The Impact of Climate Change on Meningitis in Northwest Nigeria: An Assessment Using CMIP5 Climate Model Simulations

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ABSTRACT

Meningitis remains a major health burden throughout Sahelian Africa, especially in heavily populated northwest Nigeria with an annual incidence rate ranging from 18 to 200 per 100 000 people for 2000–11. Several studies have established that cases exhibit sensitivity to intra- and interannual climate variability, peaking during the hot and dry boreal spring months, raising concern that future climate change may increase the incidence of meningitis in the region. The impact of future climate change on meningitis risk in northwest Nigeria is assessed by forcing an empirical model of meningitis with monthly simulations of seven meteorological variables from an ensemble of 13 statistically downscaled global climate model projections from phase 5 of the Coupled Model Intercomparison Experiment (CMIP5) for representative concentration pathway (RCP) 2.6, 6.0, and 8.5 scenarios, with the numbers representing the globally averaged top-of-the-atmosphere radiative imbalance (in W m⁻²) in 2100. The results suggest future temperature increases due to climate change have the potential to significantly increase meningitis cases in both the early (2020–35) and late (2060–75) twenty-first century, and for the seasonal onset of meningitis to begin about a month earlier on average by late century, in October rather than November. Annual incidence may increase by 47% ± 6%, 64% ± 9%, and 99% ± 12% for the RCP 2.6, 6.0, and 8.5 scenarios, respectively, in 2000–75 with respect to 1990–2005. It is noteworthy that these results represent the climatological potential for increased cases due to climate change, as it is assumed that current prevention and treatment strategies will remain similar in the future.

1. Introduction

Projecting the potential impact of climate change on meteorologically sensitive infectious diseases is essential for regions where changes to disease may have adverse health impacts (Murray et al. 2012; WHO 2013). Many areas in the Sahel, including northwest Nigeria, are identified as “hot spots” of climate change (Diffenbaugh and Giorgi 2012) and are projected to be disproportionately affected due to the vulnerability of the populations (Suk and Semenza 2011). Records from the World Health Organization (WHO) archives indicate that over 35% of reported meningitis cases in Africa between 1996 and 2010 came from Nigeria, with 95% of these occurring in the northern part of the country.

Projecting the future risk of meningitis involves a number of uncertainties because many factors in addition to climate influence the disease and may change in the future, such as vaccination, cultural and behavioral practices, and prevalence of other related diseases. An example is the recent introduction of conjugate vaccine that provides long-term protection against serogroup A (Greenwood and Stuart 2012), which may greatly reduce the disease burden in the future. Despite such uncertainties, the present study is useful because it indicates the potential impact of climate change on future meningitis risk in the absence of interventions such as vaccination

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campaigns (or in the case that meningitis serogroups that are not vaccinated against become more common). In turn, estimates of the potential future meningitis burden inform authorities as they develop mitigation and adaptation strategies to protect the vulnerable populations (Mendelsohn et al. 2006).

In this study we assess the potential impact of future climate change on meningitis incidence in northwest Nigeria. Statistically downscaled variables from atmosphere-ocean global climate model (AOGCM) projections from phase 5 of the Coupled Model Intercomparison Experiment (CMIP5; Taylor et al. 2012) are used as explanatory variables in a meningitis model specifically developed for northwest Nigeria (Abdussalam et al. 2014).

2. Materials and methods

a. Study area

Northwest Nigeria is located in the African Sahel savannah and has an estimated population of over 41 million people. Statistics from the WHO archive indicate that the northwest area has the highest burden of infectious diseases in Nigeria; cases ranged from 18 to 200 per 100,000 annually within 2000–11. The region has two seasons, a short wet season from approximately June to September and a prolonged dry season for the remainder of the year. Annual rainfall ranges from 500 to 1500 mm, while average temperatures range from 25°C to 28°C with daily maxima of up to 47°C during March–May. The meningitis season peaks in February–April during the months that are collectively the warmest and driest (details in Abdussalam et al. 2014).

b. Meningitis models

Abdussalam et al. (2014) and Dukic and Hayden et al. (2012) developed models to explain and predict meningitis incidence in West Africa. The models employ a Poisson generalized additive modeling (GAM) approach that accounts for the seasonally varying influence of additional factors that may influence meningitis. The models were developed based on 1990–2011 monthly aggregate counts of clinically diagnosed cases of meningitis from three regional hospitals (Fig. 1) and seven monthly meteorological variables from nearby weather stations (average minimum and maximum temperatures, relative humidity, wind speed, sunshine hours, total rainfall, and number of dusty days). Threefold cross validation of predicted versus independent case data not
used in model fitting was performed for the 22-yr model development period (details in Abdussalam et al. 2014).

Here we use a model from Abdussalam et al. (2014) specifically designed for climate change studies, in which meningitis cases were adjusted to filter the bias of vaccination campaigns carried out during the model development period. Predicted cases have a cross-validation correlation of 0.75 ($p < 0.01$) with 1990–2011 observed cases, and a skill score of 52%. This model was used to project potential meningitis risk for two time slices, 2020–35 and 2060–75, by forcing it with an ensemble of downscaled future climate simulations. Projected outcomes are expressed as the rate of cases per 100,000 persons within the hospitals’ catchment population. The catchment population of each hospital was estimated by taking the ratio of its cases versus the total cases in the district for the period 2007–11, during which district-level data were available, and then multiplying the ratio by the entire district population, which gave us an estimated population of 660,684 for the three hospitals. We assume the hospitals’ catchment populations remain approximately constant over time, because other medical facilities have been built periodically to accommodate population growth. The catchment population of the three hospitals was aggregated for our analysis. It is noteworthy that the results, in terms of percentage change, are not sensitive to the aggregate estimate of catchment population; we estimate and express results in monthly case rates per 100,000 persons solely to ease interpretation.

c. Climate change experiments

Monthly output from 13 coupled AOGCMs are employed (model details are given in Table 1), obtained from the Earth System Grid–Program for Climate Model Diagnosis and Intercomparison (ESG-PCMDI). Model scenarios used include the historical simulation and three future projections. The historical simulations were forced by observed natural and anthropogenic atmospheric composition changes spanning 1861–2005. The future projections are distinguished by the values of their representative concentration pathways (RCPs; Moss et al.

<table>
<thead>
<tr>
<th>Model Expansion</th>
<th>Modeling center/institution</th>
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<tbody>
<tr>
<td>BCC_CSM1.1 Beijing Climate Center (BCC), Climate System Model, version 1.1</td>
<td>BCC/China Meteorological Administration</td>
</tr>
<tr>
<td>CESM1 (CAM5) Community Earth System Model, version 1 (Community Atmosphere Model, version 5)</td>
<td>National Science Foundation (NSF)–Department of Energy (DOE)–National Center for Atmospheric Research (NCAR)</td>
</tr>
<tr>
<td>CSIRO Mk3.6.0 Commonwealth Scientific and Industrial Research Organisation (CSIRO) Mark, version 3.6.0</td>
<td>CSIRO in collaboration with the Queensland Climate Change Centre of Excellence (QCCCE)</td>
</tr>
<tr>
<td>GFDL-ESM2G Geophysical Fluid Dynamics Laboratory (GFDL) Earth System Model with Generalized Ocean Layer Dynamics (GOLD) component</td>
<td>National Oceanic and Atmospheric Administration (NOAA) GFDL</td>
</tr>
<tr>
<td>GFDL-ESM2M GFDL Earth System Model with Modular Ocean Model 4 (MOM4) component (ESM2M)</td>
<td>NOAA GFDL</td>
</tr>
<tr>
<td>GISS-E2-R Goddard Institute for Space Studies (GISS) Model E, coupled with the Russell ocean model</td>
<td>National Aeronautics and Space Administration (NASA) GISS</td>
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<tr>
<td>HadGEM2-ES Hadley Centre Global Environment Model, version 2–Earth System</td>
<td>Met Office Hadley Centre</td>
</tr>
<tr>
<td>IPSL-CM5A-LR L’Institut Pierre-Simon Laplace (IPSL) Coupled Model, version 5, coupled with NEMO, low resolution</td>
<td>IPSL</td>
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<tr>
<td>MIROC5 Model for Interdisciplinary Research on Climate (MIROC), version 5</td>
<td>MIROC/Atmosphere and Ocean Research Institute (AORI; The University of Tokyo), National Institute for Environmental Studies (NIES), and Japan Agency for Marine-Earth Science and Technology (JAMSTEC)</td>
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<tr>
<td>MIROC-ESM MIROC, Earth System Model</td>
<td>MIROC/JAMSTEC, AORI, and NIES</td>
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<tr>
<td>MIROC-ESM-CHEM MIROC, Earth System Model, Chemistry Coupled</td>
<td>MIROC/JAMSTEC, AORI, and NIES</td>
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<tr>
<td>MRI-CGCM3 Meteorological Research Institute (MRI) Coupled Atmosphere–Ocean General Circulation Model, version 3</td>
<td>MRI</td>
</tr>
<tr>
<td>NorESM1-M Norwegian Earth System Model, version 1 (intermediate resolution)</td>
<td>Norwegian Climate Centre (NCC)</td>
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In this study the RCP2.6, RCP6.0, and RCP8.5 scenarios for 2006–2100 are used, with the numbers representing the globally averaged top-of-the-atmosphere radiative imbalance (in W m$^{-2}$) in 2100. The use of these three scenarios is intended to span the full range of potential greenhouse gas trajectories, from modest (RCP2.6) to aggressive (RCP8.5). Assuming there are sufficient models in the ensemble to get reliable estimates of a potential climate change signal and its uncertainty, only the first ensemble member from each CMIP5 model and scenario is used here. The variables used include near-surface maximum and minimum temperature, precipitation, relative humidity, wind speed, and cloud fraction (to estimate changes in sunshine hours), while the present-day dust was assumed to remain constant in the future (because an analogous AOGCM variable for dust does not exist). A comparison of the annual cycle of the historical AOGCM simulations versus observations for some climatic variables relevant to the present study is shown in Fig. 2. 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. This lends confidence that our statistically downscaled climate projections are based on models that, on average, reasonably simulate the climate of northwest Nigeria on this time scale.

The AOGCM outputs were statistically downscaled to each of the three cities (Kano, Sokoto, and Gusau) used in the meningitis model development. Statistical

![Graphs showing annual cycle of observed and simulated climate variables](image_url)
downscaling is necessary because AOGCM output is too coarse to be directly suitable for assessing local-to-regional scale climatic impacts (e.g., Wilby and Dawson 2013). We employ a gamma method similar to that of Ines and Hansen (2006), Michelangeli et al. (2009), and Hopson and Webster (2010), referred to as cumulative distribution function-transform (CDF-t). CDF-t is similar to quantile matching, but takes into account the change in the AOGCM CDF from historical to future periods. The approach involves three steps: 1) bilinearly interpolating the AOGCM output to the coordinates of each city, 2) computing the AOGCM climate change signal for a given variable for a specified future RCP period relative to the AOGCM historical period that overlaps with the observational record (1990–2005), and 3) applying this climate change signal to the probability density function of the 1990–2005 observational record to compute a new CDF of the downscaled future climate in 2020–35 or 2060–75 for a given model, variable, and city. A gamma function was used to estimate the observed present-day CDF for each variable for a given month across all years using maximum likelihood estimation. The future CDF is computed by adjusting the observed present-day gamma function rate parameter for the mean AOGCM climate change signal, and thus is an observationally constrained estimate of the future climate. Therefore, we do not directly utilize the AOGCM CDFs (present or future) as is done in Michelangeli et al. (2009), because the AOGCM gamma functions may not adequately represent regional-scale climate effects.

The mean change was expressed in fractional terms for rainfall, wind speed, and sunshine because 1) AOGCMs often show deficits in simulating the magnitude of rainfall and wind speed and 2) future changes in sunshine hours must be estimated by changes in the AOGCM cloud fraction fields because “sunshine hours” are not an output field in the AOGCMs. A CDF was then constructed using the new value for the rate and the present-day shape parameter. Inverting the CDF (i.e., the quantile function) yields the downscaled future value of variable $X$. Finally, all the monthly values of the downscaled variables for the three cities that correspond with the data used in training the meningitis models were averaged. Student’s $t$ tests were used to test for significance between the observed present-day climatic variables and meningitis cases versus their respective future projections. The tests account for the uncertainty due to the interannual variability within each period, and the uncertainty due to the climate model projections. For example, there are 13 climate models for the RCP6.0 scenario, and each is used to simulate meningitis for a 16-yr present-day and a 16-yr future period, representing a total of 208 members for each period. This test compares the mean and variance of each period to determine if the meningitis incidence is statistically different between the periods. Where meningitis changes are expressed as percentages in the text, the uncertainty is given as the 95% confidence interval bounding the projected mean change.

3. Results

a. Climate projections

Figure 3 shows the annual cycle of the observed present-day maximum temperature, rainfall, and relative humidity, in comparison with the RCP6.0 simulations for 2020–35 and 2060–75. Even in the near future (2020–35), maximum temperature increases of about 0.5°–1°C are statistically significant ($p < 0.01$) compared to 1990–2005 in 7 out of 12 months, including those months from February to April in which meningitis cases are greatest. In the far future (2060–75), statistically significant ($p < 0.01$) maximum temperature increases of 1°–3°C occur in 9 of 12 months, and increases are also significant ($p < 0.1$ or 0.05) in the other three months. Humidity does not change significantly in the near or far future except for a small but significant increase in December of about 1% ($p < 0.10$; 2020–35) to 2% ($p < 0.05$; 2060–75). Other variables (not shown) also exhibit statistically significant changes in the future, but they do not impact the model results as much as maximum temperature and relative humidity (Abdussalam et al. 2014). Rainfall, for example, exhibits statistically significant changes during December and January in both future periods but rainfall amounts are nearly zero during these months already, so the changes are almost imperceptible. Likewise, July–August rainfall is projected to increase in the future, a result consistent with Vizy et al. (2013), but meningitis cases are already very low during these rainy months.

b. Meningitis projections

Results indicate statistically significant increases in meningitis cases during most months of the meningitis season (approximately November–May) in the future, across both time periods and RCPs used in the projections (Fig. 4). Changes are largest and have the strongest statistical significance ($p < 0.01$) in the hot, dry peak months of the meningitis season, with increases during March from a present-day rate of 22 cases per 100 000 population to rates ranging from 29 (RCP2.6) to 30 (RCP8.5) for 2020–35 and 31 (RCP2.6) to 42 (RCP8.5) for 2060–75. The months with the largest increases coincide with the months in which maximum temperature increases are largest (Fig. 3). Significant changes in the timing of the onset and cessation of cases are projected in the 2060–75 results, suggesting that the meningitis season
Fig. 3. Annual cycle of the observed present-day (1990–2005) maximum temperature (°C), relative humidity (%), and rainfall (mm month$^{-1}$) averaged for the three cities, in comparison with the ensemble of downscaled RCP6.0 AOGCM projections in (left) 2020–35 and (right) 2060–75. The red and black lines and gray shading are as described in the Fig. 2 caption. The dots on top represent the significance level ($p < 0.01$, $p < 0.05$, $p < 0.10$) of the future changes vs the observations, as indicated in the legend (top left).
could lengthen. On a percentage basis, there is little difference in projected meningitis case rates among the three scenarios for 2020–35; for example, in March increases range from 32% ± 5% (RCP2.6) to 38% ± 6% (RCP8.5) but larger differences among the scenarios occur for 2060–75 after the RCP emissions scenarios diverge (Moss et al. 2010), with March increases of about 43% ± 6% (RCP2.6) to 91% ± 8% (RCP8.5).

Fig. 4. The annual cycle of meningitis cases for the present day (1990–2005) compared with projected cases using the ensemble of 13 downscaled AOGCMs in (left) 2020–35 and (right) 2060–75 for the three different future scenarios: (top) RCP2.6, (middle) RCP6.0, and (bottom) RCP8.5. The red and black lines and gray shading are as described in the Fig. 2 caption, but for meningitis cases. The dots and legend are described in the Fig. 3 caption.
Because there are no AOGCM projections of changes in the number of dusty days, and yet dust may be a potentially important driver of meningitis transmission (e.g., Agier et al. 2013; Martiny and Chiapello 2013), we performed a sensitivity experiment in which future dusty days for each month were increased or decreased by 15% for the RCP6.0 scenario (Fig. 5). The results clearly exhibit sensitivity to the number of dusty days (cf. Fig. 5 to middle panels of Fig. 4). For example, March cases in 2020–35 are projected to be 32 per 100 000 (25 per 100 000) for the +15% dust (−15% dust) case compared to projections of 29 cases per 100 000 for our assumption of no change in dust, with the +15% dust case results being significantly different from each other and from the no change case ($p < 0.01$). Changes of a similar magnitude occur for the 2060–75 period. How dust may change is uncertain, although humidity, rainfall, and wind are not projected to change significantly during the peak of the season, suggesting dustiness may change little, all else being equal (e.g., Shao et al. 2011). On the other hand, land use may change dramatically in the future; for example, widespread irrigated agriculture may become established in the region, which may reduce the number of dusty days (e.g., Cowie et al. 2013), or conversely overgrazing could lead to dustier conditions.

4. Discussion and conclusions

There is an increasing need to assess the potential impact of climate change on infectious diseases. Even though many promising developments may reduce the future risk for meningitis transmission despite enhanced risk due to climate change, there may also be increased challenges for preventing and controlling disease outbreaks (Ebi et al. 2013).

Our results suggest that meningitis cases in northwest Nigeria may increase in the future, primarily as a result of warmer temperatures. During the peak of the season
cases could potentially increase because of climate change by 32%–38% for 2020–35 and by 43%–91% for 2060–75. Given that projected climate changes in north-west Nigeria are similar for other regions of the Sahel (Chou et al. 2013), as are the climate-driven dynamics of meningitis transmission (e.g., Dukic et al. 2012), these results may be more broadly applicable throughout Sahelian Africa. It is noteworthy that the West African monsoon (WAM), which brings about precipitation in the Sahel, is not well simulated in climate models (Bock et al. 2011; Marsham et al. 2013). Also, model results are primarily a function of climate change and therefore represent the potential for increased cases if current prevention and treatment strategies, land use patterns, and lifestyles remain similar in the future. Clearly, some or all of these factors will change, and therefore these results may encourage governments and public health workers to enhance efforts to control meningitis incidence, for example by intensifying the administration and evaluation of the current conjugate vaccine that protects against serogroup A, and to focus on less common serogroups that could potentially cause epidemics.

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REFERENCES


World Health Organisation, cited 2013: Climate change and health. [Available online at http://www.who.int/mediacentre/factsheets/fs266/en/].