



Modeling the impact of climate variability on diarrhea-associated diseases in Taiwan (1996–2007)

Wei-Chun Chou^a, Jiunn-Lin Wu^b, Yu-Chun Wang^c, Hsin Huang^{a,d}, Fung-Chang Sung^{d,e}, Chun-Yu Chuang^{a,*}

^a Department of Biomedical Engineering and Environmental Sciences, National Tsing Hua University, Hsinchu, Taiwan

^b Department of Computer Science and Engineering, National Chung Hsing University, Taichung, Taiwan

^c Department of Bioenvironmental Engineering, Chung Yuan Christian University, Chung-Li, Taiwan

^d Graduate Institute of Environmental Health, China Medical University College of Public Health, Taichung, Taiwan

^e Institute of Environmental Health, National Taiwan University, Taipei, Taiwan

ARTICLE INFO

Article history:

Received 15 March 2010

Received in revised form 27 August 2010

Accepted 3 September 2010

Available online 13 October 2010

Keywords:

Diarrhea

Climate change

Poisson regression model

Morbidity

ABSTRACT

Diarrhea is an important public health problem in Taiwan. Climatic changes and an increase in extreme weather events (extreme heat, drought or rainfalls) have been strongly linked to the incidence of diarrhea-associated disease.

This study investigated and quantified the relationship between climate variations and diarrhea-associated morbidity in subtropical Taiwan. Specifically, this study analyzed the local climatic variables and the number of diarrhea-associated infection cases from 1996 to 2007. This study applied a climate variation-guided Poisson regression model to predict the dynamics of diarrhea-associated morbidity. The proposed model allows for climate factors (relative humidity, maximum temperature and the numbers of extreme rainfall), autoregression, long-term trends and seasonality, and a lag-time effect. Results indicated that the maximum temperature and extreme rainfall days were strongly related to diarrhea-associated morbidity. The impact of maximum temperature on diarrhea-associated morbidity appeared primarily among children (0–14 years) and older adults (40–64 years), and had less of an effect on adults (15–39 years). Otherwise, relative humidity and extreme rainfall days significantly contributed to the diarrhea-associated morbidity in adult. This suggested that children and older adults were the most susceptible to diarrhea-associated morbidity caused by climatic variation. Because climatic variation contributed to diarrhea morbidity in Taiwan, it is necessary to develop an early warning system based on the climatic variation information for disease control management.

© 2010 Elsevier B.V. All rights reserved.

1. Introduction

Due to anthropogenic climate changes, the global average temperature is continuing to increase, and extreme hydrologic cycles (such as floods and droughts) are projected to increase as the ambient temperature increases. Extreme weather events indicate that global climate continues to change, damaging human activity, and health. Increasing evidence shows that such changes in the global-scale climate system may already pose a threat to humans through increased morbidity and mortality caused by heat, cold, drought or rainfalls, changes in air and water quality, and the ecology of infectious diseases (Stott et al., 2004; Gregory et al., 2009; Semenza and Menne, 2009). Several prevalent human diseases have been linked to climate-mediated changes for susceptible populations such as infants and the elderly, who often have relatively poor immunity (Patz et al., 2005). Therefore, an understanding of the impact of climate change on disease patterns is critical to control efforts.

Infectious (bacterial, viral and parasites) and non-infectious (food intolerances or intestinal diseases) diarrhea remains a major public health problem around the world. Diarrhea is one of the primary causes of morbidity and mortality on a global scale, leading to 1 billion disease episodes and 1.8 million deaths each year (WHO, 2008). Previous studies have showed that climate factors significantly affect seasonal diarrhea in susceptible populations (Gajadhar and Allen, 2004; Emch et al., 2008; de Magny et al., 2008). Checkley et al. (2003) presented that higher temperatures increase bacterial and parasitic diarrhea, and extend the survival of enterogastroitis-causing bacteria, such as *Escherichia coli*, in contaminated food. Higher temperatures may also indirectly affect behavior patterns, such as increased consumption of water, lax hygiene, which may promote diarrhea transmission. Checkley et al. (2000) observed that daily hospital admissions for diarrhea exhibited a twofold increase per 5 °C increase in the mean ambient temperature. Diarrhea outbreaks are related to periods of heavy rainfall and runoff when subsequent turbidity compromises the efficiency of the drinking water treatment plants (Kramer et al., 1996). For example, Auld et al. (2004) found that heavy rainfall increases diarrhea outbreaks due to contamination of the water distribution systems. Zhang et al. (2010) revealed a strong

* Corresponding author. 101, Sec. 2 Kuang-Fu Road, Hsinchu 300, Taiwan. Tel.: +886 3 5715131x34229; fax: +886 3 5733592.

E-mail address: cychuang@mx.nthu.edu.tw (C.-Y. Chuang).

correlation between heavy rainfall events and gastroenteritis (*Salmonella* infection) in Australia. These studies suggested that temperature/precipitation factors have a strong effect on triggering diarrhea.

Previous researchers have used time-series analysis to analyze the correlation between diarrhea epidemics and climatic factors (Pascual et al., 2000; Rodo et al., 2002). A time-series regression model has been applied to assess the impact of long-term climate change, especially for extreme diarrhea epidemics (Kale et al., 2004; Hashizume et al., 2007; de Magny et al., 2008). This weather variation-guided modeling approach employs a Poisson regression model to fit hospital surveillance and mortality data for diarrhea diseases to estimate the temporal pattern of diarrhea in susceptible populations. This approach provides support for decisions about the prevention and control of this disease. Fernandez et al. (2009) appropriately applied the Poisson regression model to estimate the impact of daily maximum temperature and rainfall on the number of hospitalizations for cholera diarrhea in Zambia.

Hashizume et al. (2007) indicated that high temperature and heavy rainfall are associated with an increased number of diarrhea cases. This suggests that rainfall and temperature have a sufficient force to forecast the epidemics of diarrhea, and implies that these weather factors provide valuable insights into the seasonality of diarrhea. de Magny et al. (2008) adopted a generalized linear model with Poisson distribution to identify how environmental signatures (chlorophyll a concentration) and climatic factors (rainfall anomalies) can significantly influence the dynamics of the cholera epidemics in India and Bangladesh. Therefore, surveillance data is useful to predict disease occurrence through regional climatic factors such as temperature or rainfall.

Global warming has directly affected the weather in Taiwan. Hsu and Chen (2002) indicated a 0.9–2.7 °C temperature raise from 1961–1999 relative to the past 100 years, and significant changes in precipitation. Typhoon Morakot struck Taiwan, bringing nearly 9 ft (around 2.5 m) of rain and the island's worst floods in over 50 years. Such extreme weather events increase the number of waterborne disease cases, especially diarrhea. Hence, a robust early warning system that considers how climatic factors affect diarrhea diseases in Taiwan is necessary for decision-making in policy and public health.

This study investigated the correlation between climatic variables and diarrhea cases in Taiwan from 1996 to 2007. The time-resolved meteorological data in this analysis included temperature, humidity, and rainfall during the entire 12-year study period. The purpose of this study was (1) to estimate the relationship between climate variations and occurrence of diarrhea cases and predict the impact of diarrhea-associated morbidity in Taiwan, and (2) to predict the dynamics of diarrhea epidemics by a best-fit Poisson regression model.

2. Methods

2.1. Surveillance data

The National Health Insurance Research (NHIR) Database, a public healthcare system in Taiwan, was founded in 1995, and insured 98.70% of Taiwanese citizens in 2005. The NHIR database records hospital admissions in terms of gender, age, sex, hospital identification, case of admission, cure items, disease duration, and expense. This study collected monthly numbers of hospital admissions associated with diarrhea for the period 1996–2007 from the NHIR Database. This study also extracted information on diarrhea from ICD9 001–009 for infectious diarrhea, and ICD9 535, ICD9 555 and ICD9 558 for non-infectious diarrhea. The monthly number of cases was divided by the year-end population to express morbidity per 1,000,000 population, and the diarrhea cases were aggregated by age into the groups of 0–14 years, 15–39 years and 40–64 years.

2.2. Meteorological data

Daily temperature, rainfall, and relative humidity in Taiwan were obtained from the Taiwan Central Weather Bureau. The average monthly maximum temperature was calculated from the daily record. This study also calculated the monthly numbers of extreme rainfall days and monthly levels of rainfall accumulating within rainy days from 1996 to 2007. This study defined extreme rainfall as daily accumulative rainfall exceeding 40 mm.

2.3. Statistical analysis

This section presented a descriptive statistical analysis of the variables relevant to number of diarrhea diseases and climatic factors such as daily temperature, total rainfall, extreme rainfalls days and relative humidity during 1996–2007. The surveillance data of diarrhea was categorized by age group (0–14, 15–39 and 40–64 years old).

This study used a time-series Poisson regression that considered autocorrelation, seasonality, long-term trends, and lag effects to determine the best-fit model in relation to diarrhea, and estimate the morbidity of diarrhea attributed to climate factors. To build a robust model, this study estimated the deviance in explanation and the relative contribution of each variable in the model. The relative contribution of each variable was determined through a process of manually entering and omitting variables from the model in a stepwise manner, with the regulation for elimination being a p -value >0.05 . Spearman's correlation was used to calculate the relationship between the number of diarrhea cases and climatic factors for the present or lag time with one or two months. The regression model was described as follows:

$$\ln(Y_t) = \alpha_0 + \alpha_1 t + \alpha_2 \sin \frac{2\pi t}{12} + \alpha_3 T_{MAX,t-n} + \alpha_4 Rain_{EXT,t-n} + \alpha_5 RH_{t-n}, \quad (1)$$

where Y_t denotes the incidence of diarrhea confirmed cases at time t , α_0 through α_5 individually represent the coefficients, and T_{MAX} , $Rain_{EXT}$ and RH are the monthly maximum temperatures (°C), the extreme rainfall intensity (mm) and the relative humidity (%), respectively. The term $t-n$ in the subscript represents the n -month lag time. This model includes lag values to control for the autocorrelation of explanatory variables. To consider how seasonality and long-term trends may be associated with weather conditions, the proposed model includes a triangular function, $\sin(2\pi t/12)$, to reveal the seasonal component in series.

The regression coefficients of climate variables (α_3 , α_4 , α_5) were transformed using the equation

$$100(e^{\alpha} - 1), \quad (2)$$

This equation revealed the percent change in morbidity associated with a unit change of climatic factors, including maximum temperature, extreme rainfall, and relative humidity.

The monthly morbidity attributed to extreme weather events was calculated as the difference between observed and predicted baseline morbidities during the study period. The baseline morbidities during the study period were defined as the lower limit of the 95% confidence interval (CI) (i.e., 1.96 standard deviations with sample size great than 30) predicted by this model.

The probabilistic density function was then applied to characterize the excess morbidities for 1996–2007. A lognormal distribution (LN(geometric mean, geometric standard deviation)) was optimally fitted to the averaged excess morbidity estimates per 1,000,000 population during the study period. The overall expected excess risk

Table 1
Description of diarrhea diseases by age and climatic variables from 1996 to 2007.

	Total	Mean ± SD	Minimum	Maximum
Number of diarrhea diseases by ages				
All	1,212,621	9186 ± 6945	3298	20,356
0–14 group	290,331	2199 ± 388	57	4905
15–39 group	643,099	4871 ± 5114	979	12,324
40–64 group	279,191	2115 ± 2218	299	3589
Climatic variables, 1996–2007				
Daily average temperature (°C)		22.1 ± 3.9	14.5	28.8
Daily maximum temperature (°C)		29.5 ± 3.1	23.5	44.6
Daily total rainfall (mm)		197.5 ± 150.2	22.8	996.4
Extreme rainfall days per year		18.4 ± 9.3	0.0	59.0
Daily average relative humidity (%)		78.7 ± 2.9	69.3	84.6

could then be computed by the cumulative distribution curves of excess morbidity.

The Poisson regression model in Eq. (1) was fitted to diarrhea morbidity data for 1996–2007. The relative contribution of extreme weather events to diarrhea morbidity was then calculated using Eq. (2), which determined per unit changes in maximum temperature, extreme rainfall and relative humidity. All statistical analysis was performed using SPSS software (version 15.0 for windows, SPSS Inc., Chicago, IL).

3. Results

3.1. Descriptive statistics of diarrhea and climatic variables

Table 1 showed that there were 1,212,621 cases of diarrhea from 1996 to 2007, and that 24% of the infected were aged between 0 and 14 years old, 53% were aged between 15 and 39 years old, and 23% were aged between 40 and 64 years old. Because Taiwan has a subtropical environment, the daily maximum temperature varied between 23.5 and 44.6 °C, with a mean of 29.5 °C. There were 72 extreme hot days (above the 95th percentile of 35.5 °C) and 18 days of extreme rainfall (above the 40 mm for daily accumulative amount of rainfall) during the study period. The daily relative humidity was between 63.9% and 84.6%.

Table 2
Correlations between diarrhea diseases and climate variables in Taiwan from 1996 to 2007.

Monthly climate variables	Lag (months)	r ²	p-value
Monthly average temperature	0	0.409	0.36
Monthly average temperature	1	0.374	0.41
Monthly average temperature	2	0.484	0.17
Monthly maximum temperature	0	0.484	0.02
Monthly maximum temperature	1	0.583	0.02
Monthly maximum temperature	2	0.382	0.13
Total rainfall (mm)	0	-0.155	0.67
Total rainfall (mm)	1	-0.195	0.51
Total rainfall (mm)	2	-0.148	0.69
Monthly extreme rainfall days (>40 mm)	0	-0.348	0.02
Monthly extreme rainfall days (>40 mm)	1	0.283	0.11
Monthly extreme rainfall days (>40 mm)	2	0.354	0.01
Monthly average humidity	0	-0.045	0.98
Monthly average humidity	1	-0.547	0.06
Monthly average humidity	2	-0.243	0.29

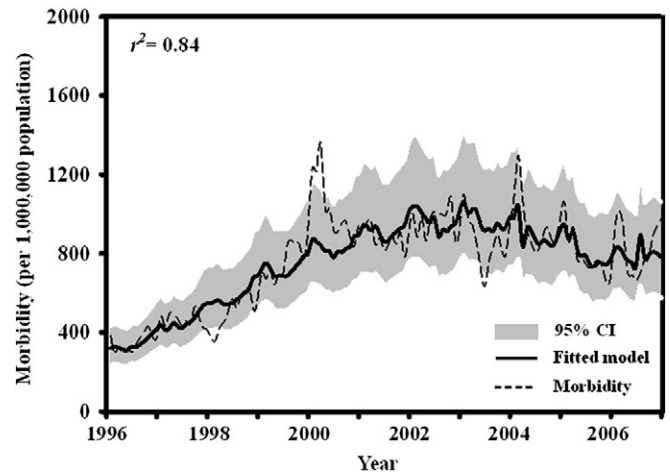


Fig. 1. Dynamics of gastrointestinal diseases in Taiwan in analysis with Poisson regression model from 1996 to 2007. Shaded region represented 95% prediction intervals.

3.2. Spearman's correlation analysis

Correlation analysis was conducted to quantify the relationship between monthly morbidity of diarrhea and climatic variables during study periods, with a lag of one to two months (Table 2). Results indicated that monthly average and maximum temperatures were positively correlated with the monthly morbidity of diarrhea in Taiwan throughout the study period (r^2 ranged from 0.37 to 0.58). The monthly relative humidity and total rainfall were inversely correlated with monthly morbidity of diarrhea (r^2 ranged from -0.04 to -0.55). There was a strong lag effect on the relationship between extreme rainfall days and monthly morbidity of diarrhea. Though, the extreme rainfall days at zero lag were adversely related to the monthly morbidity of diarrhea ($r^2 = -0.35$), the morbidity was positively

Table 3
Parameters from Poisson regression model for gastrointestinal disease-associated morbidity in Taiwan from 1996 to 2007.

	Coefficient	Std. err.	p-value	r ²
All case				0.84
Max temp (lag 1)	0.014	0.007	0.043	
Extreme rainfall (lag 2)	0.004	0.002	0.021	
Humidity (no lag)	-0.005	0.005	0.022	
sin(2πt/12)	0.067	0.030	0.028	
Month	0.029	0.001	<0.001	
Constant	5.323	0.210	<0.001	
0–14 Age group				0.27
Max temp (lag 1)	0.039	0.015	0.012	
Extreme rainfall (lag 2)	0.003	0.004	0.043	
Humidity (no lag)	-0.033	0.011	0.004	
sin(2πt/12)	0.090	0.050	0.039	
Month	-0.003	0.002	<0.001	
Constant	9.823	1.055	<0.001	
15–39 Age group				0.92
Max temp (lag 1)	0.013	0.011	0.023	
Extreme rainfall (lag 2)	0.006	0.003	0.021	
Humidity (no lag)	-0.028	0.008	0.001	
sin(2πt/12)	0.041	0.034	0.023	
Month	0.039	0.002	<0.001	
Constant	7.040	0.760	<0.001	
40–64 Age group				0.94
Max temp (lag 1)	0.023	0.007	0.003	
Extreme rainfall (lag 2)	0.004	0.002	0.026	
Humidity (no lag)	-0.004	0.005	0.042	
sin(2πt/12)	0.077	0.023	0.001	
Month	0.050	0.001	<0.001	
Constant	4.987	0.512	<0.001	

Lag 1/2 represented the lag effects of 1 or 2 months.

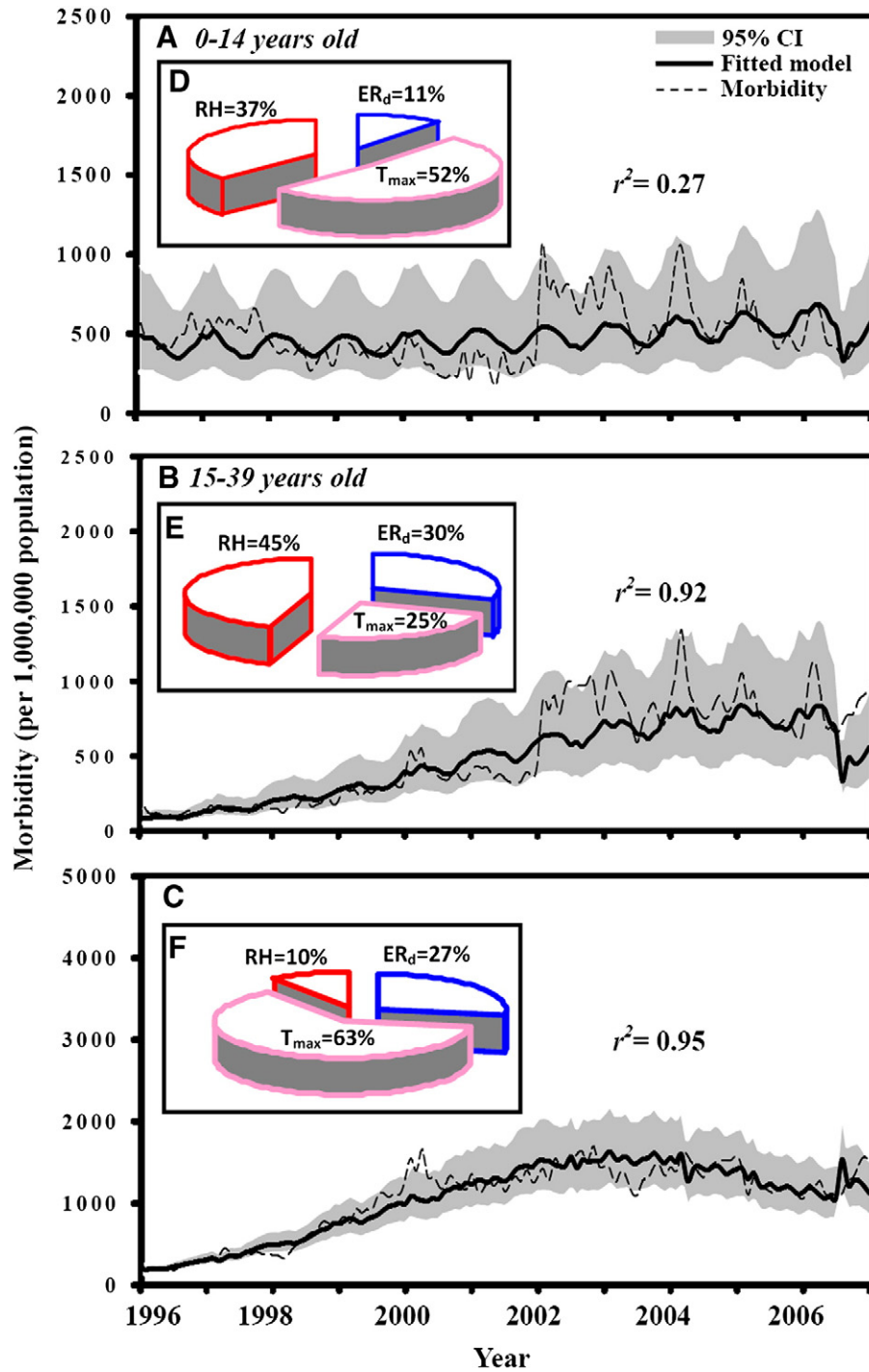


Fig. 2. A Poisson regression model fitting the trends of monthly age-specific diarrhea morbidity and monthly weather factors, including monthly maximum temperature (T_{\max}), extreme rainfall days (ER_d) and relatively humidity (RH), in age groups of (A) 0–14, (B) 15–39 and (C) 40–64 years old. Contribution of monthly maximum temperature, extreme rainfall days, and relative humidity to diarrhea-associated morbidity in age groups of (D) 0–14, (E) 15–39, and (F) 40–64 years old.

correlated with the extreme rainfall days at lag one ($r^2=0.28$) and two months ($r^2=0.35$).

3.3. Regression analysis

This study developed a Poisson regression model (Eq. (2)) with monthly diarrhea diseases and the higher correlated weather variables ($r^2 \geq 0.5$ and p -value < 0.05) listed in Table 2. This model showed that peaks in monthly diarrhea morbidity corresponded well

with this regression model during the study period (Fig. 1). The Poisson regression model was used to best-fit various age-specific morbidity of diarrhea (Table 3), and the contribution of climatic factors to diarrhea disease was examined by Poisson regression (Fig. 2). The results in Table 3 indicated that the monthly maximum temperature (1-month lag), number of extreme rainfall days (2-month lag), and relative humidity (no lag) had statistically significant effects (p -value < 0.05) on age-specific morbidity of diarrhea in the Poisson regression model. Fig. 2 demonstrated that the goodness-of-

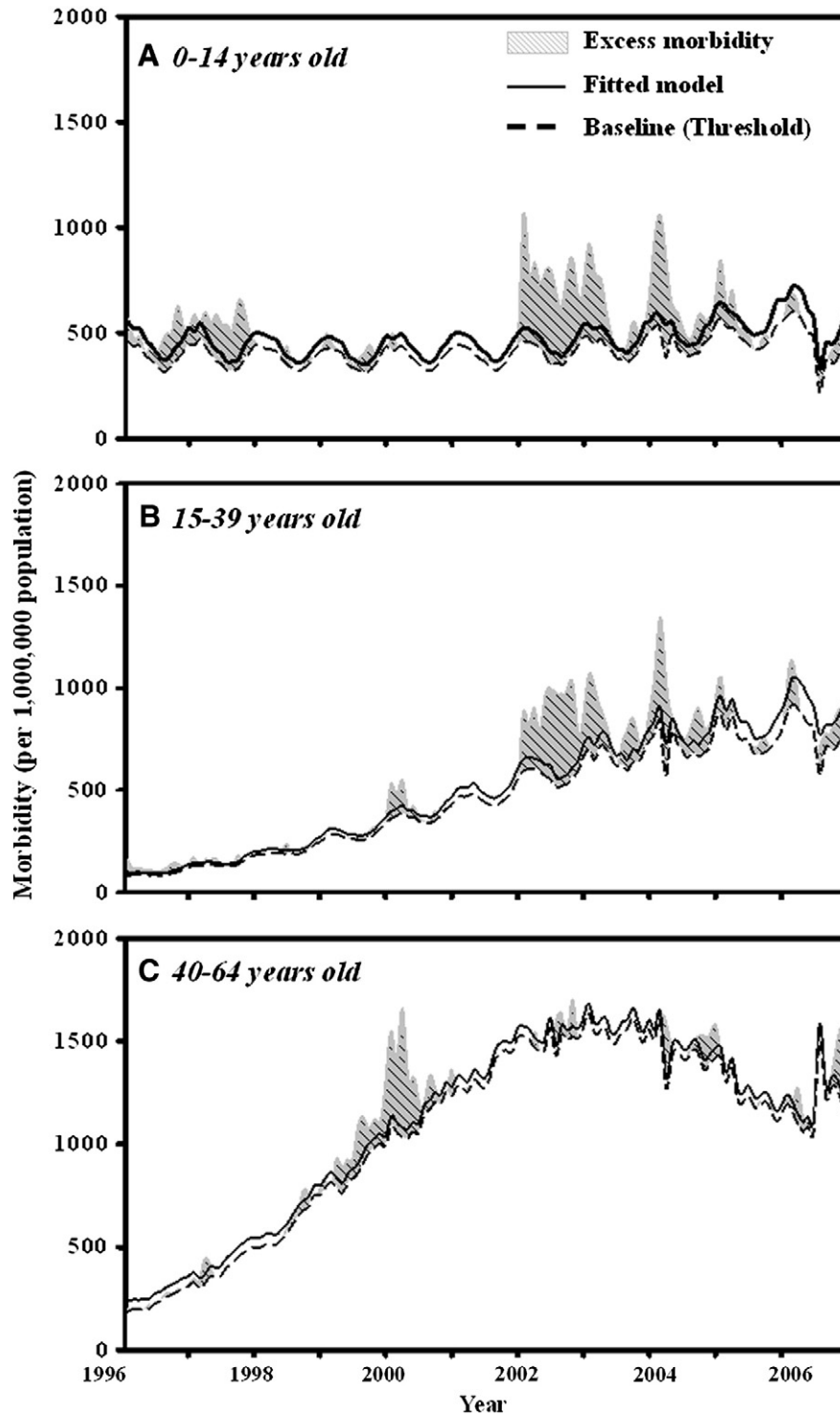


Fig. 3. Dynamics of excess diarrhea morbidity posed by extreme weather events in analysis with Poisson regression model among various age groups (A) 0–14, (B) 15–39, and (C) 40–64 years old from 1996 to 2007.

fit with a correlation between observed and expected morbidity of diarrhea exceeded 90% except for the age group 0–14 years old ($r^2 = 0.27$). This study indicated that the maximum temperature contributed approximately more than 50% morbidity of diarrhea among age groups 0–14 and 40–64 years old. Additionally, extreme rainfall and maximum temperature contributed 30% and 25%, respectively, to the 15–39 years old group.

3.4. Excess risk assessment

A baseline of moderate diarrhea morbidities among various age groups was used to estimate the excess morbidities attributed to extreme weather events (Fig. 3). Fig. 4 illustrated the excess morbidity of diarrhea for various age groups from 1996 to 2007. The highest excess diarrhea morbidity per 1,000,000 population occurred

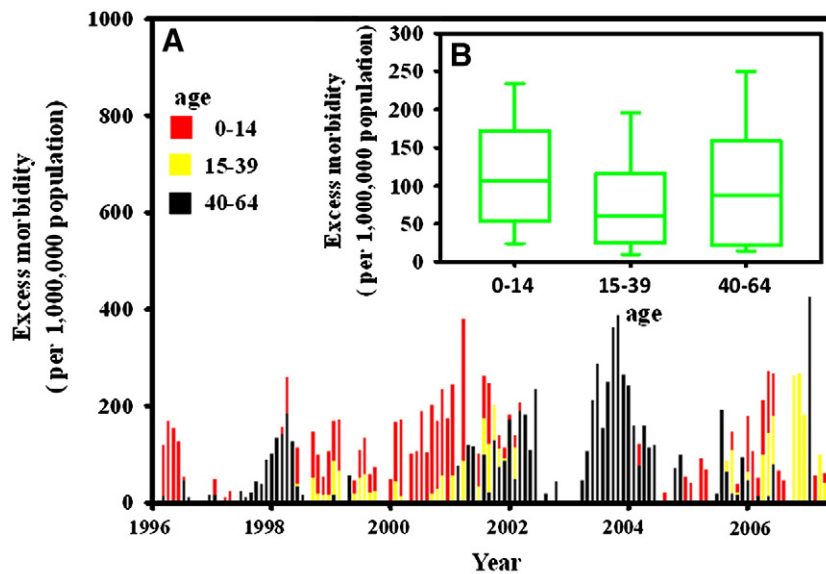


Fig. 4. (A) Bar chart and (B) box plot of excess morbidity of age-specific diarrhea.

in the age group of 0–14 years old in 2002–2003 (mean range 230.26–603.59), 15–39 years old in 2002–2003 (mean range 189.89–466.77), and 40–64 years old in 2000–2001 (mean range 0–624.15) (Table 4). The average excess diarrhea morbidity was 107.24, 57.37 and 85.38 in age groups of 0–14, 15–39 and 40–64 years old (Fig. 4B).

This study applied a lognormal distribution to optimally fit the excess diarrhea morbidity attributed to extreme weather events, and used excess risk to evaluate the excess diarrhea morbidity posed by extreme weather events (Fig. 5). The risk curves for excess diarrhea morbidity indicated that more than 20% of the population in Taiwan was susceptible to diarrhea (risk = 0.2). It was approximately 203.62 (95% CI 151.38–232.49), 157.34 (95% CI 113.96–179.02), and 201.22 (95% CI 155.35–227.22), respectively, for age groups of 0–14, 15–39 and 40–64 years old (Fig. 5D, E, F). Table 5 summarized the excess diarrhea morbidity at risk of 0.2, 0.5 and 0.8 for various age groups.

4. Discussion

Recent studies indicated that climate change poses real risk to human health (Mcmichael et al., 2006). Future climate change could exacerbate a number of current health problems, including heat-related mortality (Ostro and Roth, 2009), dengue fever, (Wu et al., 2009) and diarrhea (Hashizume et al., 2007). Taiwan is not immune to the effects of projected climate change on public health (Lin et al., 2009; Hsieh and Chen, 2009). This study applied a time-series Poisson regression model

to predict the monthly cases of diarrhea in Taiwan from 1996 to 2007 based on weather condition data. Results showed that local climatic factors significantly influenced on the dynamics of diarrhea, revealing a relationship between the time-lag effect, coincident weather conditions, and age-specific diarrhea morbidity. Interestingly, the effect of extreme weather variables (monthly maximum temperature and heavy rainfall) in this model contributed greatly to diarrhea morbidity. The significant contribution indicated a strong effect of extreme weather events on the dynamics of diarrhea epidemics.

From a modeling perspective, mathematical approaches are available for combing the cyclic forcing into the epidemiological investigations. Several researchers used the Poisson regression model to describe diarrhea-associated hospital admissions and death rates worldwide (Pascual et al., 2000; Kale et al., 2004; Hashizume et al., 2007; de Magny et al., 2008; Zhang et al., 2010). The current study used a time-series Poisson regression model to estimate the diarrhea morbidity attributed to weather conditions. The best-fitted Poisson regression model captured the effect of annual trends, seasons, monthly maximum temperatures, and the cumulative number of monthly extreme rainfall days, with a lag time of 1–2 month on age-specific diarrhea-associated morbidity (Tables 2 and 3). A higher correlations appeared for the age groups of 14–39 ($r^2 = 0.92$) and 40–65 ($r^2 = 0.94$) than for the 0–14 age group ($r^2 = 0.27$). This positive relationship between climatic variations (i.e., temperature and heavy rainfall) and diarrhea morbidity is similar to recent findings in North

Table 4
Estimated diarrhea-associated morbidity in Taiwan from 1996 to 2007.

Years	Excess morbidity (1/1,000,000 population)		
	0–14	15–39	40–64
1996–1997	99.42 (5.34–253.44) ^a	30.45 (7.97–74.39)	4.91 (0–21.23)
1997–1998	169.54 (19.39–313.74)	16.94 (0–42.75)	19.28 (0–120.69)
1998–1999	12.94 (0–83.86)	5.81 (0–47.69)	23.21 (0–93.14)
1999–2000	37.61 (0–122.59)	11.32 (0–36.31)	136.39 (0–312.86)
2000–2001	6.86 (0–82.34)	50.33 (0–171.19)	216.84 (0–624.15)
2001–2002	1.65 (0–19.79)	0.0 (0)	2.07 (0–24.86)
2002–2003	369.42 (230.26–603.59)	338.74 (189.89–466.77)	29.59 (0–165.28)
2003–2004	159.44 (0–448.54)	157.62 (0–389.22)	0.0 (0)
2004–2005	213.26 (83.05–544.57)	190.03 (61.81–521.61)	83.63 (0–315.25)
2005–2006	64.35 (0–281.76)	38.56 (0–181.38)	3.07 (0–21.41)
2006–2007	45.08 (0–122.07)	95.46 (0–216.59)	112.07 (0–396.44)

^a Mean with 95% confidence interval in the parenthesis.

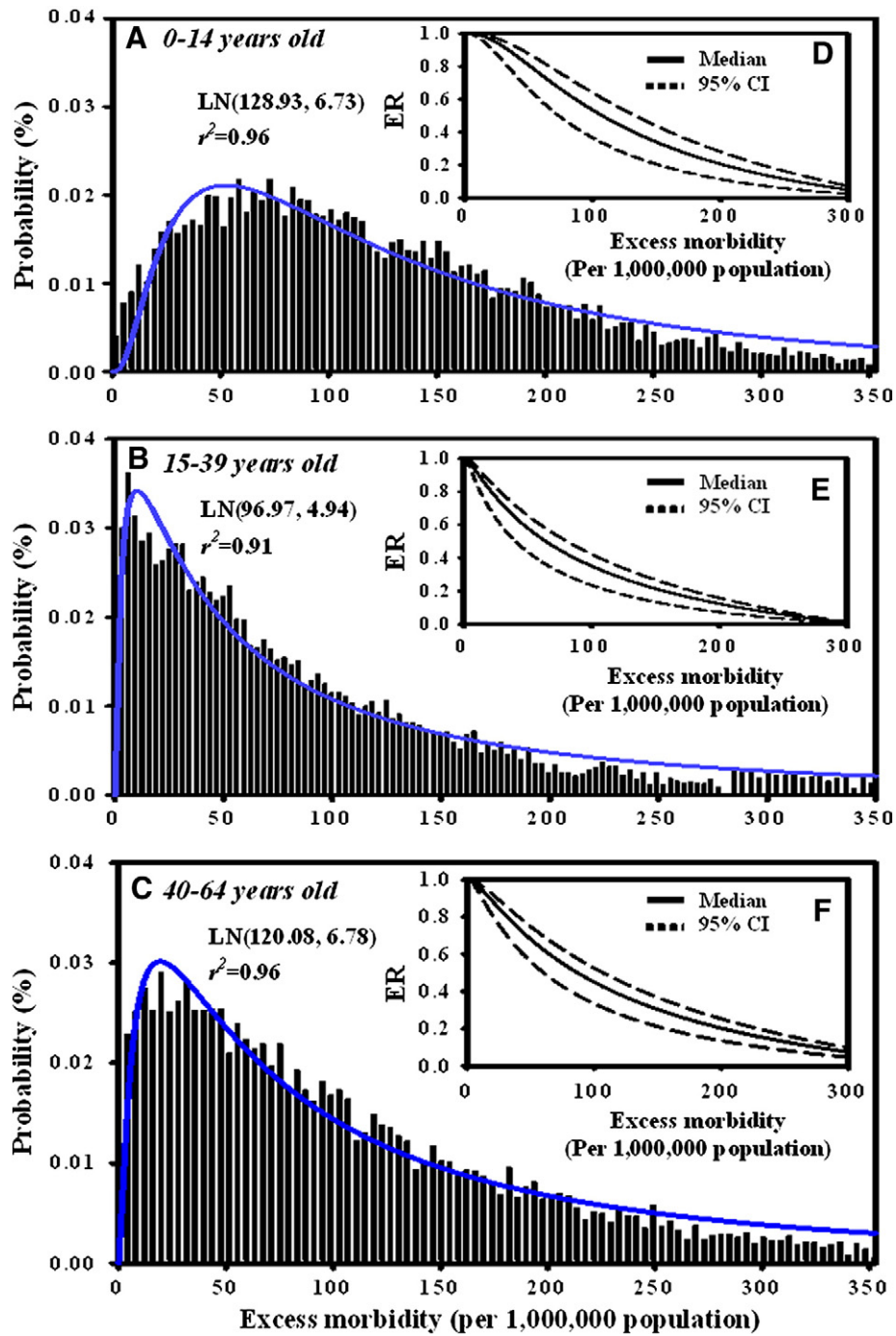


Fig. 5. A lognormal distribution for excess diarrhea morbidity at three age-specific baseline in age groups of (A) 0–14, (B) 15–39, and (C) 40–64 years old in the burden of extreme weather events. Excess risk (ER) curves among various age groups (D) 0–14, (E) 15–39 and (F) 40–64 years old.

America, Europe and Australia (Kovats et al., 2005; Fleury et al., 2006; Zhang et al., 2010).

This study revealed several important findings. First, results showed that maximum temperature contributed 52% and 63% to morbidity, respectively, in predicting the dynamics of diarrhea disease for children (0–14 years) and older adult (40–64 years) groups (Fig. 2A and C). This implied that increased temperature may influence the incidence of diarrhea. This finding revealed that children have increased exposure to many viral, bacterial and parasitic pathogens (Cama et al., 1999; Checkley et al., 2000). Therefore, this suggested that higher temperatures played an important role in the epidemics of diarrhea disease via increased viral exposure and transmission for diarrhea, and children and older adult were

Table 5
Risk analysis of diarrhea morbidity among age-specific groups.

Age group	Excess risk (ER)		
	0.8	0.5	0.2
0–14	51.03 (33.16–66.15) ^a	107.39 (73.02–133.51)	203.62 (151.38–232.49)
15–39	21.18 (12.75–28.41)	64.56 (40.46–80.22)	157.34 (113.96–179.62)
40–64	31.49 (20.78–40.66)	86.53 (106.41–60.54)	201.22 (155.35–227.22)

^a Median with interquartile range in the parenthesis.

susceptible population at high risk and exhibited significant morbidity to diarrhea diseases due to their weak immune system.

Second, the proposed model revealed that the relative humidity (45%) and number of extreme rainy days (30%) had higher proportional contribution to the diarrhea-associated morbidity among the 15–39 age group (Fig. 2B). Although relative humidity was not a statistically significant effect included in this Poisson regression model (Table 3), the relative humidity was strongly linked with the numbers of extreme rainy days, and thus its effect on morbidity was dependent on its relation with the number of heavy rainy day. This indicated that the number of extreme rainy days dominated the diarrhea-associated morbidity in the 15–39 age group rather than relative humidity. Previous studies showed evidences supporting the role of extreme rainfall in the dynamics of diarrhea (Buddemeier, 1992; Watson et al., 1998; Checkley et al., 2000). In subtropical Taiwan, however, flash flooding and water discharges rapidly into the sea without having been used effectively are frequently a problem. Thus, extreme rainfall is likely to be a worse problem for diarrhea in Taiwan.

Third, climatic variables may not directly affect the number of cases for diarrhea, but pose the disease outbreak through various pathways as mentioned above. Therefore, the lag effects of these climatic variables on the number of cases of diarrhea morbidity were observed in this study. Zhang et al. (2010) reported that the impact of temperature on diarrhea morbidity has shorter lagged time in tropical Townsville (0 month) than in this study (1 month). This difference may be relevant to the stable ambient temperature in the tropical region. However, the lag effects of rainfall on diarrhea morbidity in Townsville (3 month) are longer than in this study (2 month), which may be due to less rainfall in the tropical region. The variety of lag effect from the impact of climatic variables on diarrhea-associated morbidity has important implications. Precise local climatic conditions should be taken into account on the strategies for prevention and control of diarrhea-associated diseases.

Diarrhea-related studies have no well defined for age-specific effect on diarrhea-associated morbidity. This study indicated that different age groups were affected differently by the results obtained from the Poisson regression models and the estimates of excess morbidity. However, this study cannot exactly predict the dynamics of diarrhea-associated disease in children (0–14 years) population implying that the predicting model had the limitation in age-specific characteristics or other confound factors, such as behavior patterns, vaccination coverage, immune system and dietary habit. Therefore, more detailed age-specific information could justify the peak values in dynamics of diarrhea-associated morbidity. Yet, the predicting model considering the age-specific effect on diarrhea-associated morbidity still could provide some insights on deciding the government policy or establishing the management of an early warning system.

Predicting diarrhea-associated morbidity in Taiwan using climatic factors alone is imperfect because diarrhea epidemics involve complex and critical interactions between intrinsic dynamics and extrinsic environmental factors, as indicated by different seasonal patterns. However, these confounder factors remained consistent over the study period, and thus the association between climatic variables and diarrhea morbidity can be predicted by the time-series analysis after controlling for the confounders. Furthermore, the excess diarrhea morbidity may be overestimated by the Poisson regression model, primarily attributed to the climatic change. This is because some of the diarrhea morbidities outside these periods are likely due to the interactions between pathogens and human immune system or various individual behaviors. Therefore, more of environmental or climatic observation and detailed surveillance data (including viral, antigenic, and whole-genome analysis) would likely improve the accuracy to predict diarrhea morbidity. Moreover, it is necessary to seek novel mechanism and further provide biologically plausible and epidemiological information for an optimal early warning system.

In summary, this study provided a foundation for predicting diarrhea epidemics for various age groups (children (0–14 years), adult (15–39 years) and seniors (40–65 years)), and proposed an early warning system to enhance public health measures in Taiwan and areas of the world that suffer from climate change. A best-fitted Poisson seasonal regression model quantitatively analyzed extreme weather events relevant to the age-specific diarrhea-associated diseases in Taiwan, and the selected climatic factors effectively served as indicators of diarrhea morbidity. Results suggested that monthly maximum temperature and monthly number of extreme rainfall with a lag time of 1–2 months was contributed to diarrhea-associated morbidity. Excess risk attributed to extreme weather events in age-specific diarrhea morbidity was also probabilistically quantified. Future studies should develop a fully integrated model for diarrhea prediction that accounts for the components of human population exposed to diarrhea-associated diseases and the complexity of diarrhea epidemiology, and climatic and environmental factors and the genomics analysis of diarrhea pathogens.

Acknowledgment

This study received funding from National Science Council Taiwan NSC 94-EPA-Z-039-001.

References

- Auld H, Maclver D, Klaassen J. Heavy rainfall and waterborne disease outbreaks: the Walkerton example. *J Toxicol Environ Health A* 2004;67:1879–87.
- Buddemeier R. Climate change and island freshwater resources: climate change and sea level rise in the South Pacific Region. Presented at the second SPREP Meeting, 1–10 April 1992, Noumea, New Caledonia; 1992.
- Cama RI, Parashar UD, Taylor DN, Hickey T, Figueroa D, Ortega YR, et al. Enteropathogens and other factors associated with severe disease in children with acute watery diarrhea in Lima, Peru. *J Infect Dis* 1999;179:1139–44.
- Checkley W, Epstein LD, Gilman RH, Figueroa D, Cama RI, Patz JA, Black RE. Effects of *El Niño* and ambient temperature on hospital admissions for diarrhoeal disease in Peruvian children. *Lancet* 2000;355:422–50.
- Checkley W, Epstein LD, Gilman RH, Cabrera L, Black RE. Effects of acute diarrhea on linear growth in Peruvian children. *Am J Epidemiol* 2003;166:75.
- de Magny GC, Murtugudde R, Sapiano MRP, Nizam A, Brown CW, Busalacchi AJ, Yunus M, Nair GB, Gil AI, Lanata CF, Calkins J, Manna B, Rajendran K, Bhattacharya MK, Huq A, Sack RB, Colwell RR. Environmental signatures associated with cholera epidemics. *Proc Natl Acad Sci U S A* 2008;105:17676–81.
- Emch M, Feldacker C, Islam MSA. Seasonality of cholera from 1974 to 2005: a review of global patterns. *Int J Health Geogr* 2008;7:1–13.
- Fernandez MAL, Bauernfeind A, Jimenez JD, Gil CL, El Omeiri N, Guibert DH. Influence of temperature and rainfall on the evolution of cholera epidemics in Lusaka, Zambia, 2003–2006: analysis of a time series. *Trans Roy Soc Trop Med Hyg* 2009;103:137–43.
- Fleury M, Charron DF, Holt JD, Allen OB, Maarouf AR. A time series analysis of the relationship of ambient temperature and common bacterial enteric infections in two Canadian provinces. *Int J Biometeorol* 2006;385–91.
- Gajadhar AA, Allen JR. Factors contributing to the public health and economic importance of waterborne zoonotic parasites. *Vet Parasitol* 2004;126:3–14.
- Gregory PJ, Johnson SN, Newton AC, Ingram JSI. Integrating pests and pathogens into the climate change/food security debate. *J Exp Bot* 2009;60:2827–38.
- Hashizume M, Armstrong B, Hajat S, Wagatsuma Y, Faruque AS, Hayashi T, Sack DA. Associated between climate variability and hospital visit for non-cholera diarrhoea in Bangladesh: effects and vulnerable groups. *Int J Epidemiol* 2007;36:1030–7.
- Hsieh YH, Chen CWS. Turning points, reproduction number, and impact of climatological events for multi-wave dengue outbreaks. *Trop Med Int Health* 2009;14:628–38.
- Hsu HH, Chen CT. Observed and projected climate change in Taiwan. *Meteorol Atmos Phys* 2002;79:87–104.
- Kale PL, Hinde JP, Nobre FF. Modeling diarrhea disease in children less than 5 years old. *Ann Epidemiol* 2004;14:371–7.
- Kovats RS, Edwards S, Charron D, Cowden J, D'Souza RM, Ebi KL, et al. Climate variability and campylobacter infection: an international study. *Int J Biometeorol* 2005;49:207–14.
- Kramer K, Friend A, Leinonen I. Modelling comparison to evaluate the importance of phenology and spring frost damage for the effects of climate change on growth of mixed temperate-zone deciduous forests. *Clim Res* 1996;7:31–41.
- Lin CY, Lung SC, Guo HR, Wu PC, Su HJ. Climate variability of cold surge and its impact on the air quality of Taiwan. *Clim Change* 2009;94:457–71.
- McMichael A, Woodruff RE, Hales S. Climate change and human health: present and future risks. *Lancet* 2006;367:859–69.
- Ostro BD, Roth LA, Green RS, Basu R. Estimating the mortality effect of the July 2006 California heat wave. *Environ Res* 2009;109:614–9.

- Pascual M, Rodó X, Ellner SP, Colwell R, Bouma MJ. Cholera dynamics and El Niño-southern oscillation. *Science* 2000;289:1766–9.
- Patz JA, Lendrum DC, Holloway T, Foley JA. Impact of regional climate change on human health. *Nature* 2005;438:310–7.
- Rodo X, Pascual M, Fuchs G, Faruque ASG. ENSO and cholera: a nonstationary link related to climate change? *Proc Natl Acad Sci U S A* 2002;99:12901–6.
- Semenza JC, Menne B. Climate change and infectious diseases in Europe. *Lancet Infect Dis* 2009;9:365–75.
- Stott PA, Stone DA, Allen MR. Human contribution to the European heatwave of 2003. *Nature* 2004;432:610–4.
- Watson RT, Zinyowera MC, Moss RH. The regional impacts of climate change: an assessment of vulnerability. Cambridge, UK: Cambridge University Press; 1998.
- WHO. Water-related diseases. Water sanitation and health (WSH), vol. 2008. World Health Organization.
- Wu PC, Lay JG, Guo HR, Lin CY, Lung SC, Su HJ. Higher temperature and urbanization affect the spatial patterns of dengue fever transmission in subtropical Taiwan. *Sci Total Environ* 2009;407:2224–33.
- Zhang Y, Bi P, Hiller JE. Climate variations and *Salmonella* infection in Australian subtropical and tropical regions. *Sci Total Environ* 2010;408:524–30.