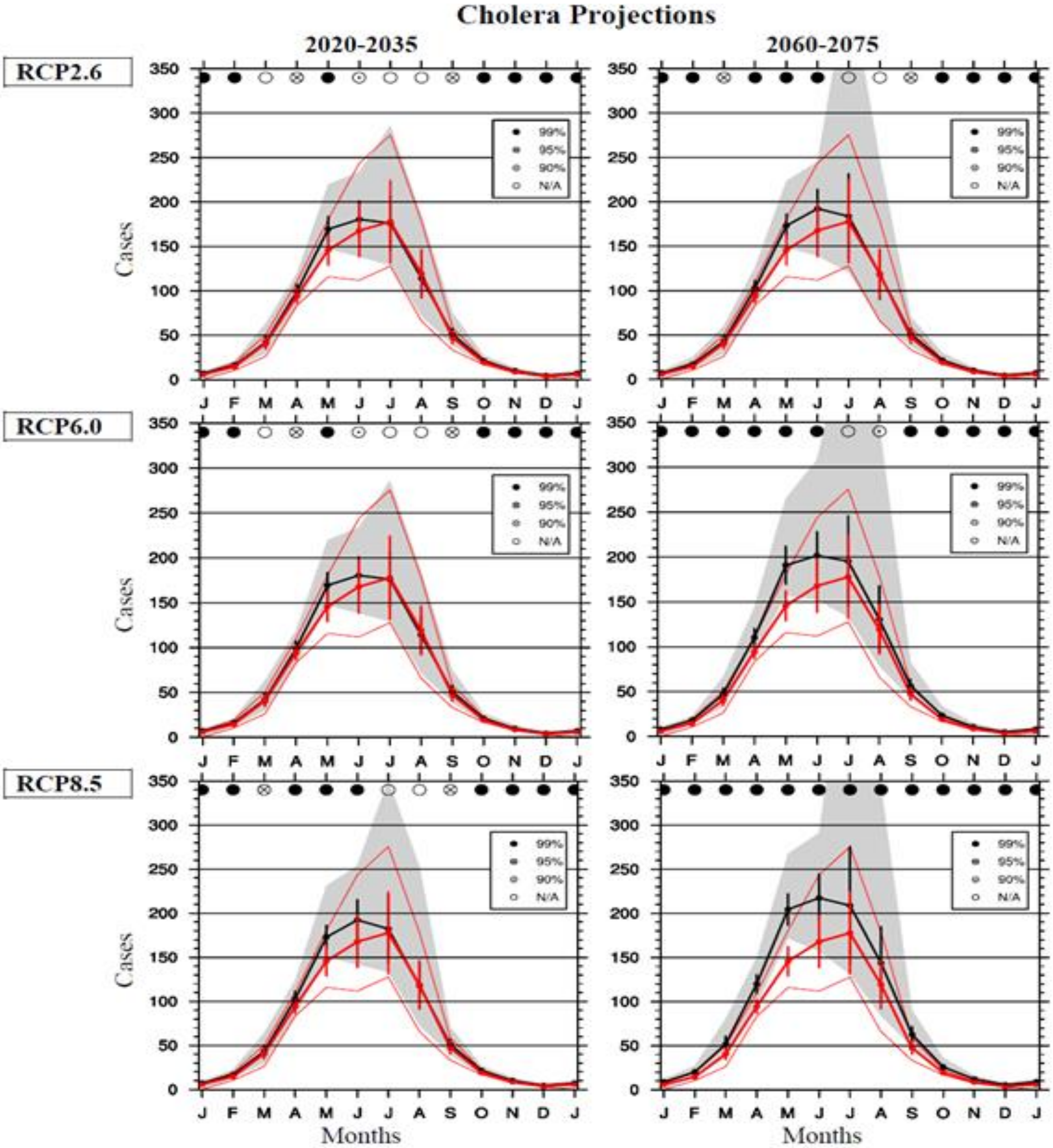

Figure 2: The annual cycle of present-day (1990-2005) cholera cases compared with projections for the ensemble of thirteen downscaled AOGCM in 2020-2035 (left) and 2060-2075 (right) for the three different future scenarios: RCP2.6 (top), RCP6.0 (middle), and RCP8.5 (bottom). The red and black lines are as described in Figure 1.

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

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

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

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

Conclusion

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

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

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