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Weather and notified *Campylobacter* infections in temperate and sub-tropical regions of Australia: An ecological study

Peng Bi [a,*], A. Scott Cameron [a,b], Ying Zhang [a], Kevin A. Parton [c]

[a] *Discipline of Public Health, The University of Adelaide, North Terrace, Adelaide, SA 5005, Australia*
[b] *National Centre for Epidemiology and Population Health, Australian National University, Australia*
[c] *School of Marketing and Management, Charles Sturt University, Orange, NSW, Australia*

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Summary *Background:* The relationship between weather and food-borne diseases has been of great concern recently. However, the impact of weather variations on food-borne disease may vary in different areas with various geographic, weather and demographic characteristics. This study was designed to quantify the relationship between weather variables and *Campylobacter* infections in two Australian cities with different local climatic conditions.
Methods: An ecological–epidemiological study was conducted, using weekly disease surveillance data and meteorological data, over the period 1990–2005, to quantify the relationship between maximum and minimum temperatures, rainfall, relative humidity and notifications of *Campylobacter* infections in Adelaide, with a temperate Mediterranean climate, and Brisbane, with a sub-tropical climate. Spearman correlation and time-series adjusted Poisson regression analyses were performed taking into account seasonality, lag effects and long-term trends.
Results: The results indicate that weekly maximum and minimum temperatures were inversely associated with the weekly number of cases in Adelaide, but positively correlated with the number of cases in Brisbane, with relevant lagged effects. The effects of rainfall and relative humidity on *Campylobacter* infection rates varied in the two cities.
Conclusion: Weather might have different effect on *Campylobacter* infections in different cities. Further studies are needed for a better understanding of these relationships for they may indicate epidemiologic factors important for control of these infections.

Background

Campylobacter infection has emerged as a leading bacterial cause of gastroenteritis in developed countries since the 1970s.[1] New Zealand and Australia have the highest

* Corresponding author. Tel.: +61 8 8303 3583; fax: +61 8 8303 6885.
E-mail address: peng.bi@adelaide.edu.au (P. Bi).

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incidence rates.[2,3] In Australia, enteric infection is an important public health issue with approximately 17 million cases annually and 4—7 million of these estimated as food-borne.[3] It is estimated that food-borne diseases cause about 76 million illnesses in the US each year.[4] High incidence of enteric infections was also found in the UK[5] and Canada.[6] In Australia, the cost of enteric infections was estimated to be over $1.2 billion each year approximately.[7] In 2004, the Australian national food-borne diseases surveillance system, recorded 24,313 notifications of eight potentially food-borne diseases, along with 118 outbreaks of food-borne disease. The most common sporadic disease was *Campylobacter* infections (15,640 cases).[8] All age groups are affected, but infections are prominent in children under five years and in young adults.[8]

The relationship between environmental factors and enteric infections has been studied, and the results from the USA and Europe indicate that environmental factors, including weather variables, may influence the reservoir, the growth and dissemination of the micro-organisms responsible for enteric infections including *Campylobacter* infection.[5,6,9—12] It is not certain whether the results from these previous studies can be applied to different ecological/meteorological regions, given various population characteristics, eating behaviors, food processing chains, socio-economic status and climate types. Therefore, we have studied the relationship between weather variables and weekly notified *Campylobacter* infections, using time-series analysis, in two Australian cities, Brisbane and Adelaide, with sub-tropical and temperate climatic conditions, respectively. The objective of this study is to determine whether there is an association between weather variables and *Campylobacter* infection in different climatic areas in Australia, because this may lead to discerning of epidemic factors important for control of these infections.

Materials and methods

Background information

Adelaide is the capital city of the State of South Australia. Situated at the intersection of latitude: 34°56′S and longitude: 138°35′E with an altitude of 43 m (Fig. 1). The population was approximately 1.1 million over the study period. The city has a typical Mediterranean climate with mild-to-cool, wet winters and hot, dry summers. Brisbane is the capital city of the State of Queensland, lying at the intersection of latitude: 27°23′S and longitude: 153°7′E (Fig. 1). Over the study period, the population was approximately 1.6 million. It has a sub-tropical climate with very hot humid summers and mild, dry, sunny winters. Most rain falls during summer, between November and February.

Data collection

Disease surveillance data

Laboratory-confirmed *Campylobacter* infections from 1990 to mid-2005 in Adelaide and Brisbane were provided by the Communicable Diseases Control Branches (CDCB) of the South Australian Department of Health and Queensland Department of Health. The data include daily, weekly and monthly counts of the cases over the study period. These notification systems record the onset of disease, which is more useful for epidemiological studies than the date of notification which for the most part has been used in previous research.

Meteorological data

The weather stations used in this study are the Kent Town station in Adelaide and Brisbane Airport station. Both stations have a long history of weather records which represent the local weather variability very well, according to the Australian Bureau of Meteorology. Daily, weekly and monthly weather variables, including mean maximum and minimum temperatures, relative humidity at 9 am and 3 pm and rainfall over the study period were provided.

Data analysis

After a descriptive summarization of weather variables and disease incidence, Spearman's correlation coefficients were calculated between weather variables and the notified number of the cases on a weekly basis. To examine lagged effects, lags of 1—15 weeks were included. The lagged effects of climatic variables were explored by cross-correlation analysis and the climatic variables with the maximum correlation coefficient are presented.

In contrast with standard regression models, it is desirable to allow the dependent variable to be influenced by both the past values of independent variables and possibly by its own past values.[13]Time-series adjusted Poisson regression analysis was performed, using Stata,[14] allowing consideration of autocorrelation, seasonality and lag effects. Potential seasonal variation was controlled for by including a categorical seasonal variable. Test of the possibility of over-dispersion of Poisson distribution was performed, and the result did not demonstrate extra-Poisson variation in this study. Seasons in Australia were defined according to local weather: 0-summer (weeks 49—8), 1-spring (weeks 37—48), 2-autumn (weeks 9—22), 3-winter (weeks 23—36). Moreover, in order to control for the interannual trend in the number of cases over the 15-year study period, a variable was included in the regression model specifying the year of onset. To avoid the problem of multicollinearity due to the high correlation among the climatic variables in both cities, particularly between weekly mean minimum and maximum temperatures ($r > 0.8$), and between relative humidity at 9am and 3pm ($r > 0.7$), two models were set up. Model I had maximum temperature and humidity at 9am as explanatory variables, and Model II had minimum temperature and humidity at 3pm.

The primary Poisson regression model adjusted for autocorrelation for this study was: $\ln(Y_t) = \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t\text{-}2} + \cdots + \beta_p Y_{t-p} + \beta_{p+1}\ \text{temperature}_t + \beta_{p+2}\ \text{temperature}_{t-1} + \cdots + \beta_{p+q}\ \text{temperature}_{pt-q} + \beta_{p+q+1}\,\text{rainfall}_t + \beta_{p+q+2}\,\text{rainfall}_{t-1} + \cdots + \beta_{p+q+r}\ \text{rainfall}_{t-r} + \beta_{p+q+r+1}\,\text{humidity}_t + \beta_{p+q+r+2}\text{humidity}_{t-1} + \cdots + \beta_{p+q+r+s}\text{humidity}_{t-s} + \beta_{p+q+r+s+1}\text{Season} + \beta_{p+q+r+s+2}\text{Year}$, where p, q, r are the lags determined by correlation analysis. The stepwise method was used in the analysis to include variables as long as there was a significant improvement determined by calculation of the maximum likelihood.[15] Only final parameter estimates of regression Model I are presented.