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Climate change impacts the epidemic of dysentery: determining climate risk window, modeling and projection

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Abstract

Dysentery, an acute infectious disease still prevalent in many parts of the world, especially in developing counties, is caused by a group of bacteria known as *Shigella*. Because of the sensitivity of dysentery to climate change, the relationship between dysentery incidence and climate factors has become a growing research interest. Previous studies have mainly focused on identifying key climate factors and examining the relationship between dysentery incidence and climate change. However, there has been little research on modeling and projecting the occurrence of dysentery based on key climate factors. Here we selected Binyang County in China, a subtropical monsoon climate region where epidemics are typical, as the study area. We used heat maps to extract climate risk windows (with minimum temperatures of 24 °C–26 °C, precipitation amounts of 160–380 mm, and relative humidities of 69%–85%) for dysentery transmission. We then developed a climate-dysentery model and validated its reliability. Finally, based on climate risk windows and the developed model, three earth system models (BNU-ESM, IPSL-CM5A-MR, and MIROC-ESM) were used to project future occurrence periods and incidence of dysentery under future climate condition. The projected results showed that May to August were high-incidence periods, and the occurrence of dysentery exhibited an upward trend in the future. Accordingly, we provided two practical recommendations for defeating dysentery: seasonal control in the study area, and advocacy of prevention in potentially pandemic regions. This study hopes to provide a theoretical basis for developing a dysentery warning system from the perspective of climate change.

1. Introduction

Dysentery is a major diarrheal disease characterized by fever, stomach cramps, and uncontrolled loose or watery stools containing visible red blood (Patrick *et al* 2004). Caused by four *Shigella* serogroups with multiple serotypes, the disease is transmitted through the fecal–oral route including via polluted water, food, daily person-to-person contact, and flies (Niyogi 2005). One study estimated that over 80 million people are at risk of contracting dysentery and that about 700 000 deaths occur globally, mostly in developing counties (World Health Organization 2005). In China, dysentery is ranked third most prevalent notified infectious diseases, after tuberculosis and hepatitis B. In 2011, 237 930 new notified cases were recorded (Gao *et al* 2014). The prevention and control of dysentery remains a challenge in China.

Climate change—a change in weather conditions, such as mean temperature, precipitation, or humidity (Wu *et al* 2014b, 2016)—can affect the incidence of dysentery either directly or indirectly. Climate conditions and weather factors have a direct effect on the incidence of dysentery (Yang *et al* 2008, Alexander *et al* 2013). For example, higher temperatures and more precipitation can directly increase the replication and prolong the survival time of bacteria and pathogens (Alexander *et al* 2013). Climate change is also able to affect dysentery indirectly (Curriero *et al* 2001, Hall...
et al 2002, Li et al 2013). For instance, increased temperature combined with poor hygiene may affect the chain of food supply, including production, processing, transport, and storage, which helps dysentery pathogens reproduce and multiply (Hall et al 2002). Climate change can impact human behaviors, including eating habits, which may indirectly affect dysentery transmission (Curriero et al 2001).

With global warming becoming a growing concern, research on dysentery with respect to climate change has become an active area of research. First and foremost, several studies have demonstrated a distinct seasonality of dysentery occurrence and identified some of the key climate factors responsible. For example, an obvious seasonal pattern with a peak in summer and fall was observed in Binyang County, China (Liu et al 2017). The study using principal component analysis showed that minimum temperature, precipitation, and relative humidity played key roles in determining the transmission of dysentery in Binyang County, China (Liu et al 2017). Next, previous studies have investigated the relationship between climate factors and dysentery incidence. For instance, a study conducted in the city of Changsha indicated that temperature indices were significantly positively correlated with dysentery cases and that a 1 °C rise in minimum temperature, mean temperature, and maximum temperature may relate to about 15.5%, 14.8%, and 12.9% increases in dysentery incidence, respectively (Gao et al 2014). Finally, a few studies have established dysentery models based on climate factors. A study used generalized additive models to examine the climate-dysentery association in Beijing at a daily scale, and thresholds for the effects of relative humidity (>40%) and temperature (>12.5 °C) on bacillary dysentery were detected (Zhang et al 2007). Yet little research has been conducted to detect climate risk windows and predict incidence of dysentery based on a specific climate-dysentery model and earth system models in the future.

Climate risk windows and projected incidence of dysentery could shed light on the impact of climate change on dysentery transmission. Therefore, in this study, we determined the climate risk windows using the heat maps and developed a specific climate-dysentery model using historical data in a typical region of China. Based on the model, we projected occurrence periods and incidence under future climate condition. These results could provide theoretical guidance for the prevention and control of dysentery in the future.

2. Materials and methods

2.1. Study area

After Xinjiang Province, Guangxi Province has the second highest morbidity (17.9 per 10 000 individuals) in China in terms of dysentery incidence (Wang et al 2006, Guan et al 2008). In Binyang County, dysentery accounts for 81% of all intestinal diseases, which is typical throughout the Guangxi region. Dysentery is more likely to occur in tropical and subtropical regions owing to favorable climate conditions (Zhang et al 2012). Binyang County has a subtropical monsoon climate that is characterized by sufficient rainfall and sunshine. Therefore, we chose it as our study area. Binyang County is located in south-central Guangxi Province, with the geographical coordinates of 22° 54′–23° 27′ N and 108° 32′–109° 15′ E. It is one of the most important transportation hubs in Guangxi Province. The annual mean temperature in Binyang County is about 20.8 °C. The average annual rainfall in the county is 1589.2 mm. All the meteorological and demographic conditions of Binyang County are favorable for dysentery transmission.

2.2. Data collection

2.2.1. Disease data

In China, each case of a notable disease (including dysentery) must be reported to the Chinese Center for Disease Control and Prevention (CDC) through the real-time and online National Infectious Diseases Monitoring Information System Database. In this study, dysentery cases are just reported bacillary dysentery cases. Collected dysentery cases were all collected by hospital diagnosis and reported to the CDC. Based on the principle of the temporal scale for a disease data (Wu et al 2014a), we chose monthly scale. Furthermore, many previous studies have also used monthly data of dysentery cases to investigate the relationship between the disease and climate change (Huang et al 2008, Zhang et al 2008, Wang et al 2010, Gao et al 2014, Wu et al 2014a, Fang et al 2017). Therefore, we collected monthly data for all bacillary dysentery cases in Binyang County from January 2004 to December 2010 from China CDC.

2.2.2. Meteorological data

Monthly climate data for Binyang County from January 2004 to December 2010 were retrieved from the China Meteorological Data Sharing Service System. The data included 25 climate factors, such as temperature index and precipitation. Based on our previous research (Liu et al 2017), three climate factors were identified as key factors and thus considered in this study, including monthly average minimum temperature (MinT), monthly average cumulative precipitation (Pre), and monthly average relative humidity (Rh).

2.2.3. Climate model data

Future climate data were derived from three earth system models included in the Coupled Model Intercomparison Project Phase 5 (CMIP5). IPSL-CM5A-MR and MIROC-ESM performed well for simulating precipitation and temperature in China, and BNU-ESM proved excellent in projecting the incidences of
some infectious diseases in previous studies (Wu et al 2015, Li et al 2017). Therefore, these three models were employed in this study. Table 1 showed the attributions of the three models. A set of emission scenarios referred to as Representative Concentration Pathways (RCPs) reflect various possible combinations of economic, demographic, technological, and policy developments (Moss et al 2010). Radiative forcing in RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5 peaks at about 2.6 W m$^{-2}$, 4.5 W m$^{-2}$, 6.0 W m$^{-2}$, and 8.5 W m$^{-2}$ for year 2100, respectively, relative to pre-industrial conditions (Clarke et al 2007). The outputs under the RCP 4.5 scenario, a secondary emission scenario, were selected and analyzed in our study. Since these three models are global-scale models, we used bilinear interpolation to downscale the data to a city level (Wang et al 2010). That is, based on the latitude and longitude of the study area, we used bilinear interpolation to process the data of adjacent grids to obtain the climate model data of Binyang County. A multi-model ensemble can decrease initial condition, boundary condition, parameter, and structural uncertainties (Tebaldi and Knutti 2007). Thus, we used an equally weighted ensemble of the three models to derive climate model data in this study.

2.3. Data analysis

Statistical analyses were conducted to determine the relationship between monthly dysentery cases and various climate factors (Huang et al 2008, Wang et al 2010, Gao et al 2014). The analysis comprised two steps, including heat map analysis and model building.

First, the rough associations between dysentery cases and climate factors were graphically explored using a heat map. Based on the heat map analysis, a climate risk window was further defined by a high proportion of the total cases (Fang et al 2017). When dysentery cases were at a high level (above the 3rd quartile; i.e. 75%–100%) and their distribution in heat maps was more clustered (Li et al 2015), a climate risk window was determined.

Proposed and developed in recent years, distributed lag nonlinear models (DLNM), are flexible and simultaneously estimate the nonlinear and lagged exposure-response relationship (Gasparrini et al 2016). DLNM has been widely used in studies on infectious diseases, such as dengue (Xiang et al 2017), measles (Yang et al 2014), mumps (Hu et al 2018), and childhood bacillary dysentery (Wen et al 2016). Given the nonlinear climate-dysentery relationship and lagged effects of climate factors on dysentery incidence in previous research (Zhang et al 2008, Li et al 2013, Ma et al 2013), DLNM was used as a base to demonstrate the climate-dysentery correlations in this study.

The model incorporated monthly dysentery cases as the dependent variable, monthly key climate factors as the independent variables. We added quasi-Poisson generalized linear models to DLNM to deal with the over-dispersion of monthly dysentery cases. The DLNM can be expressed as follows:

$$\log (E(Y)) = a + \sum_{i=1}^{n} cb(x_i, df_{x_i}, lag_{x_i}, df_{lag_{x_i}}) + NS(Time),$$

(1)

where $E(Y)$ denotes the expected number of monthly dysentery cases, $x_i$ denotes key climate factor $i$, and $cb$() denotes the cross-basis function for the climate factors. The cross-basis function, a bi-dimensional function expressed by the combination of two basic functions, describes the effects of predictor and lags simultaneously (Gasparrini et al 2016). $NS(Time)$ represents the natural cubic spline function to control for long-time trends and seasonality.

3. Results

3.1. Determination of climate risk window

A total of 2853 dysentery cases were reported in Binyang County from January 2004 to December 2010, with the average incidence was 0.034% / 1000. Table 2 showed the descriptive statistics for monthly climate factors and dysentery cases. The MinT, Pre, and Rh were in the ranges of 6.5 °C–26.7 °C, 0–380 mm, and 58%–86%, respectively. The number of monthly dysentery cases ranged from 4 to 157.

To explore the relationship between dysentery cases and climate factors, a heat map was generated to extract risk windows for the three climate factors conducive to dysentery spread (figure 1). Considering MinT is the most important key climate factor (Liu et al 2017), it was used as the determining factor for generating heat maps. The heat map of dysentery transmission against MinT and Pre was shown in figure 1(A), and that against MinT and Rh was shown in figure 1(B). In figure 1, each cell represented the number of dysentery cases under the corresponding climatic conditions. To control seasonal effects, the number of dysentery cases per cell was the average number of cases under a given climate condition. Based on the determining criteria of the climate risk window, we extracted two climate risk windows, which were represented as blue boxes (figure 1). One risk window (MinT range of 24 °C–26 °C and Pre range of 160–380 mm) specified a climate condition for high-risk dysentery transmission. Similarly, we obtained the other risk window, corresponding to a MinT range of 22 °C–26 °C and Rh range of 69%–85% for dysentery virus infection, which included 1693 dysentery cases (59.34%) of the total cases.

Based on the above analyses, climate risk windows favorable for dysentery transmission were determined —i.e. MinT interval of 24 °C–26 °C, Pre interval of 160–380 mm, and Rh interval of 69%–85%. Upon combining this with descriptive statistics (table 2), we found that when MinT was at a high level (above the 3rd quartile), a high proportion of dysentery cases...
| Model         | Institution                           | Atmospheric model resolution (Lon°*Lat°/Levels) | Emission scenario | Data download website                                                                 | References          |
|--------------|---------------------------------------|-----------------------------------------------|-------------------|--------------------------------------------------------------------------------------|---------------------|
| BNU-ESM      | Beijing Normal University, China       | 2.81°*2.81°/L26                              | Rep2.6            | http://cera-www.dkrz.de/WDCC/CMIP5/Compact.jsp?acronym=BUBUr4                        | Ji et al (2014)     |
|              |                                       |                                               |                   | Rep4.5                                                                               |                     |
|              |                                       |                                               |                   | Rep8.5                                                                               |                     |
| IPSL-CM5A-MR | Institut Pierre Simon Laplace, France   | 2.50°*1.27°/L39                              | Rep2.6            | http://cera-www.dkrz.de/WDCC/CMIP5/Compact.jsp?acronym=IPIMr4                        | Krinner et al (2005) |
|              |                                       |                                               |                   | Rep4.5                                                                               |                     |
|              |                                       |                                               |                   | Rep6.0                                                                               |                     |
|              |                                       |                                               |                   | Rep8.5                                                                               |                     |
| MIROC-ESM    | AORI, NIES, JAMSTEC, Japan             | 2.81°*2.79°/L80                              | Rep2.6            | http://cera-www.dkrz.de/WDCC/CMIP5/Compact.jsp?acronym=MIMEr4                        | Takata et al (2003) |
|              |                                       |                                               |                   | Rep4.5                                                                               |                     |
|              |                                       |                                               |                   | Rep6.0                                                                               |                     |
|              |                                       |                                               |                   | Rep8.5                                                                               |                     |
occurred if Pre was at a middle (1st–3rd quartile) or high level, or if Rh was at a high level. This result accords with the screening results using the classification and regression trees approach (Liu et al 2017).

3.2. Modeling of climate factors and dysentery cases
To identify a quantitative relationship between the three climate factors and dysentery cases, we modeled it using DLNM. We randomly selected 75% of the data for modeling and left 25% of it for model verification. We studied the collinearity between the three key climate factors. Collinear analyses showed that the correlations between the three factors were not high; correlation coefficients were 0.230, 0.459, and 0.425 for MinT and Rh, MinT and Pre, and Rh and Pre, respectively. Therefore, monthly MinT, Pre, and Rh as main independent variables were incorporated into the model (equation (1)).

In this study, the lags of climate factors were defined as 0 to 3 months to cover any possible lag effects on dysentery cases as a result of the disease incubation period (Gao et al 2014, Liu et al 2015). We adopted the principle that the smaller the Akaike’s information criterion value, the better the model, to determine degrees of freedom for all variables. In the final model, the degrees of freedom and maximum lag months for each climate factor were as follows: 3, 3 for MinT; 3, 3 for Pre; and 4, 3 for Rh. Long-time trend and seasonality were controlled by a natural cubic spline function with 7 df yr$^{-1}$. The modeling results showed a good fit with the value of $R^2$ reaching 0.846.

The remaining 25% of data were used to validate the developed model. Figure 2 showed a comparison of reported and predicted dysentery cases. The comparison demonstrated that the model fitted the real-world data well. The predicted cases are included in the 95% prediction interval, except for those in January 2004. The discrepancy that the reported cases were higher than the predicted cases in January 2004 was related to the Spring Festival Fair. First held in the city of Nanning in January 2004, the Spring Festival Fair is an annual event during which people gather to watch art performances and consume traditional snacks. The increased population density and food sharing likely contributed to the higher occurrence of dysentery in that month (Feng and Meng 2005, Li et al 2016). Overall, the predicted results suggested that the developed model is reliable.

3.3. Projection of dysentery incidence
MinT, Pre, and Rh from 2021 to 2050 were provided by BNU-ESM, IPSL-CM5A-MR, and MIROC-ESM under the RCP4.5 scenario. We predicted the incidence of dysentery, including occurrence periods and dysentery cases using future climate data. The statistics of occurrence periods were based on the climate risk

Table 2. Descriptive statistics of monthly weather factors and dysentery cases in Binyang County, China, from 2004 to 2010.

| Statistics     | Minimum temperature (°C) | Precipitation (mm) | Relative humidity (%) | Dysentery cases |
|---------------|---------------------------|--------------------|----------------------|-----------------|
| Minimum       | 6.5                       | 0                  | 58                   | 4               |
| 1st quartile  | 13.5                      | 32                 | 69                   | 11              |
| Median        | 20.0                      | 77                 | 74                   | 20              |
| 3rd quartile  | 24.5                      | 187                | 77                   | 52              |
| Maximum       | 26.7                      | 382                | 86                   | 157             |
windows, and the projection of dysentery cases was according to the model result. Figure 3 showed the frequency of months in which each climate factor met its climate risk windows (figure 1) for dysentery transmission from 2021 to 2050. Statistics of potential favorable months showed obvious seasonality with a peak occurring mainly in summer, especially for MinT and Pre. We divided periods of dysentery incidence into three levels. We consider May to August to be a period of high dysentery incidence, as there is a higher frequency of climatic conditions favorable for transmission of the disease. Meanwhile, we categorize April and September as low-incidence periods, and the other months—October, November, December,
January, February, and March—as potentially susceptible onset periods. When MinT met its climate risk window, dysentery cases were more likely to occur in these months. This indicated that MinT played the most important role in increasing the incidence of dysentery, which was consistent with previous studies (Li et al 2013, Liu et al 2017). We are particularly concerned about the potential occurrences of dysentery in the next decade. Figure 4 showed the projected number of dysentery from January 2021 to December 2030 based on three earth system models under RCP4.5 scenario. Time series data of projected occurrence of dysentery exhibited an apparent seasonality and an upward trend. Dysentery incidence mostly clustered in summer and fall. This is also in agreement with classified ‘high-incidence’ periods. During periods of high dysentery incidence, climatic conditions are characterized by wetness and heat, which can increase the survival and replication of the pathogens and reproduction of disease-carrying organisms, such as flies (Lake et al 2009). In addition, there is an increased chance of contamination via food sources, such as raw foods, during the hot and humid summer months.

4. Discussion

This study indicated that climate factors were one of the major environmental predictors for the risk of dysentery incidence. Using Binyang County as our study area, we investigated the quantitative relationship between dysentery cases and climate factors and projected the incidence of dysentery under future climate condition. First, climate risk windows for the three key climate factors were specified based on heat maps: MinT interval of 24 °C–26 °C (at a high level), Pre interval of 160–380 mm (at a medium or high level), and Rh interval of 69%–85% (at a high level).

Second, we developed a climate-dysentery model and verified its credibility. Finally, based on the model, we used data from an ensemble of three earth system models to project occurrence periods and incidence of dysentery in the future.

According to our projections, key climate factors should be included as significant indicators in early warning systems for dysentery. Therefore, we proposed two practical recommendations to better cope with the disease in the future. First, seasonal control of dysentery should be strengthened in Binyang County. Considering the clear seasonality of dysentery occurrence, relevant public health strategies should be developed for different seasons. During periods of high dysentery incidence (May–August), more attention should be paid to controlling dysentery transmission. For example, people should refrigerate food to prevent spoiling in high temperature and humidity environments. Improvements in water storage systems and sanitation would also be good interventions. During low-incidence periods (September and April), people should reduce their intake of raw food and potentially contaminated drinking water to prevent dysentery. Second, for regions where climatic conditions meet the risk windows, prevention of dysentery should be advocated. For vulnerable population, including older people and children, advanced measures, such as vaccination, should be taken to reduce infection.

Our research has made three important contributions to advancing our current knowledge of the relationship between climate change and dysentery occurrence. First, we developed a climate-dysentery model to quantify the relationship between climate factors and dysentery cases. Compared with previously developed models including Tem and Pre (Ma et al 2013), ours incorporated more climate factors to provide a clearer explanation of the relationship...
between climate change and dysentery incidence. In addition, we validated our developed model using the remaining 25% of data, thereby ensuring the model’s reliability. Second, this study identified a range of climatic conditions favorable for dysentery occurrence —i.e. climate risk windows. Previous studies merely identified the minimum thresholds for climate factors favorable for dysentery transmission (relative humidity $>$40% and temperature $>$12.5 °C) (Zhang et al 2007), but the maximum values had not been defined. Additionally, only the temperature range (12 °C–22 °C) suitable for dysentery had been determined (Ma et al 2013), yet the occurrence of dysentery is affected by multiple climate factors. Our study detected the ranges of three climate factors associated with high incidences of dysentery, so it is more valuable for practical prevention and control. Third, future climate factors provided by BNU-ESM, IPSL-CM5A-MR, and MIROC-ESM under RCP4.5 scenario were used to project occurrence periods and incidence of dysentery. The equally weighted ensemble of the three models ensured the accuracy of the input future climate data; thus, the projection of dysentery occurrence periods could provide a reliable basis for dysentery control.

However, a few limitations of this study should be acknowledged. First, dysentery transmission could be impacted by many factors, such as behaviors related to human hygiene, diet, population characteristics, and climate change. This study only examined dysentery occurrence from the perspective of climate factors. Therefore, better models incorporating more comprehensive factors, including socio-economic ones, need to be developed in future studies. Second, this study used monthly data; further study using finer-scale weekly or even daily data could make predictions and estimations more accurate (Ma et al 2013). Although there are some data scale limitations, this study can help us to better understand how climate change might affect the incidence of dysentery, and shed light on the relationship between climate change and dysentery occurrence for improved understanding.

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Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request. The data are not publicly available for legal and/or ethical reasons.

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