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Projecting the impact of climate change on dengue transmission in Dhaka, Bangladesh

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Abstract

Weather variables, mainly temperature and humidity influence vectors, viruses, human biology, ecology and consequently the intensity and distribution of the vector-borne diseases. There is evidence that warmer temperature due to climate change will influence the dengue transmission. However, long term scenario-based projections are yet to be developed. Here, we assessed the impact of weather variability on dengue transmission in a megacity of Dhaka, Bangladesh and projected the future dengue risk attributable to climate change. Our results show that weather variables particularly temperature and humidity were positively associated with dengue transmission. The effects of weather variables were observed at a lag of four months. We projected that assuming a temperature increase of 3.3^{o}C without any adaptation measure and changes in socio-economic condition, there will be a projected increase of 16,030 dengue cases in Dhaka by the end of this century. This information might be helpful for the public health authorities to prepare for the likely increase of dengue due to climate change. The modelling framework used in this study may be applicable to dengue projection in other cities.

Keywords

Dengue, climate change, projections, temperature, Dhaka, Bangladesh

1. Introduction

According to the Intergovernmental Panel on Climate Change (IPCC), the global temperature increased significantly over the 20th century (IPCC 2007). Recent trends in anthropogenic emissions and their modelled impacts of global climate strongly suggest that both emissions and warming trends will continue to affect the atmospheric process in the 21st century. It has been predicted that the global mean temperature will increase by 1.1-6.4 ^{o}C by the end of this century (IPCC 2007). Annual average temperature for the South Asia region has been projected to rise by 3.3^{o}C (range, 2 - 4.4 ^{o}C) in 2100, with summer temperature increases of 2.7 ^{o}C (IPCC 2007). A growing body of literature suggests that warmer temperatures will enhance the transmission rate for mosquito-borne disease and will widen its geographical distributions (Hales et al., 2002; Jetten and Focks 1997; Kan et al., 2012; McMichael et al., 2006).

Dengue is one of the most important mosquito-borne disease of humans, and has emerged as a global public health concern throughout the tropical and subtropical regions of the world (Gubler 1998). Dengue transmission in these areas typically follows a seasonal pattern which reflects the influence of weather on the transmission cycle (Johansson et al., 2009). Dengue is weather sensitive due to its mosquito vector, which requires standing water to breed and warm ambient temperature for larval development and virus replication (Banu et al., 2011; Hopp and Foley 2001; Patz et al., 1998). The incidence of dengue has increased significantly in last 35 years and various factors including urbanization, globalization and climate change are thought to be the major contributors (Gubler 2011; Hopp and Foley 2001).

Several recent studies have demonstrated an association between weather variability and dengue (Chen and Hsieh 2012; Hii et al., 2009; Hu et al., 2012; Wu et al., 2007). Temperature, rainfall and humidity were found to be associated with dengue transmission (Bangs et al., 2006; Karim et al., 2012; Ram et al., 1998; Wu et al., 2007). However, the magnitude of the association between weather and dengue varied with geographical location and socio-environmental conditions (Arcari et al., 2007; Thammapalo et al., 2007). It is also evident that El Niño events have strongly associated with dengue epidemics, although spatial heterogeneity exists in this relation (Cazelles et al., 2005; Hu et al., 2010). Mathematical modelling has recently been used to measure and predict the impact of weather variation on dengue and significant advances have been achieved in modelling approaches (Hu et al., 2010; McMichael et al., 2006). Many studies around the world have developed different models to predict the future distribution of dengue in response to climate change (Hales et al., 2002; Hopp and Foley 2003; Patz et al., 1998). Such projections can help to combat the increased risk of dengue due to climate change by taking necessary adaptation measures. However, very few studies were conducted to identify the association between weather variables and dengue transmission in the South Asian region and long term scenario-based projections are yet to be developed (Banu et al., 2011; Chakravarti and Kumaria 2005; Karim et al., 2012; Oo et al., 2011). In this study, we examined the effects of weather variability on dengue transmission and projected the potential impact of climate change on the pattern of dengue in the megacity of Dhaka.

2. Material and Methods

2.1 Study area

This study carried out in Dhaka, the capital of Bangladesh. Our previous study showed that Dhaka is the highest risk area for dengue transmission in Bangladesh and the underlying cause of increased risk of dengue in this location remains unknown, which requires further investigation (Banu et al., 2012). Dhaka is located in central Bangladesh at 23°42′ north latitude and 90°22′ east longitude with an area of 1,464 square kilometres. Dhaka along with its metropolitan area had a population of 11.8 million (2011 census), making it the biggest city in Bangladesh. Dhaka has a hot, wet and humid tropical climate. The city is within the monsoon climate zone, with an annual average temperature of 25 °C and monthly means varying between 18 °C in January and 29 °C in August. Nearly 80% of the annual average rainfall of 1,854 millimetres occurs between May and September.

2.2. Data collection

Data on the monthly number of notified dengue cases in Dhaka city were obtained from the Directorate General of Health Services (DGHS) from January 2000 to December 2010. As dengue is a notifiable disease in Bangladesh, any case detected based on the World Health Organization (WHO) clinical criteria must report to the DGHS by the hospital. According to the WHO clinical criteria, a dengue case was defined by the presence of acute fever accompanied by any two of the following clinical symptoms such as headache, myalgia, arthralgia, rash, positive tourniquet test and leucopenia (WHO 2000). We also obtained monthly weather data on maximum, mean and minimum temperature, relative humidity and rainfall from Bangladesh Meteorological Department (Dhaka, Bangladesh) between January 2000 and December 2010. Population data were collected from Bangladesh Bureau of Statistics (BBS).

2.3. Data analysis

We used Spearman's correlation coefficients to summarize the relationships between independent variables. A Poisson time series model combined with distributed lag model (DLM) was used to estimate the effects of weather on dengue transmission. The observed number of dengue cases followed a quasi-Poisson distribution and the model allows for over dispersion.

$Y_t = \text{Poisson}(\mu_t)$, $t=1,..........,n$

$$\log(\mu_t) = \alpha + \sum_{l=1}^{L} \beta_0(T_{t,l}) + \sum_{l=1}^{L} \beta_1(H_{t,l}) + \sum_{l=1}^{L} \beta_2(R_{t,l}) + \log(N_t) + s(t,\lambda) + \mathcal{E}_t$$

Where t is the month of the observation; Y_t is the observed monthly dengue counts in month t; α is the intercept; $T_{t,l}$,$H_{t,l}$ and $R_{t,l}$ are the matrices obtained by applying the DLM to temperature, humidity and rainfall, respectively; l is the lag months; L is the maximum lag; β_0, β_1 and β_2 are the coefficients for $T_{t,l}$,$H_{t,l}$ and $R_{t,l}$, respectively, N_t is an offset to control for population using a linear function of time based on the 2001 and 2011 census. The $s(t,\lambda)$ is the natural cubic spline smoothing function of time with assigned λ of 2 degrees of freedom per year to control for seasonal pattern.

We used a DLM that modelled the main effects as a linear function and the delayed effects as a polynomial function. The selection of maximum lag was conducted using model residual checking and we checked maximum lag up to 6 months. We used second order quadratic polynomial smoothing for the lag. The mean value of each weather variable was used as a baseline (referring value) to measure the relative risks. We plotted relative risks against weather variables and lags to show the entire relationship between weather conditions and dengue.

The climate and dengue relationship were examined using different temperature measures (maximum, mean and minimum temperature) in the DLM. The deviance was used to choose the best model. Model including maximum temperature was associated with lower deviance value (Supplementary Table 2). We also compared the deviance for the association between each weather variables and dengue using DLM. The deviance was also lower compare to other models when maximum temperature and relative humidity were included (Supplementary Table 3). The goodness-of-fit was performed to check the model adequacy using auto-correlation functions of residuals and normality of the residuals. Figure 1 shows that there was no significant auto-correlation between residuals at different lags in the DLM when maximum temperature and humidity were used as predictor variables. The scatter plot shows that the residuals in the model fluctuated randomly around zero with no obvious trend. Thus the goodness-of-fit analyses show that the model fits the data reasonably well. Therefore, we selected the model including maximum temperature and relative humidity as the best model and used it to estimate the effects of weather variation on dengue transmission.

The constructed model was then validated by dividing the data file into two data sets. The data between January 2000 and December 2008 were used to develop a DLM and those between January 2009 and December 2010 were used to validate the model. The validation indicates that the model had reasonable accuracy as the observed and predicted values were mostly coincided (Supplementary Figure 1). In addition, adequacy of the model predicting outbreak ($\geq$ 168) was evaluated by sensitivity analyses. For sensitivity analyses, the monthly number of dengue cases was transformed into a categorical variable (i.e., outbreak/non-outbreak). Then the sensitivity or true positivity rate (predicted number of months with dengue outbreak/observed number of months with dengue outbreak) and specificity or true negativity rate (predicted number of months without dengue outbreak/observed number of months without dengue outbreak) of the predictive model were calculated.

The results of the validated model were then applied to future climate change situations to generate projections for dengue risk in the 2100. We used IPCC regional climate change projection for South Asia, which results in an increase of 3.3 ^{o}C in annual mean temperature between 1980 to 1999 and 2080 to 2099 (IPCC 2007). We assumed that warming will be similar to south Asia in Dhaka. We estimated the future monthly temperature in Dhaka by combining recorded baseline data with projection. We added 1, 2 and 3.3 ^{o}C to the observed monthly temperature in 2010 to simulate monthly temperatures in 2100. We assumed that there will be no adaptation to climate change in Dhaka. We calculated the projected temperature related dengue risk in 2100 after adjusting for the 1.3% increase in population, which is the current population growth rate in Dhaka (population census 2011).

All statistical tests were two-sided and the p <0.01 were considered statistically significant. We used R software (version 2.12.0; R development Core Team 2009) to fit all models, with its "dlnm" package to create the DLM (Gasparrini and Armstrong 2011).

3. Results

There were 25,059 dengue cases in Dhaka during the study period. The average monthly number of dengue cases was 168 with an incidence rate of 1.8 per 100,000 populations. The highest monthly incidence rate was 35.2 per 100,000 populations in August 2002. Descriptive statistics for each independent and dependent variable are shown in Table 1. The monthly mean minimum and maximum temperature, rainfall and relative humidity were 21.9^{o}C, 30.7^{o}C, 180.2 mm and 72.77%, respectively, between 2000 and 2010 in Dhaka.

The three dimensional plots show the entire relationship between mean maximum temperature and relative humidity with dengue incidence at different lags (Figure 2). The estimated effects of weather variables on dengue incidence were linear in current months and were nonlinear along lags. Temperature and humidity were positively associated with dengue incidence and the highest effects observed at two months lag. The sensitivity analyses indicate that the overall model agreement was 89%, sensitivity was 84% and specificity was 91% (Table 2).

Table 3 reveals the estimated dengue cases associated with the variation in temperature due to climate change by the year 2100. We estimated 377 dengue cases attributable to temperature variation in 2010. Assuming a 1^{o}C temperature increase in 2100, we projected an increase of 583 dengue cases. For a 2 ^{o}C increase, we projected an increase of 2,782 dengue cases. If temperature increase by 3.3 ^{o} C as the IPCC projected, the consequence will be devastating, with a projected increase of 16,030 cases by the end of this century.

4. Discussion

Our results show that the monthly temperature and humidity were significantly associated with the monthly dengue incidence in Dhaka, with highest lag effects of two months. These results are consistent with findings of other studies and may assist to forecast dengue outbreaks in different regions (Descloux et al., 2012; Hii et al., 2009; Hsieh and Chen 2009; Johansson et al., 2009). Temperature and humidity are the most important weather factors in the growth and dispersion of mosquito vector and potential predictors of dengue outbreaks (Chen et al., 2010; Wu et al., 2007). Temperature influences the life cycle of *Aedes* mosquitoes including growth rate and larval survival and the length of reproductive cycle (Hopp and Foley 2001; Patz et al., 2005). Maximum mosquito survival rate of 88-93% were observed between temperature ranges of 20-30 ^{o}C (Tun-Lin et al., 2000). Temperature also affects the virus replication, maturation and period of infectivity. Higher temperature decreases the length of viral incubation within the vector, and thus increases the chance of mosquitoes to become infective in their life span (Hopp and Foley 2001; Patz et al., 1998; Yang et al., 2009). Adult mosquito survival also depends on humidity (Hopp and Foley 2001; Patz et al., 1998). Given the relationship between temperature and dengue, the projected change in temperature due to climate change may exacerbate disease transmission in Dhaka. According to the IPCC, the annual mean temperature increase will be 3.3 ^{o}C by the end of the 21st century in Dhaka. The projected warming will occur both in summer and winter (IPCC 2007). As summer will be warmer than before, it is likely that warmer condition will enhance disease transmission and will increase dengue incidence. In previous years, there were few reported dengue cases in Dhaka during winter season. If the winter temperature increases as projected, it may become more favourable for dengue transmission and extend the outbreak season. Hence dengue outbreak may become more intense in future, if the climate change happens.

There has been a significant emergence of dengue in Dhaka during the last decade; the reasons for this can be multiple. Both climatic and non-climatic factors like socio-ecological changes, viral serotypes, herd immunity and mosquito control can influence the risk of dengue transmission (Gubler 2011). Rapid urbanization around Dhaka city can deteriorate the environmental condition and increase the dengue incidence through enhancing the mosquito breeding habitats. Increased air travel can facilitate the introduction of new dengue serotypes from neighbouring endemic countries and can make this region hyper endemic (presence of all four dengue virus serotypes), which will obviously increase the likelihood of dengue epidemic (Karim et al., 2012; Tatem et al., 2006). Additionally, effective vector control can reduce the vector density and can decrease the dengue transmission.

Temperature and humidity affect the dengue occurrence in several subsequent months. We found that monthly maximum temperature and relative humidity were associated with dengue transmission through a 4-months lag period (highest effects in two months) which includes the time of replication and development of mosquito and the incubation period of the virus (time of replication both in vector and host). Therefore, observed lag effects were biologically plausible and consistent with the findings of other studies (Arcari et al., 2007; Hii et al., 2012; Wu et al., 2007). A previous study in Dhaka reported the positive association between maximum temperature, relative humidity and dengue which is consistent with our findings (Karim et al., 2012). They also observed the highest lag effects at two months which is similar to our observation. An accurate early warning system to predict dengue epidemics and enhance the effectiveness of preventive measures largely relies on the sufficient lag time. Thus, four months lag time could be sufficient to warn people about the possible disease outbreak and take necessary measures to prevent the epidemic.

Different emissions scenarios were developed by IPCC which have been widely used in the analysis of possible climate change impacts and options to mitigate climate change. Each emission scenario represents different demographic, social, economic, technological and environmental developments which are driving forces of greenhouse gas emissions. “The A1 scenario family describes a future world of rapid economic growth, global population that peaks at mid-century and declines thereafter, and the rapid introduction of new and more efficient technologies”(IPCC 2000). The A1B emissions scenarios is one of the A1 group scenarios which assumes the balanced use of energy system like fossil fuel and non-fossil energy system. The B2 scenario families focus on local and regional environmental protection and social equity where global population will increase continuously with comparatively lower rate with intermediate level of economic development and less rapid and more diverse technological developments than A1 or B1. Climate change projections for all continents and sub continental regions of the world were provided by IPCC (IPCC 2007). These projections were generated using multi model dataset (MMD) and three emission scenarios B1, A1B and A2. However, the results of most projections were presented and discussed by IPCC on the basis of A1B scenario as the global mean surface temperature responses in the ensemble mean of the MMD model follows a ratio of 0.69:1:1.7 for B1: A1B:A2 scenarios. The local temperature responses for almost all regions also follow the same ratio. Similar to the IPCC regional climate projections, we used the MMD-A1B projection scenario to predict and discuss the future temperature related dengue risk in Dhaka.

To the best of our knowledge, this is the first study to project the impact of climate change on dengue transmission in Dhaka. We showed that dengue incidence will increase by more than 40 times in Dhaka in the year 2100 relative to 2010, if the ambient temperatures increase by 3.3 ^{o}C according to the IPCC regional climate projection. It will have devastating consequences for the already stretched public health systems in Dhaka due to the population ageing and increased burden of disease (including chronic disease, infectious disease and injury). Human adaptation to climate change may influence the likelihood of dengue transmission. People may adapt to higher temperatures through improved building design with glazed windows, piped water, insect screening and air-conditioning. These facilities may effectively reduce their contacts with vector mosquitoes and even if infected mosquitoes gain entry to these buildings, the low ambient temperature and artificially dry environment may decrease their survival rate and reduce the risk of disease transmission (Reiter 2001). On the other hand, water storing for domestic purposes in summer months or during droughts may provide increase number of breeding sites for mosquitoes and increase the risk of dengue transmission (Beebe et al., 2009). However, there is no information available on how people will adapt to climate change in Dhaka. Therefore, in our study, we assumed that there will be little adaptation to climate change in the study site.

The weaknesses of this study must be acknowledged. This is a large scale, ecologic assessment of the relationship between climate and the dengue transmission at a city level. For a comprehensive and systematic risk assessment, more detailed risk assessment at a community and individual level is required. Inclusion of other factors such as mosquito density, population immunity, viral factors and human behaviours may improve the model. Due to the lack of seroprevalance and entomological data, these variables could not be included into our model. Therefore, our model prediction underestimated some of the observed number of cases and the biggest outbreak. Adaptation to climate change and changes in socio-economic trends might influence the likelihood of disease occurrence. However, we have not accounted for all possible socio-economic features and climate adaptation behaviour. Underreporting bias is inevitable in the surveillance data to some extent as people infected with subclinical dengue infection did not seek for medical advice. This model is only applicable to Dhaka and areas with a similar socio-ecologic background as local data were used in the construction of this model.

5. Conclusions

This study shows that maximum temperature and relative humidity were best predictors among the major determinants of dengue transmission in Dhaka for the period of 2000-2010. Projected climate change will increase mosquito activity and dengue transmission in this area. Assuming a temperature increase of 3.3 ^{o}C by 2100 as projected by IPCC, there would be a substantial increase in dengue incidence in Dhaka. Therefore, public health authorities need to be well prepared for likely increases of dengue transmission in this region.

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Contributors:

SB performed all data analyses and wrote the manuscript. ST and WH supervised the study and assisted with writing the manuscript. CH contributed to statistical support and YG helped with the R software and related packages.

Conflict of interest

We declare that we have no conflict of interest.

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Figure Legends

Figure 1: Auto-correlation function, partial auto-correlation function and scatter plot of residuals for DLM model.

Figure 2: Association between climatic variables (maximum temperature and relative humidity) and dengue at different lags.

Table 1: Descriptive statistics of monthly weather conditions and dengue cases in Dhaka, Bangladesh, 2000-2010.

Variables	Number of months	Minimum	Maximum	Mean	Standard Deviation
Dengue cases	132	0	3155	168	394
Minimum Temperature (^oC)	132	11.7	26.8	21.9	4.3
Mean Temperature (^oC)	132	16.7	30.7	26.3	3.5
Maximum Temperature (^oC)	132	21.7	35.5	30.7	2.9
Rainfall (mm)	132	0	839	180.2	195.1
Relative Humidity (%)	132	53	85	72.8	8

Table 2: Sensitivity and specificity of DLM for dengue occurrence

Predicted	**Observed**		**Total**
	Outbreak	**Non-outbreak**	
Outbreak	27	9	36
Non-outbreak	5	91	96
Total	32	100	132

Sensitivity, 27/32 = 84%; Specificity, 91/100 = 91%; Crude agreement or accuracy, (27+91)/132 = 89%.

Table 3: Changes in annual dengue cases under different scenarios of temperature increase by 2100 in Dhaka, Bangladesh.

Climate change scenarios	**Projected annual number of dengue cases**	**Changes in annual number of dengue cases**
Baseline	377	
1^{0}C increase	960	583
2 ^{0}C increase	3,159	2,782
3.3 ^{0}C increase	16,407	16,030