Dengue transmission risk in a changing climate: Bangladesh is likely to experience a longer dengue fever season in the future

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Abstract

Our changing climate is already affecting the transmission of dengue fever, the fastest growing vector-borne viral disease in the world. This issue presents a significant public health concern for some nations, such as Bangladesh, which already experience regular seasonal outbreaks of dengue fever under present day conditions. To provide guidance for proactive public health planning to potentially mitigate the severity of future outbreaks, we explored the impact of climate change on dengue infections by calculating the change in vectorial capacity (VC) of \textit{Aedes aegypti} mosquitoes at a seasonal level for all regions in Bangladesh under two scenarios for future atmospheric greenhouse gas concentrations. For each of the four climate models used, and for both scenarios, our analysis revealed that the annual VC remains at a level that would enable potential dengue epidemic transmission in all regions in Bangladesh. We found a slight decline in VC in half of the regions examined during the last two decades of the 21st century for the lower-concentration scenario, with a pronounced decline in VC in all geographic regions beginning in 2060 for the higher-concentration scenario. The likely reason is that in many regions, warming will lead to sub-optimal mosquito breeding temperatures. However, seasonal differences in VC will dissipate as the climate warms, to the point that there is almost no observable seasonality for the higher-concentration scenario during the last two decades of this century. This finding suggests the dengue transmission season could eventually extend to all-year-round transmission, with outbreaks occurring at any time. Consequently, disease surveillance and control activities would need to be geographically and temporally adapted to mitigate dengue epidemic risk in response to climate change.

1. Introduction

Dengue virus infections are the cause of most common and fastest growing vector-borne human disease in the world, accounting for an estimated 105 million infections globally per year, of which 51 million manifest the disease at some level of clinical or sub-clinical severity [1,2]. While most dengue virus infections are asymptomatic, some can result in death [3].

Bangladesh, an Asian country with more than 165 million people living in an area of about 130,000 km\textsuperscript{2}, is one of the countries most affected by dengue epidemics [4]. In 2000, the first reported outbreak of dengue occurred with at least 5551 cases and 93 deaths recorded across three major cities [5]. Since then, a substantial number of dengue cases and deaths have been reported each year [6] despite high levels of underreporting [7]. Nationwide serosurveys have estimated that 40 million people had been previously infected by the end of 2015 with 2.4 million new infections occurring each year [8]. Dengue incidence is much higher in the three major conurbations of Dhaka, Chittagong, and Khulna, where ~50% of the urban population live, in comparison to the more dispersed rural villages in the rest of the country [8].
Dengue virus is transmitted to humans by infected female mosquitoes of the *Aedes* species, predominantly *Aedes aegypti*, and to a lesser extent *Aedes albopictus* [9, 10]. Survival and proliferation of *Aedes* mosquitoes are profoundly influenced by changes in mean temperature and temperature variations. They are daytime feeders and transmit dengue optimally at around 29.3 °C when the diurnal temperature range (DTR) is close to 0 °C. Rainfall and human population density are also important as *Aedes* mosquitoes prefer to lay eggs in man-made containers more commonly found in urban areas [11]. This means dengue is a highly climate-sensitive disease and, as a result, dengue cases in Bangladesh show significant year-to-year variability and seasonality. There are four distinct seasons in Bangladesh—the dry winter season (December–February); the pre-monsoon hot summer season (March–May); the rainy monsoon season (June–September); and the post-monsoon autumn season (October–November)—with dengue cases occurring mostly in the monsoon and post-monsoon seasons.

The annual mean temperature of Bangladesh has increased at an average rate of 0.02 °C yr⁻¹ between 1971 and 2010, which is considerably higher than the global average increase [12]. Projected future increases in mean temperature for Bangladesh relative to the pre-industrial period (1861–1880) are as much as 3.2 °C–5.8 °C by the end of the 21st century for a high greenhouse gas emission scenario [13]. In this context, understanding the relationship between dengue incidence and climate variables is crucial for determining the future magnitude, timing, and spatial distribution of dengue burden in Bangladesh. Further, country-specific evidence is needed to inform appropriate public health responses and development of an official strategy for adaptation and risk mitigation.

One approach to understanding the impact of climate change on dengue transmission is to calculate the vectorial capacity (VC), which describes the epidemic potential of a vector-borne disease and provides a threshold for an epidemic to occur [14–16]. Recent formulations of VC include temperature dependent parameters that characterise host, virus, vector, and interaction factors related to transmission [17]. Temperature observations obtained from weather stations can be used to identify historical trends in VC and, thus, to explain past dengue distribution [17]. However, quantifying likely future trends in VC requires information about the future climate. One source of information about future climate conditions are global climate model (GCM) simulations. Although GCM simulations are imperfect representations of the climate (especially at regional scales) and do not project all possible trajectories for future climate change, they can provide information and appropriate scenarios for exploring climate change impacts on disease [18, 19].

The Coupled Model Intercomparison Project Phase 5 (CMIP5) [20] provides simulations of many different GCMs for the four Representative Concentration Pathway (RCP) scenarios specified by the Intergovernmental Panel on Climate Change [21]. The RCPs provide information on possible future trajectories for the main forcing agents of climate change, e.g. atmospheric concentrations of greenhouse gases and other air pollutants, and changes in land use [21]. Varying underlying assumptions and simulation approaches means that the different CMIP5 GCMs simulate varying future climate projections for the same RCP. Assessments of future climate change, or its impacts, usually address this uncertainty by using multiple GCM outputs for analysis [22]. Further, the outputs for GCMs can be biased relative to climate observations. For example, GCM temperature data can be warmer or colder than observational data for the same historical period. When analysing climate impacts for a specific region, the output from GCMs needs to be bias-adjusted. This is particularly important when assessing variables that respond in a non-linear manner to changes in climate variables [23], as is the case with VC.

Dengue transmission risk is spatially heterogenous which needs careful consideration when developing plans for proactive dengue disease management [24]. Earlier studies projecting the impact of climate change on dengue focused on global or broad regional scales and lack the spatial detail to be useful for informing local adaptation policies and risk mitigation strategies [17, 18]. Bangladesh, where dengue is endemic, needs information on when and where to increase surveillance and implement control measures for dengue now and in the future in the context of a changing climate. We performed a Bangladesh-specific study using bias-adjusted data from multiple GCMs to provide a range of climate scenarios for the 21st century. Using these scenarios, we investigated the projected changes in VC at the national and divisional level.

2. Methods

2.1. Collection of climate data

2.1.1. Observed temperature data for Bangladesh

The Bangladesh Meteorological Department measures weather parameters at 35 stations that are well-distributed across the country (figure 1). We received daily temperature observations (mean, minimum and maximum) at these weather stations for the period 1975–2016 (the latest year of data available) [25]. We checked the temperature values in the downloaded dataset by comparing them to the data reported in published literature and searching for extreme values (figure S1 in the supplementary material (available online at stacks.iop.org/ERL/16/114003/mmedia)).
2.1.2. Climate data from GCMs
Bias-adjusted daily temperature data derived by the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) from five CMIP5 GCMs (HadGEM2-ES, GFDL-ESM2, IPSL-CM5A-LR, MIROC-ESM-CHEM and NorESM1-M) have been used previously for projecting dengue epidemic potential in Europe under a changing climate [17]. ISIMIP applied a statistical bias-adjustment approach to correcting GCM data towards an observed reference climate dataset for the 1960–1999 period (the WATCH Forcing Data) [26]. More recently, the ISIMIP project applied the same bias-adjustment method to a different set of GCMs (HadGEM2-ES, GFDL-ESM2, IPSL-CM5A-LR, MIROC5) to compile a new reference dataset EWEMBI as part of the ISIMIP2b simulation round [27, 28]. In this simulation round, NorESM1-M was disregarded because of a lack of wind data and, pertinently to the climate of Bangladesh, MIROC-ESM-CHEM was replaced by MIROC5 due to a better representation of the monsoon by the latter [28]. For each of the four GCMs, daily gridded (0.5° × 0.5°, approximately 50 km² resolution) temperature data were available for a single historical dataset for the period 1950–2005 and for four different datasets corresponding to four RCP scenarios for the period 2006–2099 [29].

Of the four RCP scenarios, we analysed RCP 8.5, which corresponds to greenhouse gas emissions that continue to increase significantly until near the end of the 21st century, and RCP 4.5, which corresponds to a greenhouse gas emissions pathway that peaks in 2040 and then declines to 1960s emission levels by 2090. RCP 8.5 was selected because it broadly reflects...
a scenario that best matches recent emissions and a future in which little additional action on reducing greenhouse gas emissions is taken. RCP 4.5 was selected as a contrast because it assumes that emissions reduction policies are introduced that attempt to stabilise the climate. RCP 2.6 assumes much more ambitious emissions reduction policies that lead to global carbon dioxide emissions peaking and declining substantially before 2030. This scenario was excluded on the grounds that it is unlikely that cuts in emissions of the scale consistent with the scenario can be achieved by 2030, given the continuing overall upward trend in emissions [30, 31]. RCP 6.0, which corresponds to a greenhouse gas emission pathway that lies between RCP 4.5 and RCP 8.5, was not analysed as it would not have contributed further to the sampling of uncertainty in emissions.

To compare temperature data derived by ISIMIP2b with observed temperature data in Bangladesh, daily temperature data for all 35 weather station locations in Bangladesh (shown in figure 1) were extracted from gridded ISIMIP2b data using Climate Data Operators (version 1.9.8) available for Linux platform [32]. As GCMs are only robust over long periods and are not designed to reproduce individual weather events we did not perform a day-by-day comparison of the ISIMIP2b data and observations. We compared climatological mean annual cycles of monthly averaged mean, maximum, and minimum temperature for 1986–2005 for the observed and ISIMIP2b datasets at all 35 weather stations through visual inspection. We chose 1986–2005 as a comparison period because it is well-observed and the GCM simulations are forced with data consistent with observed (rather than projected) atmospheric greenhouse gas concentrations for this period. Good alignment of annual temperature cycles was observed for all weather stations except Dinajpur, where a warm bias was observed in daily maximum temperature (figures S2, S3, and S4; details in supplementary material).

2.2. Calculation of VC
To calculate VC, we applied one of the standard formulations that has been used in several studies to link changes in temperature to the potential for dengue transmission, including the Lancet Countdown on health and climate change [17, 33, 34]. VC is given by:

\[
VC = \frac{ma^2b_h b_m e^{-\mu_m t}}{\mu_m}.
\] (1)

Equation (1) has six vector-related parameters that depend on temperature: the average vector biting rate \(a\); the probability of vector-to-human transmission per bite \(b_h\); the probability of human-to-vector infection per bite \(b_m\); the duration of the extrinsic incubation period \(\tau\); the vector mortality rate \(\mu_m\); and the female vector-to-human population ratio \(m\). The temperature relationship of each of the vector parameters was derived from previously published literature for the primary vector A. aegypti [35] and are included in the supplementary material (table S1). Although the parameter representing the female vector-to-human population ratio is temperature dependent, its maximum value is assumed to be 1.5 [17] and it is not dependent on either the actual human population size or the level of immunity in the population. Assuming the infectious period for dengue is five days, then when VC reaches a threshold value of 0.2 d\(^{-1}\), one infectious person will infect at least one other person in a dengue naïve population [35, 36].

2.3. Calculation of outputs and VC estimation
VC varies from hour-to-hour throughout the day as temperature and mosquito activity (with A. aegypti being a daytime feeder) vary. To account for the impact of hour-to-hour temperature fluctuations within each day, a sinusoidal hourly temperature variation between the daily maximum and minimum temperature within a period of 24 h was assumed [35]. VC was calculated for the hourly temperature points and then averaged to yield a daily mean estimate. Daily VC for eight divisions, the first level administrative unit in Bangladesh, were calculated by averaging the daily VC at the location of the weather stations located within the divisional boundaries to facilitate regional analysis. From the daily VC we then calculated monthly, seasonal, and annual VC for each of the two RCPs and four GCMs specified above at the divisional level and the overall national level by averaging the corresponding daily estimates. We validated the VC results from the ISIMIP2b data by comparing them with the observationally derived VC data over the 1986–2005 period. It was also convenient to use 1986–2005 as a baseline period against which to compare future VC values. During this period, differences in the RCPs do not contribute to differences between the GCM simulations and the characteristics of dengue in Bangladesh are relatively well-known.

Our results and figures were produced using R version 4.0.2 [37] with the packages ‘ncdf4’ (extraction of temperature data from climate model netCDF files) [38] and ‘tidyverse’ (data cleaning, summarisation and plotting) [39].

3. Results

3.1. Annual average VC
The national average annual VC of A. aegypti mosquitoes in Bangladesh over 1975–2016 ranged between 0.7 and 1.1 d\(^{-1}\) when calculated using the observed data from weather stations. This is well above the threshold value for epidemic dengue transmission (0.2 d\(^{-1}\)) and reflects the ongoing dengue outbreaks that have occurred since 2000. The national average
Figure 2. Average annual vectorial capacity of *A. aegypti* mosquito in Bangladesh over 1951–2099 for each division of Bangladesh and each ISIMIP2b GCM under RCP4.5 and RCP8.5. The dashed black line represents average annual vectorial capacity over 1986–2005 calculated with observed data. The solid black line represents results averaged over the four GCMs.

Annual VC declined slowly but significantly at an average rate of 0.002 yr$^{-1}$ over the period 1975–2016 ($p < 0.001$) (figure S5 in the supplementary material). Some regional differences over the same period were observed with lowest average annual VC in Sylhet (0.8, range: 0.8–0.9) and highest average annual VC in Barisal (1, range: 0.9–1.1).

Regional annual VC calculated with the four ISIMIP2b GCMs for 1986–2005 period fluctuated around the 20 year (1986–2005) average of regional annual VC calculated with observed data (figure 2). This indicates that the annual VC values calculated with the ISIMIP2b data were comparable to the annual VC calculated with observed temperature data, giving us some confidence in future projections of VC derived from the ISIMIP2b data.

We now consider future changes in average annual VC projected by the ISIMIP2b data. For all four GCMs, the average annual VC in 2030–2049 period for the lower-concentration scenario, RCP 4.5, was found to increase slightly in Chittagong and Sylhet and to remain unchanged in Dhaka and Khulna, relative to the 1986–2005 average annual VC (figures 2 and 3). For the same RCP scenario, a slight decrease in the average annual VC was noted in Dhaka, Khulna, and Rajshahi divisions over the last two decades of the 21st century, relative to 1986–2005, particularly for the HadGEM2-ES and IPSL-CM5ALR models. For RCP 8.5, average annual VC over the 2030–2049
Figure 3. The spatial distribution of average vectorial capacity in each division of Bangladesh for two 20 year periods for the four ISIMIP2b GCMs under RCP4.5 and RCP8.5. The change of vectorial capacity for each model is relative to its own vectorial capacity for 1986–2005.

Irrespective of RCP, the annual VC calculated for all four ISIMIP2b GCMs for all years in the 1950–2099 period remained above 0.2 in all eight divisions (figure 2). This indicates a level suitable for potential dengue epidemic transmission at least some time during all these years.

3.2. Seasonality of VC

Strong seasonality of VC was found with the observed data, with VC peaking during the rainy monsoon season and reaching a minimum during the dry winter season. Similar seasonality patterns of VC for all four ISIMIP2b models were found for the historical data (1986–2005) as well as for the two RCP scenarios for the 2030–2049 period in all eight divisions (figure 4). The seasonal cycle in VC for all four ISIMIP2b models became less pronounced during 2080–2099 for RCP 4.5, with increased VC during the winter/dry months and decreased VC during the monsoon months. During the last two decades of the 21st century, the four ISIMIP2b models differ in their results for RCP 8.5. There is relatively little seasonality in VC for the GFDL-ESM2M and MIROC5 models, though it is still generally highest during the monsoon. However, the seasonal cycle is inverted for the HadGEM2-ES and IPSL-CM5A-LR models, with lower VC during the monsoon compared with the winter/dry months (figure 4).

Although VC is a function of both mean temperature and DTR (figure 5), these seasonal differences in VC are driven by seasonal changes in mean temperature. The climate change scenarios for both RCPs and all four GCMs show little change in DTR. However, the RCP 8.5 scenario of all four GCMs is consistent with increasing mean temperature during
both monsoon (i.e. away from the optimum temperature) and winter (i.e. towards the optimum temperature). These changes are more prominent towards the end of the century and with the HadGEM2-ES and IPSL-CM5A-LR models. The RCP 4.5 results are due to this mechanism as well, only less pronounced due to less warming. Irrespective of RCP, the monthly average VC remains well above the threshold value of 0.2 d\(^{-1}\) throughout the year for all four ISIMIP GCMs for the entire 21st century, indicating potential for epidemic dengue transmission at all times of the year.

4. Discussion

We used bias-adjusted GCM data for two RCPs to estimate the VC for *A. aegypti* mosquitoes in Bangladesh to explore the potential of dengue transmission at a national and sub-national level to the end of the 21st century. Our analysis showed that annual VC for all divisions in Bangladesh is projected to be substantially above the threshold for epidemic dengue transmission throughout this century irrespective of the RCP or GCM. During the second half of the century, the annual VC is projected to decline compared to the 1986–2005 level, particularly for the RCP 8.5 scenario, due to a rise in mean temperature beyond the optimal level for the vector (see figure 5). However, the fall in annual VC masks substantial changes in monthly VC, with the VC for the winter/dry season increasing to a level close to a reduced monsoon peak. This suggests that in the future, the dengue fever season could become longer, with outbreaks occurring at any time of the year. Also, the fall in VC may not mean smaller dengue outbreaks, as the changes in population and likely continued migration to urban settings in Bangladesh could offset the reductions in VC.

Projections of VC may provide insight as to where and when there is likely to be a risk of transmission given the existence of other relevant factors. The decline in VC for RCP 8.5 for all four GCM simulations during second half of the 21st century in Bangladesh is consistent with continued increase in global greenhouse gas emissions resulting in an increase in temperature to sub-optimal conditions for the mosquito vector. This long-term projection of decreased dengue risk is in contrast with earlier projections for Dhaka, Bangladesh, where a 40-fold rise in dengue case numbers was predicted by the end of the 21st century compared to 2010 level with an assumed increase in temperature of 3.3 °C \[40\]. The contrasting directions of these two projections might be explained by the fact that in the earlier study, a positive linear relationship of notified dengue cases and temperature was assumed, whereas the relationship of temperature and vector parameters of VC is non-linear with high temperatures being sub-optimal for *A. aegypti* mosquito behaviour and survival (figure 5) \[35\]. The regional differences in

![Figure 4. Monthly average vectorial capacity of A. aegypti mosquitoes for three 20 year periods in each division of Bangladesh for each ISIMIP2b GCM under RCP4.5 and RCP8.5. The dashed line represents monthly average vectorial capacity calculated with observed data, 1986–2005.](image-url)
Figure 5. Vectorial capacity as a function of temperature and diurnal temperature range. Seasonal temperature and diurnal temperature data for three 20 year periods for RCP8.5 from the four ISIMIP2b GCMs are superimposed.

annual VC change to the mid-21st century highlight the need for improved disease surveillance, control, and health system adaptation activities in eastern and north-eastern Bangladesh over the coming decades. The importance of these improvements and the need for focused interventions has become even more apparent with the recent surge in dengue cases within Bangladesh [41].

VC shows strong seasonality in both temperate and tropical regions [17]. For the recent past, current, and projected near future climate of Bangladesh, strong seasonality of VC is similarly observed in this study. Dengue epidemic potential projected for the European cities [17] showed that VC is only sufficiently high for dengue transmission to occur for a few months in a year. This is explained by the strong seasonal cycle in temperature in European cities. However, as in tropical cities (e.g. Singapore, Colombo, and Miami) [17], VC in Bangladesh never drops below the transmission threshold (0.2 d\(^{-1}\)) in our results for the 21st century, indicating that the risk of dengue outbreaks will persist. Further, our results show that the transmission period will be extended year-round, irrespective of the RCP scenario, consistent with the results of other studies for this region [18]. In contrast, a global study has estimated that dengue risk could increase or decrease by the end of the century depending on the altitude and population density of a specific region and the climate scenario used [18]. Despite the year-round potential for dengue transmission in Bangladesh, almost no dengue cases were recorded in the past two decades during the winter/dry season due to a lack of rainfall required for replenishment of common mosquito breeding sites [7, 42]. However, during the latter part of the 21st century, projected seasonality is quite different from what we experience now, particularly for the RCP 8.5 scenario. Season to season variability is expected to decline due to an increase in temperature above the optimal (29.3 °C) in the monsoon period and towards the optimal during winter, though the projected change does not lead to a decline in VC below the 0.2 d\(^{-1}\) threshold value.

The VC calculation provides a measure of the risk of an outbreak and does not depend on the size of the population at risk of dengue infection. However, the
larger the population the larger the potential size of any outbreak. Bangladesh’s population size is projected to reach its peak by 2053 and then decline to the current level by 2090 [4]. This means the potential reductions in VC we found by the end of the century (for the high emissions scenarios) would correspond to a reduction in the size of dengue outbreaks. However, climate change induced displacement of population [43], water storage due to the current lack of a continuous water supply in parts of Bangladesh, and the abundance of breeding sites in urban areas [42] may offset a decline in VC and lead to an increase in dengue transmission.

Since GCMs are not perfect representations of the climate system, it is important to consider the robustness of our results with respect to the variations in climate projections produced by GCMs. Although we have used bias adjusted GCM data, we recognise that bias adjustment may not resolve issues with the simulation of climate processes that affect simulated future climate changes. We note previous work has highlighted deficiencies in the IPSL-CM5A-LR and MIROC5 models [36]. However, even if these models were disregarded, our conclusions would be unchanged as the GFDL-ESM2M and HadGEM2-ES models also support these conclusions. We also note that the set of GCMs that we have used spans the range of temperature increase simulated for the region by the full range of CMIP5 GCMs [37]. This means that we have sampled the uncertainty in future VC changes related to uncertainty in future warming simulated by CMIP5.

It is also worth considering the robustness of our results to variability in the parameter values used in our calculation of VC. The point estimates of vector parameters used in this study were obtained from fitted experimental data on A. aegypti in different regions of the world, incorporating uncertainties around these and specific empirical estimates for the region would better inform the uncertainty in our VC estimates. However, for the range of temperature used in this analysis, the optimum VC temperature is unlikely to be very different for different parameter values [35], giving us confidence that our conclusions are robust to variations in the underlying VC parameter values.

Finally, we did not consider other changes in climatic variables such as rainfall and humidity, which could be important drivers of dengue risk [40], especially at a seasonal or regional level. For example, currently, the winter is dry in Bangladesh and hence, there are fewer mosquito breeding sites and outbreaks of dengue do not occur despite VC being above 0.2 [44]. Higher rainfall is projected for this season by regional climate models which means this risk [13] could be realised or result in further increases in dengue outbreak potential in this season, relative to our results for the late 21st century. Longer term dengue transmission risk is likely to be influenced by non-climatic factors like importation and co-circulation of different dengue virus serotypes and cross-immunity [40, 45], the development of more sophisticated epidemiological models of dengue transmission in Bangladesh are required to incorporate these factors.

As long as the dengue virus, mosquito vectors, susceptible population and suitable environmental conditions prevail, there is no reason to curtail ongoing prevention strategies or delay adoption of newer and more effective measures for disease control. Possible seasonal and geographic extension of dengue risk throughout the latter half of this century suggests that the spatiotemporal coverage of dengue surveillance and vector control activities will need to be broadened to mitigate future epidemics of dengue in Bangladesh.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: https://zenodo.org/badge/latestdoi/365786828.

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Conflict of interest

None declared.

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