The Relationship between Climate Variation and Selected Infectious Diseases: Australian and Chinese Perspectives

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“Those who continue to ignore the threat will be doing the greatest disservice imaginable to current and future generations.” - Marthinus van Schalkwyk, Environmental Affairs Minister for South Africa

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Peer-reviewed Journals:

1. Zhang Y, Bi P, Wang G and Hiller JE. *El Nino Southern Oscillation and dysentery in Shandong province, China.* Environmental Research. 2007, 103: 117-20.
2. Zhang Y, Bi P, Hiller JE, Sun Y and Ryan P. *Climate variation and bacillary dysentery in northern and southern cities of China.* Journal of Infection. 2007, 55: 194-200.
3. Zhang Y, Bi P and Hiller JE. *Climate variation and salmonellosis transmission: a comparison of regression models.* International Journal of Biometeorology. Published online 11 July 2007. DOI 10.1007/s00484-007-0109-4.
4. Zhang Y, Bi P and Hiller JE. *Climate variations and the transmission of bacillary dysentery in Jinan, northern China: A time-series analysis.* Public Health Reports. Article in press. Accepted July 2007.
5. Zhang Y, Bi P and Hiller JE. *Climate change and disability adjusted life years.* Journal of Environmental Health. Article in press. Accepted July 2007.
6. Zhang Y, Bi P and Hiller JE. *Climate change and the transmission of vector/rodent-borne diseases: A review.* Asia-Pacific Journal of Public Health. Article in press. Accepted March 2007.

Non-peer-reviewed Journals[*]:

1. Bi P and Zhang Y. *Climate change and water-borne diseases.* Public Health Bulletin South Australia. 2007, 4: 23-5.
2. Bi P and Zhang Y. *Vector-borne diseases in Australia.* Public Health Bulletin South Australia. 2006, 4: 9-11.

[*] Contribution to these two papers: conducted the literature review and completed the first draft.

Conference presentations:

1. Zhang Y, Bi P and Hiller JE. *Climate and transmission of bacillary dysentery in Jinan, Eastern China: a time-series analysis (Oral).* The Earth System Science Partnership (ESSP) Global Environmental Change Open Science Conference (OSC). Beijing, China, November 2006, p458.
2. Zhang Y, Bi P and Hiller JE. *Meteorological variables and the transmission of bacillary dysentery: any differences between northern and southern China (Oral)?* The 18th Conference of the International Society for Environmental Epidemiology. Paris, France, September 2006, p328.
3. Zhang Y, Bi P and Hiller JE. *Climate and transmission of malaria in Jinan, a temperate city in China (Oral).* The 15th Annual Scientific Meeting of the Australasian Epidemiological Association. Melbourne, Australia, September 2006, p62-3.
4. Zhang Y, Wang G, Bi P and Hiller JE. *Dysentery and Southern Oscillation Index (SOI) in Shandong, China: a time-series analysis (Oral).* The 14th Annual Scientific Meeting of the Australasian Epidemiological Association. Newcastle, Australia, October 2005, p54.
5. Zhang Y, Bi P and Hiller JE. *Climate variation and salmonellosis in Adelaide, South Australia: a time-series analysis (Oral).* The XVII International Scientific Meeting of the International Epidemiological Association (IEA). Bangkok, Thailand, August 2005, p156.

AWARDS RECEIVED DURING CANDIDATURE

- Chinese government award for outstanding self-financed students abroad. China Scholarship Council. 2007.
- Postgraduate travelling fellowship. Faculty of Health Sciences Research Committee, University of Adelaide. 2006.
- Travel grant. The International Society of Environmental Epidemiology and Exposure (ISEE/ISEA) Conference Committee. Paris, France. 2006.
- Travel grant. The Earth System Science Partnership (ESSP) Open Science Conference Committee. Beijing, China. 2006.
- Student bursary. The Australasian Epidemiological Association Annual Conference Committee. Newcastle, Australia. 2005.
- International postgraduate research scholarship (IPRS). Australian Government. 2004-2007.
- Postgraduate research awards. University of Adelaide. 2004-2007.

LIST OF ABBREVIATIONS

AIC:	Aikake Information Criterion
ARIMA:	Autoregressive Integrated Moving Average
CRA:	Comparative Risk Assessment
DALY:	Disability Adjusted Life Year
EBD:	Environmental Burden of Disease
ENSO	El Nino-Southern Oscillation
GBD:	Global Burden of Disease
GCM:	General Circulation Model
GHG:	Greenhouse Gas
GIS:	Geographic Information Systems
HFRS:	Haemorrhagic Fever with Renal Syndrome
IPCC:	Intergovernmental Panel on Climate Change
NBD:	National Burden of Disease
RRV:	Ross River Virus
SARIMA:	Seasonal Autoregressive Integrated Moving Average
SOI:	Southern Oscillation Index
UNEP:	United Nations Environment Programme
WHO:	World Health Organization
YLD:	Years Lost due to Disability
YLL:	Years of Life Lost

ABSTRACT

Background

Climate variation has affected diverse physical and biological systems worldwide. Population health is one of the most important impacts of climate variation. Although the impact of climate variation on infectious diseases has been of significant concern recently, the relationship between climate variation and infectious diseases, including vector-borne diseases and enteric infections, needs greater clarification.

Australia is grappling with developing politically acceptable responses to global warming. In China, few studies have been conducted to examine the effect of climate variation, including global warming, on population health. As residents of developing countries may suffer more from climate change compared with people living in more developed countries, this thesis has significance for both countries.

Aims

This study aims to contribute to a better understanding of the impact of climate variation on population health, and to provide scientific evidence for policy makers, researchers, public health practitioners and local communities in the development of public health strategies at an early stage, in order to prevent or reduce future risks associated with ongoing climate change.

The objectives of this study include:

(1) to quantify the association between climate variation and selected vector-borne diseases and enteric infections in different climatic regions in Australia and China;

(2) to project the future burden of selected vector-borne diseases and enteric infections based on climate change scenarios in different climatic regions in Australia and China.

Methods

This ecological study has two components. The first uses time-series analyses to quantify the relationship between meteorological variables and infectious diseases, whereas the second projects the burden of selected infectious diseases using future climate and population scenarios.

Temperate and subtropical climatic zones in both Australia and China were selected as the primary study areas, and a study of an Australian tropical region was also conducted. Study of Australia's temperate zones was conducted in Adelaide, South Australia, as well as the Murray River region in that State. The study of China's temperate zone was carried out in Jinan, Shandong Province. Subtropical studies were conducted in Baoan, Guangdong Province, China, and Brisbane in Queensland, whilst research for the tropics centred on Townsville, also in Queensland, Australia.

The selected infectious diseases - one vector-borne disease and one enteric infection in each country - are Ross River Virus (RRV) infection and salmonellosis in Australia, and malaria and bacillary dysentery in China. Study periods vary from eight to sixteen years (depending upon the availability of data). Climate data, infectious disease surveillance data and demographic data were collected from local authorities.

Data analyses conducted in the ecological studies include Spearman correlation analysis, time-series adjusted Poisson regression and the Seasonal Autoregressive Integrated Moving Average (SARIMA) model with consideration of lag effects, seasonality, long-term trends, and autocorrelation, on a weekly or monthly basis depending on data availability, and Hockey Sticky model to detect potential threshold temperatures. In the burden of disease component, analyses include the calculation of an indicator of the burden of disease - Years Lost due to Disabilities (YLDs) - and use scenario-based models to project YLDs for the selected diseases in 2030 and 2050 in Australia and 2020 and 2050 in China respectively. The projections consider both different scenarios of projected temperature and future population change.

Results

Relationship between climate variation and selected infectious diseases

In all the study regions in Australia, maximum temperature, minimum temperature, rainfall and humidity are all significantly related to the number of RRV infections, with lag effects varying from 0 to 3 months. Additionally, high tides in the two seaside regions with tropical (Townsville) or subtropical (Brisbane) climates, and river flow in the temperate region (Murray River region), are related to the number of cases without any lag effects. A potential 1°C increase in maximum or minimum temperature may cause 4%~23% extra cases of RRV infection in the temperate region, 5~8% in the subtropical region, and 6%~15% in the tropical region.

Maximum temperature, minimum temperature, humidity and air pressure are significantly related to malaria cases in the temperate city Jinan and subtropical city Baoan in China, with a lag effect range of 0 to 1 month. An association between rainfall and malaria cases was not detected in either region. A potential 1°C increase in maximum or minimum temperature may lead to 4%~15% extra malaria cases in the temperate region, and 12%-18% in the tropical region in China.

Maximum temperature, minimum temperature, rainfall and humidity are all significantly related to the number of salmonellosis cases in the three study cities in Australia, with lag effects varying from 0 to 1 month. A potential 1°C increase in maximum or minimum temperature may cause 6%~19% extra salmonellosis cases in the temperate region (Adelaide), 5%~10% in the subtropical region (Brisbane), and 4%~15% in the tropical region (Townsville). The thresholds for the effects of maximum and minimum temperatures are 20ºC and 12ºC respectively in Adelaide. No threshold temperatures are detected in Townsville and Brisbane.

Maximum temperature, minimum temperature, humidity, air pressure and rainfall are significantly related to bacillary dysentery cases in the temperate city Jinan and subtropical city Baoan in China, with the lag effect range of 0 to 2 months. A potential 1°C increase in maximum or minimum temperature may cause 7%~15% extra bacillary dysentery cases in the temperate region and 10% ~ 19% in the subtropical region in China. The thresholds for the effects of maximum and

minimum temperatures on bacillary dysentery are 17ºC and 8ºC respectively in Jinan. No threshold temperatures are detected in Baoan.

Projection of YLDs from target diseases

In Australia, considering both climatic and population scenarios, if other factors remain constant, compared with the YLDs observed in 2000, the YLDs for salmonellosis might increase by up to 48% by 2030, and nearly double by 2050 in South Australia, while the YLDs might double by 2030 and increase by up to 143% by 2050 in Brisbane, Queensland. The YLDs for RRV infection might increase by up to 66% by 2030, and nearly double by 2050 in South Australia. They might increase by up to 61% by 2030 and double by 2050 in Brisbane, Queensland.

In China, considering both climatic and population scenarios, if other factors remain constant, compared with the YLDs observed in 2000, the YLDs for bacillary dysentery might double by 2020 and triple by 2050 in both Jinan and Baoan. The YLDs for malaria might increase by up to 108% by 2020 and nearly triple by 2050 in Jinan, the temperate city, and increase by up to 144% by 2020 and nearly triple by 2050 in Baoan, the subtropical city.

Conclusions

1. Both maximum and minimum temperatures are important in the transmission of vector-borne diseases in various climatic regions in both Australia and China. River flow or high tides may also play an important role in the transmission of such diseases.
2. Both maximum and minimum temperatures play an important role in the transmission of enteric infections in various climatic regions in both Australia and China, with a threshold temperature detected in the temperate regions but not in subtropical and tropical regions.
3. The effects of rainfall and relative humidity on selected infectious diseases vary in different study areas in Australia and China.
4. The burden of temperature-related infectious diseases may greatly increase in the future if there is no effective preventive intervention.

Public health implications

1. Implication for health practice
    - Public health practitioners, together with relevant government organisations, should monitor trends in infectious diseases, as well as other relevant indexes, such as vectors, pathogens, and water and food safety. They should advise policy makers of the potential risks associated with climate change and develop public health strategies to prevent and reduce the impact of infectious disease associated with such change.
    - Doctors and other clinical practitioners should be prepared and supported in the provision of health care for any expected extra cases associated with climate variation and should play an important role in relevant health education on climate change.
    - Community participation is of significance to adapt to and mitigate the risk of climate change on population health. Community involvement helps to deliver programmes which more accurately target local needs. Therefore, community should be involved in the partnerships of climate change as early as possible.
    - Relevant education programs on the potential health impact of climate change should be conducted by government at all levels for different stakeholders, including industries, governments, communities, clinicians and researchers.
    - Advocacy for adapting to and mitigating climate change should be a longstanding public health activity.

2. Implication for researchers
    - The main task for researchers is to identify the independent contribution made by key climatic variables and whether there are exposure thresholds for infectious disease transmission. Further studies should include various infectious diseases in different climatic regions.
    - Developing countries and rural regions are more vulnerable to the impact of climate change so more research should be conducted for people living in those regions.
    - Studies using summary measures that combine prevalence of disease, quality of life and life expectancy, such as Disability Adjusted Life Years (DALYs),

to assess the burden of disease due to climate change is necessary to assist in decision making.

- More research should be conducted on the assessment of adaptive strategies and mitigation to future climate change.

3. Implication for policies
    - Public and preventive health strategies that consider local climatic conditions and their impact on vector and food borne diseases are important in reducing such impact due to climate change in the future.
    - The extra health burden that may be caused by future climate change may have a great impact on the currently overloaded public health system in both developed and developing countries. Long-term planning about health resource allocation, infrastructure establishment, and relevant response mechanisms should be developed at relevant government levels.
    - Effective prevention and intervention strategies will be possible only if the efforts of relevant sectors, including governments, communities, industries, research institutions, clinical professionals and individuals, have coordinated responses
    - International and regional collaborations are necessary to address this global issue. In addition, strategies of an international dimension should be translated into regional and local actions. This is extremely important to developing countries such as China and India.
    - Sustainable development policies with consideration given to reducing green house gases and environmental degradation need immediate action which will benefit future generations. Health priorities should include the prevention of climate change.

DECLARATION

I certify that this thesis does not incorporate any material previously submitted for a degree or diploma in any university. It does not contain any material previously published or written by another person except where due reference is made in the text. I give consent to a copy of my thesis being available for loan and photocopy in the University Library.

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Ying Zhang
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INTRODUCTION

There is substantial evidence showing that global climate has been changing and will continue to change. There is a clear increase in the world surface temperature during the last century [1]. It is projected that global average temperature will increase by up to 6ºC by 2100 compared to 1990 [1]. Climate change has already affected a diverse set of physical and biological systems worldwide, with the costs associated with climate change estimated to be about US$ 60 billion in 2003 [2]. This is obviously a global problem but the effects are already evident at a local level. Similar trends in warming have been projected in Australia and China. Most of Australia may warm by 1~6ºC by 2070 [3] and the average temperature in China may have increased by more than 2ºC by 2050 [4].

Among the potential impacts of climate change, public health may be one of the most important. In addition to the excess deaths, injuries and illness directly attributable to extreme weather events and climate-induced natural disasters, meteorological variables (such as ambient temperature, rainfall, relative humidity and air pressure), and El Nino Southern Oscillation may indirectly cause increased risk of infectious diseases by altering the distribution of vector species, influencing the reproduction of the pathogens, affecting the frequency and level of contamination of drinking water and affecting the behaviours of human beings to increase chances of contact [5].

Understanding the relationship between climate change and infectious diseases poses an unusual challenge to the scientific community. Firstly, it is difficult to collect high quality health surveillance, climatic and demographic data on a large population scale over a long period of time, particularly in developing countries. Secondly, advanced mathematic and statistical models with few uncertainties have yet to be developed to quantify this association. Thirdly, it is highly possible that the effects of climate change on infectious disease transmission may vary from context to context, given various climatic conditions, different vector or pathogen species, and the socio-economic status of populations in different regions. Moreover, so far, there have

been no published studies examining the burden attributable to climate change at a local (sub-national) level.

There is evidence suggesting an association between climate variability and infectious diseases, including vector-borne diseases and enteric infections [6]. Ross River virus infection (RRV) is the most notified vector-borne disease in Australia, with about 5,000 human cases reported annually [7]. Although studies on the impact of climate change on RRV infection have been conducted within Australia, most have focused only on tropical/subtropical areas; little is known about temperate areas such as South Australia. The association between climate variation and enteric infections is far from clear in Australia. Salmonellosis is one of the most commonly and widely distributed enteric infections, with millions of cases being reported worldwide every year [8]. In 2004, there were 7,842 notified cases in Australia [9]. Studies examining the relationship between climate variation and salmonellosis are limited.

In China, infectious diseases are still a public health threat. Recently, a re-emergence of malaria has been reported with more than 40,000 cases in China in 2003 [10]. Although the impact of climate variation on malaria has been investigated by many researchers, there are few studies conducted in China [5]. Enteric infection is still very serious in China, with approximately 500,000 cases of bacillary dysentery being notified in 2005 [11]. People living in developing countries with a higher population density, relatively crowded living conditions, and poor socio-economic status may suffer greater adverse impact of climate change.

The objectives of this study are to quantify the relationship between climate variation and selected vector-borne diseases and enteric infections in different climatic regions in Australia and China, and to project the climate attributable burden of the study diseases in these different climatic regions, in order to provide scientific evidence for local policy makers and communities to develop public health strategies to prevent or reduce future risks as climate change continues.

This study is composed of two parts. The first part uses time-series analyses to quantify the relationship between meteorological variables and infectious diseases, including RRV infection, salmonellosis, malaria and bacillary dysentery in regions with diverse climatic conditions in Australia and China. The second part projects the

burden of selected infectious diseases, in terms of Years Lost due to Disability (YLDs), under various future climate and population scenarios in the study areas in Australia and China.

Literature reviews on climate change and population health and the burden of disease attributable to climate change are presented in the first two chapters, followed by a chapter describing the overall study design. The two parts of the study are presented independently in chapter four and chapter five. Conclusions are summarised in the last chapter to address the key findings, discuss the limitations of the study, and suggest research directions for further studies.

CHAPTER I

LITERATURE REVIEW: CLIMATE CHANGE AND POPULATION HEALTH

1.1 Introduction

The relationship between climate change and population health has been of considerable concern recently. In the early 1990s, there was little public awareness of the health risks posed by global warming and climate change [1], which was reflected in the first report of the United Nation's Intergovernmental Panel on Climate Change (IPCC) [12]. Although there was little empirical data in the first assessment, three global assessments of health impact (in 1991, 1996 and 2001) and the latest report from the IPCC in 2007 have been conducted as a result of a growing awareness of climate change [13].

According to the report from the IPCC in 2007, during the 20th century the world average surface temperature has increased approximately 0.74°C [14]. Scientific evidence has shown that climate change in the last century could be, at least partly, attributable to human activities, and that further changes in climate are inevitable at both global and regional levels. It is projected that global average temperature will increase in the range of 1.4 to 5.8 ºC by 2100, compared to 1990 [15]. At a regional level, in Australia for instance, annual average temperatures will be 0.4~2.0°C higher by 2030, than those of 2002 [16]. Meanwhile, China also has shown a similar trend in warming and the average temperature there will have increased 2.2 ºC by 2050 [17].

The effects of climate change - direct and indirect - have been reported in many publications [6]. There is now good evidence that regional change in climate, particularly increases in temperature, have already affected a diverse set of physical and biological systems in many parts of the world [14]. The United Nations Environment Programme (UNEP) has reported that, in 2003, the worldwide cost of climate change was about US$ 60 billion, 10% higher than in 2002 [2]. Extreme temperature, heavy precipitation, and climate-induced natural disasters may directly cause excess deaths, injuries and illness. For example, McMichael et al [16] assessed that, in 2002, extreme temperatures contributed to the death of about 1,100 people over 65 years old in 10 Australian and two New Zealand cities. Moreover, many other effects may result from climate change, such as the degradation of the local

environment, reduction in yields of agricultural production and the loss of biodiversity [18].

The indirect impact of climate change on population health, including the effect of climate variation on infectious diseases, is not clear. Although evidence exists suggesting the association between vector-borne diseases, such as malaria, and meteorological variables, there are limitations and uncertainties in these studies in terms of data availability and reliability, study design, statistical methods and confounder control. Furthermore, the effects of climate change may vary in different regions with varying levels of economic development. The association between meteorological variables and enteric infections has received relatively little attention.

In this chapter, the extent of climate change, globally and regionally in Australia and China, is described, followed by a brief review of the impact of climate change on population health. The literature examining the association between climate variation and infectious diseases, including vector-borne diseases and enteric infections, is reviewed. Methodological issues arising in this research field are discussed and a summary is presented.

1.2 Changing climate

There are many factors including physical, chemical and biological processes that interact to affect the climate on the earth's surface, including factors intrinsic to the climate system itself and external factors derived from human activities. There is strong evidence to show that most of the warming observed over the last 50 years is the result of human activities [19].

It has been demonstrated that climate change is happening at a global level. According to the IPCC 2007 report [14], the global average surface temperature has increased approximately 0.74ºC during the last century. In addition, the warming trend has nearly doubled over the last 50 years. Observed changes in precipitation suggest that annual precipitation has continued to increase in the middle and high latitudes of the Northern Hemisphere (likely to be 0.5 to 1% per decade), except

eastern Asia. The rate of the global mean sea level rise during the 20th century is in the range of 1.0-2.0 mm per year. The activity of the El Nino-Southern Oscillation (ENSO) has been unusual since the mid-1970s compared with the previous 100 years, with warm phase ENSO episodes being relatively more frequent, more persistent and intense than the opposite cool phase [20].

A projected range of global average surface warming of 1.4 to 5.8 ºC by 2100, compared to 1990, suggests a rate of warming almost two to ten times higher than that observed during the last century. Global average precipitation and evaporation are projected to increase by about 1% to 9% by 2100, depending on which scenario and climate change model is used. Regionally, projected rainfall changes vary, making some regions wetter and others drier [1].

Australia has been identified as vulnerable to climate change because of its geographic and meteorological characteristics. From 1910-1999, the continental average temperature in Australia rose by about 0.7°C [16]. The Commonwealth Scientific and Industrial Research Organisation (CSIRO) has used results from a range of global climate models to assess likely changes over Australia in the coming decades. By 2030, it will be 0.3ºC to 1.4ºC warmer in temperature with 5% to 30% more days over 35ºC; there will be 10% to 60% fewer frosts; it will be 0 to 10% drier in winter; there will be more storms, and heavy rain, and the sea level will rise by 5 to 25 cm, compared with 1990 [3].

Recently, significant increases in temperature have been observed in most parts of China [21]. Surface temperature in northeast China increased in winter but decreased in summer during the last century. However, annual rainfall in China has been decreasing continuously since 1965, more substantially since the 1980s [21]. The summer monsoon is reported to be stronger in northern China. There will be an increasing trend in warming from south to north China [21]. The average temperature in China will have increased 1.2 ºC by 2030 and 2.2 ºC by 2050, compared to 1990[17].

1.3 Effect of climate change on population health

1.3.1 Introduction

The climate change described in the previous section may have an impact on many aspects of human and natural systems, including population health, agriculture and biological systems [22]. Some of the effects may be positive, such as cold-related deaths in colder regions [23]. Globally, the impacts are adverse to most people in the world. Both direct and indirect impact of climate change is discussed in this section. Table 1 summarizes the potential impact of climate change on population health (Table 1- 1).

1.3.2 Direct effects of climate change on population health

The most direct thermal effect is heat stress, which can lead to heat exhaustion and heatstroke. Many studies have shown that there is a U-shape, V-shape or J –shape [24] relationship between extreme temperature and mortality. For example, during 1979-1999, 8,015 extra deaths in the United States were heat-related [25]. The summer heatwave of 2003 in Europe was exceptional for the extensive loss of life, with 14,800 deaths in France during 9 days of extreme temperatures [26]. In Australia, it is stated that heatwaves kill more people than any other natural hazard [27]. South Australia had the highest death rate (1.14/100,000) caused by excessive heat between 1807 and 1994[28]. Interaction with humidity can increase the hazards of heat stress [29].

Other extreme weather events including floods, storms and drought may have a direct impact on population health. Immediate effects are mostly deaths and injuries. For example, river floods in central Europe in 1997 killed over 100 people. A tropical cyclone in Bangladesh in 1991 affected 10 million people, with 138,000 dead and 460,000 injured [30]. Drought affects population health mainly via its impact on food production. ENSO-related extreme weather events, which are associated with extremely dry conditions in many areas and extensive flooding in others, may also have a significant impact on population health [30].

Table 1- 1 Potential effects of climate change on population health

Exposure Factors	Health outcome
Direct effects	
Thermal extremes	Heat or cold-related illness and deaths
Other extreme events	Deaths, injuries, psychological disorders, damage to public health infrastructure
Indirect effects	
Effect on range and activity of vectors and infective parasites	Changes in geographical ranges and incidence of vector-borne disease
Changed local ecology of water-borne and enteric infective agents	Changed incidence of diarrhoeal and other infectious diseases
Changed food productivity through changes in climate and associated pests and diseases	Malnutrition and hunger, and consequent impairment of child growth and development
Sea level rise with population displacement and damage to infrastructure	Increased risk of infectious disease, psychological disorders
Biological impact of air pollution changes	Asthma and allergies; other acute and chronic respiratory disorders and deaths
Social, economic and demographic dislocation through effects on economy, infrastructure and resource supply	Wide range of public health consequences: mental health and nutritional impairment, infectious disease, civil strife

(Modified from McMichael and Haines, 1996 [6])

Different people may have varying sensitivity to extreme weather. It has been observed that the elderly and children, people with low socio-economic status, and people under intense physical stress or with pre-existing disease are the most vulnerable populations [1]. For example, in the Chicago heatwaves of 1994 and 1995, people over 65 years old accounted for 63% and 72% of the deaths, respectively [31].

Populations in developing countries may be especially vulnerable because of a lack of the resources and infrastructure to adapt to heat waves. In China, for example, an increase in mortality from heatstroke was observed when maximum daily temperatures in Nanjing exceeded 36°C for 17 consecutive days in July 1988 [32, 33]. It is estimated that in China the annual incremental costs for adaptation to climate change would be from 0.8 billion US dollars in 2000 to 3.48 billion US dollars in 2050 [34]. Despite these significant implications, there has been relatively little research in developing countries on the health impact of climate change.

In summary, most research on the direct impact of climate variation on population health has been conducted in North American and European countries, and few studies have been performed in Asia, Australasia and Africa. Most previous studies focus on deaths rather morbidity, while the later is more sensitive in the assessment of health loss. Furthermore, potential confounders, such as air pollution, health facilities and socio-economic status have not been considered in the above studies. In addition, most of the research described above is cross-sectional and conducted within one country alone.

1.3.3 Indirect effects of climate change on infectious diseases

Many studies have reported the impact of climate variation on infectious diseases, such as vector-borne diseases and enteric infections, including malaria, dengue fever, Ross River virus infection (RRV) and haemorrhagic fever with renal syndrome (HFRS), salmonellosis and *Campylobacter* infection [35-40]. A systematic review has been conducted summarizing studies examining the relationship between these diseases and climate. The main results of these studies and their study periods, target populations, geographic distribution and statistical approaches, as well as brief comments on these studies, are presented in Table 1- 2.

1.3.3.1 Vector/Rodent-borne diseases

Climate conditions primarily affect the transmission of vector-borne diseases in three ways [41,42]. Firstly, climate variation may alter the distribution of vector species depending on whether conditions are favourable or unfavourable for their breeding places and reproductive cycles. An increase in temperature will accelerate the propagation of vector species. In addition, rainfall and relative humidity, in various ways, all have effects on the life cycle of vectors. Thus, the transmission patterns of these diseases may be affected. Secondly, temperature can also influence the reproduction of pathogens within the vector organism (external incubation period, EIP). Thirdly, changes in weather can affect the behaviour of human beings, eg increasing exposure opportunities to vectors and thereby cases of infection.

Malaria is considered the most important vector-borne disease worldwide, with cases occurring in more than 92 countries [43]. Human malaria is caused by four identified species of Plasmodia, namely, *Plasmodium vivax, P. falciparum, P. ovale* and *P. malariae*. About 70 species are vectors of malaria under natural conditions found most abundantly in tropical and subtropical regions, with female *Anopheles* mosquitoes as the major vectors [44]. It is re-emerging as the top infectious killer and the top tropical disease according to WHO priorities [43]. Malaria is still one of the important infectious diseases in China, with 40,506 cases and an annual incidence rate of 3/100, 000 in 2003 [10]. While malaria has been wiped out in Australia since 1981, the vectors remain and there were approximately 700 imported cases of malaria notified each year in recent decades [45]. Climate change may increase the risk of the reintroduction of malaria to Australia because of the frequency of international travel to and from endemic countries, eg Papua New Guinea, unless programs of vector control are maintained or enhanced [30].

The relationship between malaria and meteorological variables has been assessed in many regions, including Africa, Europe, Asia, South America and Australia [46-60]. Increases in malaria incidence were strongly associated with higher temperatures and rainfall. However a too high temperature might have a negative impact on the growth of mosquitoes. The length and intensity of wet seasons has a significant effect on the distribution of the main vector in Australia, *Anopheles farauti* [59]. For instance, modelling shows that global warming will enlarge the potential range of this vector;

by the year 2030 it could extend to Gladstone along the Queensland coast, 800 km south of its present limit [57].

Concurrent factors, such as socio-economic status, have not been considered in these studies. Most of these studies did not take vectors into account as an independent variable (eg the density of mosquito populations) due to the unavailability of data. Moreover, inappropriate statistical methods limit the reliability of previous results. For example, auto-correlation and seasonal variation in both dependent and dependent variables were not controlled in most studies, which may confound the association between climate variation and infectious diseases.

Dengue Fever is the most common and widespread arthropod-borne viral infection in the world. There are four distinct virus serotypes, ranging from a sub-clinical infection to the severe disease known as dengue hemorrhagic fever, even dengue shock syndrome and death within 24 hours, without proper hospital care [61]. Currently, vector control is the major approach for disease prevention and control. *Aedes aegypti,* the principal vector, has adapted well to urban environment conditions of poor housing, overcrowding and inadequate sanitation [62]. The number of dengue cases has increased 30-fold globally during the last 50 years. A pandemic in 1998, in which 1.2 million cases of dengue fever and dengue hemorrhagic fever were reported from 56 countries, was unprecedented [61]. In Australia, 2,595 cases of dengue have been notified since 1991 [16]. It is also projected that if other contributing factors remain constant, in 2020, 300,000 to 500,000 people living in northern Australia would be at risk of dengue infection [14].

Climate change would substantially increase the magnitude and spatial extent of the risk of dengue fever occurring in New Zealand under present climatic conditions [63]. In Australia [64], by 2100, if no effective policy and public health measures have been developed, the zone of potential transmission of dengue fever may expand 1,800 kilometres south, as far as Sydney. In contrast, by markedly constraining greenhouse gas emissions immediately, this southward extension could be limited to 600 km.

Only a few studies have linked meteorological data with this disease. It has been observed that *Ae. aegypti* mosquitoes, the only dengue vector currently present in

mainland Australia, increases directly with temperature [65]. Climate change may increase the area of land with a wet and warm climate suitable for *Ae. Aegypti*. Additionally, the southern Australian mainland, with a slight increase in temperature, may begin experiencing epidemics of dengue fever [66]. In south China and Malaysia, the association between meteorological variables and dengue fever has also been documented [67, 68].

However, time series analysis has not been used in previous studies to examine the impact of climate variation on infectious disease. Time-series analysis strengthens the investigation of association between climate variation and diseases by control of auto-regression, seasonality and long-term trends [69, 70]. Climate change has been observed at different points in time and the obvious correlation between adjacent points in time can severely restrict the applicability of the many conventional statistical methods traditionally dependent on the assumption that these adjacent observations are independent and identically distributed.

In Australia, Bi et al [71] have investigated the association between an outbreak of dengue in north Queensland and meteorological variables, but a one-year study period for a time series analysis is too short. They also found an association of SOI with the transmission of dengue in Australia [71]. Pontes [72] found that the vector population developed independently of rainfall in a Brazilian city, which could be due to the living habits of the mosquito. However, only a graphic assessment was conducted between precipitation and density of the vector in this study and no statistical analysis was applied. Additional studies on dengue fever and climate should be conducted.

Ross River virus (RRV) is the most notified mosquito-borne pathogen in Australia, with approximately 5,000 notified human cases annually [7]. During the last decade, there have been more than 41,000 cases notified, with the most serious epidemic occurring in 1996 [73]. RRV usually incubates for 7 to 9 days. RRV infection causes a characteristic syndrome, including constitutional effects, rash and rheumatic manifestations. There are multiple and diverse vectors of RRV infection with over 40 species from the genera *Aedes* recorded. The most important vectors are *A. vigilax*, *A. camptorhynchus* and *C. annulirostris* [74]. The former two species are present along

the Australian coastline with *A. vigilax* in South Australia, Western Australia and Tasmania and *A. camptorhynchus* along the Queensland coast. *C. annulirostris*, which breeds in freshwater habitats, is widely distributed in inland Australia, particularly in the Murray River regions [74]. Different vectors with different sensitivity to climate may have varied transmission when climate changes. Therefore, the impact of climate variability on RRV infection should be investigated in various climatic regions.

The influence of temperature, rainfall and tides on the transmission of RRV varies within and between regions because of different vector species. Tong et al [75] conducted a series of studies of RRV and climate change in Queensland. They claimed that rainfall, temperature and tides have been associated with the monthly incidence in Queensland. Climate variability may also contribute to the spatial change in the distribution of disease in Queensland. A different response of RRV to climate variability between coastline and inland cities in Queensland has also been identified, indicating a greater impact of maximum temperature on RRV infection in coastal rather than inland cities, while minimum temperature and relative humidity inland seem to affect RRV infection more than at the coastline [76]. Additionally, the lag times and determinants of RRV infection were different between the Cairns and Townsville regions [77, 78]. In Western Australia, different climatic scenarios for meteorological data projected that RRV would increase in activity and distribution [79, 80]. During 1988-1989, epidemics of RRV infection in Western Australia occurred after unusually heavy rainfall and high tide heights [79]. The situation in South Australia could be different because most of the cases have occurred in the Riverland region of the state. Differences may be due to climatic and geographic characteristics. A preliminary study indicated that the transmission of RRV was associated with climate variation. Table 1-2 includes comments on the analytic methods of previously published studies (Table 1- 2).

Hemorrhagic fever with renal syndrome (HFRS) is a zoonosis caused by the Hantaan or Hantaan-related virus, with characteristics of fever, hemorrhage and hypotension [38]. Rodents, mostly mice, act as a reservoir and the source of infection. Humans are infected when they come into contact with excreta from infected rodents. The epidemic situation is serious in China, where there were over 1 million

cases from 1953-1996. In 2003, the nationwide incidence rate was 1.7/100,000, a 6% increase compared with the previous year [10]. The transmission of HFRS is influenced by environmental, occupational and reservoir factors. However, the potential effects of meteorological factors on rodent-borne diseases are more uncertain and have received less attention than vector-borne diseases. Except for the work of Bi et al [38, 81], few quantitative estimates have been made of the possible impact of long-term climate change on rates of rodent-borne infections. Examination of the relationship between rainfall and the incidence of HFRS in a low-lying region of China showed a significant inverse association between the amount of precipitation and the incidence of HFRS when the density of rodents and the opportunities for human contact were considered. However, studies were only conducted in a low-lying region, and further research needs to be done to confirm the situation in other regions.

1.3.3.2 Enteric infections

Enteric infection is a problem in both developing and developed countries. Given a large proportion of enteric infections are water or food-borne diseases, this thesis will focus on food-borne enteric infections. In the United States, about 9 million cases of water-borne disease occur every year [82]. Food-related diseases account for about 10% of morbidity and mortality in the UK with costs of about UK£ 6 billion annually [83]. The cost of enteric infections was estimated at over AU$ 2.6 billion each year in Australian communities [84]. According to the WHO, in developing countries infectious diseases transmitted by contaminated food and water are a constant and frequently fatal threat to health [62]. Diarrhoeal diseases are estimated to cause an annual 2.7 billion cases and 1.9 million deaths, mostly in infants and young children [62].

Many cases of enteric infections peak in case numbers during summer. Temperature and relative humidity directly influence the rate of replication of the pathogens and the survival of enteroviruses in the environment. Rainfall, especially heavy rainfall events, may affect the frequency and level of contamination of drinking water. Moreover, climate change may influence water resources and sanitation so that water supply is effectively reduced. Such water scarcity may necessitate using sources of

fresh water of poorer quality, such as rivers, which are often contaminated. All these factors may result in an increased incidence of such diseases [82].

There is inadequate research in food- and water-borne contaminants and diseases. As a result, it is very difficult to identify where and how a change in climatic conditions might alter the hazards posed by these diseases [85]. The relationship between enteric infections and climate variation has been documented by limited studies conducted in Europe, Australia, the USA and Asia [30, 39, 40, 82, 86-88]. A dose-response relationship suggested that each 1°C increase in temperature is related to a 5% increase in the risk of severe diarrhoea [30]. The Australian study, based in Queensland, also showed a positive association between salmonellosis and temperature [86]. Recent studies have reported the association between *Campylobacter* infection and temperature [39, 88, 89]. However, published results are not consistent. Some studies report positive correlation while others claim a negative or no association. Limitations in interpreting the results exist as a consequence of inappropriate statistical analysis or considering only one climatic variable (Table 1- 2). Only one study has included the contamination of consumable animals and birds in the analysis of climate and enteric infections [88].

There have been few quantitative analyses of the association between hepatitis A and climate change. Recently, Hu et al examined a possible relationship between the Southern Oscillation Index (SOI) and the occurrence of hepatitis A in Australia. The results indicated that the SOI is statistically significantly associated with the transmission of hepatitis A [87]. However, this correlation may not be causal because other influencing factors, such as sanitation conditions and diagnostic criteria for hepatitis A, were not considered. Furthermore, the SOI is a broad index for the measurement of climate variation and more sensitive indices should be used.

So far, few studies have been conducted which examine the impact of climate on enteric infections. There is a lack of consistency in published results. Moreover, there are difficulties in studying the impact of climate variation on such diseases. Firstly, the under-reporting of infectious diseases is a common but inevitable problem in disease surveillance, especially for enteric infections. Secondly, the criteria for

diagnosis may not be identical across different regions. These factors may lead to the lack of consistency in the research results.

In summary, some meteorological variables, eg temperature, rainfall, relative humidity and tides, may be associated with the transmission of vector-borne diseases and enteric infections. However, to verify the association, additional research needs to be done because of the limitations and uncertainties in prior studies. The following issues should be addressed in further research:

- Involving different meteorological regions, eg temperate, tropical regions;
- Applying suitable methods of statistical analysis, eg time series analysis;
- Controlling potential confounders, eg socio-economic status;
- Conducting work in developing countries with higher incidence of these infectious diseases, eg China.

1.4 Methodological issues

A number of research methods, including empirical studies, mathematical modelling, geographic information systems (GIS) and remote sensing (RS), have been used to study the relationship between climate change and population health. Empirical studies are the most commonly used, in which historical data of climate observations and disease surveillance have been analysed in order to examine their association. However, inappropriate methods, inconsistent definitions of exposure and statistical analysis without the control of confounders, have limited past research. In this section, the following methodology-related questions are asked about past research:

- Which study designs were used?
- Where were previous studies undertaken? Which populations were examined?
- What definitions and criteria were used for exposure assessment and disease diagnosis? What indices were used?
- What were the sources and quality of data?
- What methods or models were used in statistical analysis?
- What were the difficulties in interpreting the results?

1.4.1 Study design

According to McMichael et al [16], there are three goals in the study of climate change and population health: (i) to find evidence of an association in the recent past; (ii) to detect early impact on a long time scale; and (iii) to create predictive models to estimate the future burden of infectious disease based on above evidence. Study design is of great importance, as it may directly affect the validity of study results.

Almost all previous studies used a historical analysis, with only a few studies using scenario-based models to estimate future burden [90, 91]. Time-series analysis is most commonly used to examine time-series data, especially in historical data analysis [77,78, 92]. This approach is convenient to control for potential confounding factors and can demonstrate sensitivity to changes using just a few years of data [93]. Although most previous studies collected time-series data, some analyses were based on annual data and did not control for variation of the time-series data, such as seasonality and inter-annual trends. Time-series data analysis will be discussed in detail in section 1.4.5.

1.4.2 Geographic distribution and target population

Most studies examining the impact of climate variability on vector-borne diseases have been conducted in tropical areas, eg Africa and India [46,48,49,52], where most malaria or dengue cases occur. Research in temperate regions has been relatively neglected. In terms of the association between climate variation and enteric infections, most previous studies have been conducted in Europe, America and Australia [30, 91, 94]. The neglect of developing countries is evident.

Some vulnerable subpopulations have received little attention by previous studies. Only a few studies examine the impact of climate on diarrhea in children [30]. It is obvious that further studies should be conducted on subpopulations, such as the elderly and children, who may be more vulnerable both to infectious diseases and any change in their frequency as a consequence of climate change.

1.4.3 Exposure assessment

The assessment of climatic exposure should be consistent to make results comparable across various regions. However, the definitions of climatic exposure and the use of

indices of exposure and outcome vary in previous studies. For example, a Dutch study claimed that a cold spell could cause greater mortality than a heatwave, which was most likely due to the much longer time period in 'cold spells' than in heatwaves [24]. Additionally, the use of different meteorological variables, such as maximum temperature, minimum temperature or mean temperature, has not been justified in most studies. Due to the high correlation among meteorological variables, it may be helpful to adopt some combined meteorological indices such as Apparent Temperature (AT) [95] and the Southern Oscillation Index (SOI) [38], although there are limitations in these indicators.

While the indicators of health outcomes depend on the aims of each study, the number of cases of a disease is frequently used as an outcome. Incidence rates, sometimes with logarithmic transformations [38], may be more reasonable over a long period of time in the presence of fluctuations in population size. Mortality is another commonly used index in examining the impact of extreme weather events. It should be noted that summary measures of the burden of disease, such as DALY, have not been chosen as an index for studying the impact of climate variability on infectious diseases in previous studies. This will be further discussed in the next chapter.

1.4.4 Data availability and quality

Generally, at least three types of data, including meteorological data, demographic information and health outcomes are necessary for studying climate/disease relationships. Sometimes, information on potential confounding factors, such as occupational factors and density of vectors, is included [38]. The time span of data analysed is commonly about 10 years, but may be up to 50 years [96], depending on data availability. Data on a long-term scale are also needed to distinguish inter-annual variation from long-term changes. Due to different disease surveillance systems, the availability and quality of data are usually not guaranteed.

For meteorological data, a high quality weather record is available in Australia with over 100 years continuous recording of climate observations [14]. In China, the meteorological record is available from 1950 with reliable quality. For surveillance data of infectious diseases, under-reporting is not uncommon in both developed and developing countries. However, data quality is better in developed countries due to

legally registration systems. The WHO encourages more studies to be conducted in less developed countries although the data quality is less reliable because much is unknown about the impact of climate change in such areas [22].

1.4.5 Statistical analysis

The statistical methods to quantify the relationship between climate and infectious diseases vary in published studies. Some use time-series analysis [30, 40, 50, 51, 75-78], while others apply logistic regression [67, 90, 97]. Although time series analysis has its advantages, many issues need to be taken into account, including seasonality, inter-annual fluctuation, autocorrelation, and multicollinearity. Several statistical analysis methods have been developed to deal with such issues. The choice of an appropriate model in a time series analysis is of importance. The autoregressive integrated moving average (ARIMA) model is commonly used in time series analysis [69]. Moreover, the Seasonal Autoregressive Integrated Moving Average (SARIMA) model may be applied [77] in order to control seasonality. These models have the advantages of controlling autocorrelation of time-series data, potential long-term trends and seasonal distribution. Although logistic regression has advantages in predicting epidemics, some information may be lost when translating continuous data into categorical data. For example, Woodruff et al [90] used logistic regression to predict epidemics of Ross River virus infection with meteorological data, however statistical power was limited following the conversion of continuous data into categorical data. D'Sonza et al [86] used Poisson regression combined with log-linear analysis to investigate the association between ambient temperature and enteric infections in several cities in Australia.

Scenario-based modelling is an essential tool for climate projection, using existing statistical or theoretical knowledge to forecast possible health impact due to climate change. However, most projections assume that all other factors, including socio-economic status and the population distribution, remain constant. In many studies, the validity and sensitivity of models have been assessed by comparing real and simulated data [49].

1.4.6 Uncertainties

A wide range of methods and tools is in use in examining the relationship between climate change and population health. There is no single optimal method to detect or project the impact of climate change as it is very difficult to assess the effects in the presence of a complicated background which includes co-existing changes in biotic and abiotic systems [22]. The effects also may be confounded with other factors such as adaptation and socio-economic development that may change on a large-time scale. Almost every paper reviewed in this chapter discussed these limitations when interpreting the results of research. These limitations may due to the following:

- The change in disease transmission is not clear because the pathways from climate to infectious diseases vary in their complexity, scale and direction, time and other factors.
- The impact of pathogen replication in vectors, eg metabolism of the mosquito, is not well understood.
- There are inherent limitations in the methodology of climate projection.
- Adaptation and mitigation may play an important part in evaluating the relationship.
- Other co-existing factors do not remain static and are hard to control, eg socio-economic status.

1.4.7 Summary

Considering so many uncertainties, no model or statistical method is perfect to detect the potential and actual impact of climate change on infectious disease transmission. However, approaches based on a combination of scientific methods or tools, careful design and current understanding can be presented. The level of uncertainty can be reduced in several ways by maximizing statistical power (large sample sizes, data gathered over a large region and over a long time period) and using study designs to control for major confounding factors (time series study) [22]. These aspects have been considered in this study to minimize potential bias.

1.5 Conclusion

Due to climate change at global and regional levels, human beings will suffer from more hot days, more extreme rainfall, and more floods and droughts, which may have effects, direct and indirect, on agricultural products, population health, and diversity of biology. In addition, a large number of papers relating to climate change and infectious disease reflect increasing research interest in this field. As a result, much scientific evidence has shown the impact of climate change on infectious diseases, including vector-borne diseases and enteric infections.

However, many potentially adverse effects remain uncertain. Thus, further research needs to be conducted to better understand the relationship between climate variability and population health. In addition, with many gaps to be filled in this research field, further research should be performed involving different population settings in various meteorological regions to further examine the association between climate and disease; more studies linking enteric infections with climate variation should be done to quantify the relationship; studies conducted in China, which has the largest population in the world should be given much more attention, and studies linking climate change with a specific infectious disease burden should be completed.

Table 1- 2 Review of studies on climate change and vector-borne diseases and enteric infections

Reference	Study population	Study period	Indicators		Statistical methods	Major findings	Comments
			Meteorological	Disease			
Malaria							
Zhou, 2004 [46]	Seven highlands in East Africa	1978-88 1989-98	Monthly temperature and rainfall	Outpatient numbers	Non-linear regression models	65-81% of the variance in the number of monthly malaria outpatients can be explained by the model; high spatial variation in the sensitivity of malaria outpatient numbers to climate fluctuation.	√ Spatial variation was detected × Vector population dynamics were not examined
Kuhn, 2003 [47]	43 counties in England	1840-1910	Annual rainfall and temperature	Death rate, Case count	Logistic analysis	Rainfall and temperature were positively associated with year-to-year variability in death rate, but not with the long-term malaria trend. By 2050, the increase in temperature may lead to an 8%-14% increase in malaria transmission.	√ Projections for future risk × Time-series analysis was not used
Abeku, 2003 [48]	Ethiopia	1986-93	Monthly minimum temp, maximum temp and rainfall	Epidemic episodes of malaria	Morbidity (log transformed series)	Positive association with minimum temp; inverse association with maximum temp and rainfall.	√ Spatial variation of risk considered

Reference	Study population	Study period	Indicators		Statistical methods	Major findings	Comments
			Meteorological	Disease			
Tanser, 2003 [49]	Africa	1920-80	Mean monthly temperature and rainfall	Person-month cases of malaria	Projection using IPCC* scenarios	The exposure to malaria may have a 16%-28% increase in Africa by 2100.	√ Produced a validated malaria transmission model for Africa × Did not consider demographic, socio-economic status and malaria control projects
Bi, 2003 [50]	A temperate county of China	1980-91	Monthly minimum temp, maximum temp, rainfall and relative humidity	Monthly incidence of malaria	Spearman correlation analysis, time-series analysis (ARIMA)	Significant association between climate variables and incidence of malaria was observed.	√ ARIMA model applied × Did not take into account socio-economic factors
Small, 2003 [51]	Africa	1911-95	Monthly rainfall, air temperature, mean diurnal temperature, malaria transmission climate suitability index (MTCSI)	Incidence of malaria	Time series analysis	Limited evidence showed significant co-variation in malaria incidence with climate; rainfall had a greater impact than temperature.	×The result may be challenged due to a decrease in rainfall in the studied regions × Did not take into account socio-economic factors
Singh, 2002 [52]	Central India	1986-2000 1967-2000	Rainfall	Annual parasite incidence	Correlation, linear regression	No relationship between rainfall and incidence was observed.	× The result may be due to a water resource improvement project
* IPCC: Intergovernmental Panel on Climate Change							

Reference	Study population	Study period	Indicators		Statistical methods	Major findings	Comments
			Meteorological	Disease			
Poveda, 2001 [53]	Colombia	1980-97	Mean monthly temperature, rainfall, dew point temperature and river discharge	Monthly record for *P. vivax* malaria	Seasonal cross-correlations, power spectral analysis	Epidemic malaria is highly associated with prevalent climatic conditions.	√ Considered more climate variables × No regression analysis was conducted
Klein-schmidt, 2001 [54]	South Africa	1994-95	Daily/monthly temperature, rainfall and seasonal data	Incidence	GIS, Poisson regression analysis	The increasing incidence of malaria is associated with higher winter rain and higher max temp with the increasing distance from water bodies.	√ Spatial analysis of small area × Short study period
Hoek, 1997 [55]	Sri Lanka	1979-95	Mean monthly relative humidity and rainfall	Incidence	Correlation analysis	Weak association between rainfall and incidence; monitoring rainfall alone is not sufficient to predict incidence.	× Confounders, eg changes in the environment, migration of people, malaria control, not considered
Bouma, 1997 [56]	Colombia	1960-92	El Nino year, Sea Surface Temperature (SST)	Cases	Correlation analysis	Significant association between SST and incidence of malaria; cases increased 35% in post-Nino year.	× No regression analysis
Bryan, 1996 [57]	Australia	Not applicable	Ecoclimatic Index	Not applicable	CLIMEX*	Potential distribution of *An. Farauti* extends a further 800 km south in coastal Queensland.	√ Prediction of malaria distribution in 2030 × Only considered vector density
*CLIMEX is a process-oriented model that examines the association between species' geographical, seasonal and inter-annual performances, and uses survival thresholds to generate potential distribution.							

Reference	Study population	Study period	Indicators		Statistical methods	Major findings	Comments
			Meteorological	Disease			
Bouma, 1996 [58]	India and Sri Lanka	1868-1943	El Nino year, Sea Surface Temperature and monthly rainfall	Cases	Correlation analysis	Significant correlation between SST anomalies and malaria cases.	×No regression analysis
Dengue							
Yi, 2003 [67]	Guangdong, China	Not applicable	Average of lowest/highest air temp, sunlight, rainfall, relative humidity, Breteau Index (an index of vector intensity)	Cases	Correlation analysis, stepwise regression, logistic regression	Lowest air temperature, rainfall and relative humidity were associated with cases of dengue fever.	√Considered density of vectors √Developed a predictive model ×Not a time series study
Hales, 2002 [97]	A global study	1975-96	Monthly vapour pressure, rainfall and temperature	Outbreak (author-defined)	GIS, logistic regression	Annual vapour pressure was the most important indicator of dengue fever.	√Sensitivity analysis was applied ×No time series analysis applied
Bi, 2001 [71]	Queensland, Australia	1992-93	Monthly maximum and minimum temperature, relative humidity and precipitation	Outbreak, Attack rate	Graphic assessment, Spearman correlation analysis, ARIMA	Monthly mean min temperature with 4-month lagged effect was the strongest predictor of dengue fever.	√Applied time series analysis to control confounders ×Only 1 year study period

Reference	Study population	Study period	Indicators		Statistical methods	Major findings	Comments
			Meteorological	Disease			
Pontes, 2000 [72]	A Brazilian city	1986-98	House Index (density of vector found during each 3 month period)	Outbreak	Descriptive study	Heavy rainfall did not correlate with elevated dengue incidence.	×No statistical analysis methods were applied
Li, 1985 [68]	Malaysia	1973-82	Monthly rainfall *Aede* House Index	Cases	Not applicable	300 mm or more rainfall will lead to 120% increase in dengue cases.	×Only rainfall considered
RRV infection							
Woodruff, 2002 [90]	South eastern Australia	1991-99	Mean monthly temperature, Rainfall	Epidemic year	Logistic regression analysis	A prediction model was developed.	√ Considered socio-economic situation × Lost information when transferring numeric data into categorical data
Woodruff, 2006 [98]	Western Australia	1991-99	Tide height, rainfall, Sea Surface Temperature	Epidemics of disease	Logistic regression models	Addition of mosquito surveillance data increased the sensitivity of the early warning model to 90%.	√ Considered vector population
Bi, 2002 [99]	Queensland, Australia	1985-96	Seasonal data of temperature, rainfall, relative humidity and mean high tide	Incidence	Not applicable	The incidence of RRV infection differed in northern, central, southern coast and inland regions; the differences in rainfall, relative humidity and mean high tide were possible contributors to the variation.	√ Considered different climatic regions × Non-meteorological factors were not considered

Reference	Study population	Study period	Indicators		Statistical methods	Major findings	Comments
			Meteorological	Disease			
Lindsay, 1993 [79]	Western Australia	1988-89 1991-92	Mean sea level, daily tide height, rainfall, SOI	Case attack rate	Not applicable	Unusual heavy rainfall and a sea level rise may contribute to epidemics.	×No statistical analysis applied
Tong, 2004 [77]	Townsville, Australia	1985-96	Monthly rainfall, Temperature, Relative humidity, High tide, Sea level	Monthly cases and incidence	Cross-correlation, SARIMA*	Significant association with these meteorological variables and both monthly malaria cases and incidence with various lag times.	√Population growth was considered √Time series analysis was applied √Controlled seasonality and lag time √Considered high tide and sea level ×Other confounding factors, eg socio-economic status, were not controlled
Tong, 2002 [75]	Queensland, Australia	1985-96	Monthly rainfall, Temperature, Relative humidity, High tide, Sea level	Monthly cases and incidence	Spearman's rank correlation analysis, ARIMA#	Rainfall and high tide were significantly related with malaria.	
Tong, 2001 [78]	Cairns, Australia	1985-96	Monthly rainfall, Temperature, Relative humidity, High tide, Sea level	Monthly cases and incidence	ARIMA#	Max temp, rainfall and relative humidity were related with malaria.	
Tong, 2002 [76]	Inland and coastline in Queensland, Australia	1985-96	Monthly rainfall, Temperature, Relative humidity, High tide, Sea level	Monthly cases and incidence	Time series adapted for Poisson model	There was a different association between inland and coastal areas in the relationship between climate variables and malaria.	√Considered seasonality and secular change √Analysis of spatial differences

∗ SARIMA: Seasonal Autoregressive Integrated Moving Average model; # ARIMA: Autoregressive Integrated Moving Average model

Reference	Study population	Study period	Indicators		Statistical methods	Major findings	Comments
			Meteorological	Disease			
Bi, 2003 [100]	Queensland, Australia	1985-96	Temperatures, rainfall and high tides	Not applicable	Not applicable	Temperatures, rainfall and high tides are possible contributors to RRV transmission in the coastal region; in inland areas temperature is main risk factor.	√ Analysis of spatial difference × Did not control for confounders
Haemorrhagic fever with renal syndrome (HFRS)							
Bi, 1998 [81]	A low-lying region of China	1961-63 1964-77 1983-95	Seasonal rainfall and water level	Incidence	Correlation analysis; Multiple linear regression Log-transformation of Incidence rate of HFRS	Inverse relation between water level, farmland inundated and incidence of HFRS.	√ Density of mice, seasonality and occupational index were considered
Bi, 2002 [38]	China	1980-96	Mean of temp, rainfall, relative humidity, SOI (July to Sep)	Notified data	Correlation analysis; Multiple regression	Rainfall, the density of mice and autumn crop production were correlated with the incidence of HFRS.	√ Density of mice, seasonality and occupational index were considered √ SOI was used to show relation between El Nino and HFRS
Bi, 2003 [101]	China	1970-96	SOI	Incidence	Correlation analysis	Inverse correlation between the SOI and the incidence of HFRS.	× No regression analysis

Reference	Study population	Study period	Indicators		Statistical methods	Major findings	Comments
			Meteorological	Disease			
Enteric infections							
Kovats, 2004 [40]	10 European countries	varying for each country, 3-18 yrs	A single national temperature series	Weekly counts (excluded travel-associated cases and outbreak-linked cases)	Poisson regression adapted for time series analysis	Above a threshold for 6℃ there was a linear association between temperature and the number of cases of salmonellosis, strongest in the 15-64 age group.	√Controlled inter-annual variation, effect of public holidays and annually repeated patterns ×Climate indices were not reliable
D'Sonza, 2004 [86]	Five Australian cities	1991-2001	Mean monthly temperature and rainfall	Cases 'Outbreak month'	Log-linear models, Poisson regression	Positive association between salmonella and temperature.	√Fitted for over-dispersion √Considered population size √Controlled the effect of outbreak ×Only considered temperature, rainfall
Curriero, 2001 [96]	USA	1948-94	Rainfall	'Outbreak'	Fisher test	Extreme rainfall was associated with the outbreaks.	√First paper to quantify the relationship between rainfall and diarrhoea outbreaks ×Did not consider other climate variables

Reference	Study population	Study period	Indicators		Statistical methods	Major findings	Comments
			Meteorological	Disease			
Singh, 2001[102]	18 Pacific Island countries	1986-94 1978-88 (Fiji)	Temperature, water availability	Average annual rates of diarrhoea in adults	Cross-sectional study, Poisson regression analysis	Positive association between temperature, extreme rainfall and diarrhoea reports, negative association between water availability and diarrhoea rates.	×Generalization of the results was limited to the study population
Checkley, 2000 [30]	Lima, Peru	1993-98	El Nino episode, mean ambient temperature	Number of cases	Time series linear regression, Poisson regression, square-root transformation of the daily number of cases	The increase in admission for diarrhoea in Lima was associated with an increase in ambient temperature and a decrease in relative humidity.	√First quantification of the relationship between climate and diarrhoea
Bentham, 1995 [91]	England and Wales	1982-91	Monthly temperature	Weekly number and monthly incidence of food poisoning	Regression analysis, log-transformation	Association between temperature and monthly incidence was observed and projected to 2010, 2030 and 2050.	×Only considered temperature
Nath, 1992 [103]	Varanasi, Indian (<5 age)	1988-89	Monthly relative humidity, rainfall, maximum and minimum temperature	Children under five diagnosed with rotavirus diarrhoea	Case control study, chi-square test and Fisher test	Diarrhoea due to rotavirus was not correlated with rainfall and relative humidity.	×Cross sectional study

Reference	Study population	Study period	Indicators		Statistical methods	Major findings	Comments
			Meteorological	Disease			
Pinfold, 1991[104]	Northeast Thailand	1982-87	Rainfall, temperature	Reported incidence of acute diarrhoea	Descriptive study	Incidence of diarrhoea appeared to be inversely related to a sharp decrease in temperature.	× No statistical analysis applied
Konno, 1983 [105]	Yamagata, Japan	1974-81	Monthly relative humidity, temperature	Acute diarrhoea admissions	Descriptive study	The infection frequency was related to temperature but not to humidity. The association was stronger in cooler months.	× No statistical analysis applied
Tam, 2006[39]	England	1989-1999	Weekly humidity, sunlight hours, mean central England temperature	Case count of *Campylo-bacter* infection	Time series adjusted negative binomial regression	1°C rise in mean temperature accounting for 5% increase in number of cases with a threshold for 14°C.	√ Laboratory confirmed cases × Aggregate meteorological variables
Kovat, 2005[90]	Countries in Europe and Oceania	1989-2002, varying for each country	Weekly representative temperature series in each country (author-defined)	Incidence of *Campylo-bacter* infection	Poisson generalised linear models	No effect of temperature or rainfall on campylobacter was detected.	√ International study × No developing countries × Rough definition of spring and winter
Hu, 2004 [87]	Australia	1991-2000	SOI	Monthly cases of Hep A	Correlation analysis	Correlation between incidence of Hep A and SOI was observed.	× No reasonable explanation of the results

Reference	Study population	Study period	Indicators		Statistical methods	Major findings	Comments
			Meteorological	Disease			
Patrick, 2004[88]	Denmark	1998-2001	Average temperature, maximum temperature, rainfall, humidity and amount of sunlight	Weekly incidence of *Campylo-bacter* infection	Linear regression	Temperature and sunlight or humidity predicted the incidence well.	√ Combined effects of meteorological variables √ Food animals (chicken) were investigated
Louis, 2005[106]	England and Wales	1990-1999	Minimum and maximum temperatures, rainfall, hrs of sunshine	Weekly incidence of *Campylo-bacter* infection	Multiple regression adjusted for auto-regression	Campylobacter rates were correlated with temperature, particularly for children under the age of 5.	√ Subgroup population by age, sex and region was investigated

CHAPTER II

LITERATURE REVIEW: BURDEN OF DISEASE ASSOCIATED WITH CLIMATE CHANGE

2.1 Introduction

The burden of disease (BoD) is a quantitative index to measure health status and relevant attributed risk factors in a given population. BoD studies have been carried out at global, national and regional levels, using summary measures such as Disability Adjusted Life Years (DALYs) to combine prevalence of disease, quality of life and life expectancy in a single health indicator.

The Global Burden of Disease (GBD) concept, first published in 1996 [107], aimed to draw a worldwide picture of disease burden to answer the question: 'How big is this health problem?' by using international uniform frameworks or calculation methods. Further, the GBD provides information for policy-makers and stakeholders by highlighting main health problems. In order to provide a more detailed international perspective, national burden of disease (NBD) studies have been carried out in 30 countries, including Australia [108]. In addition, regional BoD studies have focused on vulnerable populations [109]. These studies provide a rational basis for local priority setting and for comparison with results in other areas. Such studies are a guide to health resource allocation.

Following the estimation of the health status of a population, further evaluation assesses how much of the disease burden can be attributed to particular risk factors. The Environmental Burden of Disease (EBD) study estimated the burden of disease from 26 major environmental risk factors, including climate change [110]. Any global environmental changes that arise in the future will tend to appear first in local settings where decision making usually takes place. Therefore studies at this level are necessary. Within the EBD study, the assessment of climate change attributable burden is proposed to estimate DALYs lost in the future rather than today [109].

2.2 Global burden of disease study

Before the GBD study, it was difficult to establish an overall perspective on health burden globally. Lack of summary measures and the limitations of traditional health statistics restricted the estimation of health burden and comparison at the

international level [109]. The aims of the GBD were to incorporate non-fatal conditions and cost-effectiveness analysis of interventions to make assessments more objective and comparable worldwide. The updated objectives of GBD 2000 were to quantify the burden for additional major causes, using a comparable framework, and to project burden for the next 30 years [54].

The GBD published its first findings in 1993, providing the first plausible description of the world's health [109]. To date, the GBD study has obtained many results in measuring global health status, and the burden of disease attributed to particular risk factors within the GBD study is expanding greatly, compared with the first report in the early 1990s. Updating the original GBD Study 1990, new life tables and detailed distributions of the causes of death were developed in 2000 for all 191 WHO member states [111].

According to the results of GBD study 2000, infectious diseases remain the world's leading cause of death, accounting for one in three of all deaths. Each year, 17 million people, mostly children, die from infectious diseases, with a huge discrepancy between rich and very poor countries [107]. According to the World Health Report 2002 [109], diarrhoeal diseases and malaria ranked fourth and fifth in the leading causes of burden in both developed and developing countries. In the estimates for 2001, diarrhoeal diseases accounted for 62,451,000 DALYs and malaria for 42,280,000 DALYs in the GBD study [112]. Although there is an obvious decline in the global burden of infectious diseases in the past decade, it still affects a large number of people in developing areas [109].

Given this information, it is important to understand to which factors the burden of infectious diseases can be attributed. The GBD has made efforts to answer this question by incorporating more and more potential risk factors. Climate change is one of the selected risk factors in the category of 'environmental risks' in the GBD study 2000. It was estimated that 2% of DALYs for diarrhoeal diseases and 2% of DALYs for malaria could be attributed to climate change in the world in 2000 [109]. In total, the mortality attributed to climate change was 154,000 deaths and the attributable burden was 5,500,000 DALYs. In addition, the attributable DALYs in

the high mortality, developing countries (defined by WHO) was 2,535,000 for males, and 2,667,000 for females, but was relatively low in developed countries [109].

2.3 Burden of disease study at national or regional levels

Burden of disease studies were undertaken at national and regional levels immediately after the publication of the GBD studies. Thirty-five national Burden of Disease studies have been undertaken with some of them still in progress [109]. Although the principles and methodology were essentially derived from the studies that Murray and Lopez [107] developed for GBD, they are not totally comparable to each other because of some important modifications.

There has been much work conducted in Australia. The Australian National Burden of Disease Study was completed in 1999 and the methods and the results have been published [113]. The study provided the first detailed and internally consistent estimates for the Australian disease burden. Using the GBD methods, the study took the first step towards quantifying the burden associated with a range of risk factors, including tobacco, alcohol, illicit drugs, obesity, hypertension, high blood cholesterol, physical inactivity, unsafe sex, occupational exposures and risks, and inadequate fruit and vegetable consumption. Climate change as a risk factor was not investigated in this study.

Sub-national burden of disease studies have been implemented in several Australian states: Victoria [114], Queensland [115]and South Australia [116]. The South Australian Burden of Disease study started in July 2002. Three-year (1999-2001) averaged estimates of the BoD due to 176 mutually exclusive disease and injury categories in South Australia (SA) have been reported [116]. In addition to the DALYs, Health Adjusted Life Expectancy (HALE) was adopted as a health indicator in the assessment. The results from the Australian national study indicate that infectious diseases are not the leading burden in SA. However, infectious and parasitic disease caused more than 1,300 DALYs for the 3-year average, with more severe conditions in children and the elderly in SA [116].

In developing countries, global burden of disease studies have seldom been conducted. In China, for example, most studies used DALYs to evaluate the cost-effectiveness of specific interventions in a defined population, such as immunization campaigns to control Japanese encephalitis [117], rather than assessing the burden of disease for the country. This could be due to the relatively poor quality of data and limited coverage of disease reporting systems. However, it is recommended [107] by the GBD study that, even if data quality is poor, it is better to estimate the burden of a disease than to ignore it. Therefore, these studies should be conducted in such areas.

2.4 Methodological issues

As described above, the BoD study is still in an early stage due to methodological issues. The following questions will be discussed in this section:

- Why use summary measures of population health combining mortality and morbidity?
- Why is morbidity important in addition to mortality?
- Can we estimate burden of disease attributed to climate change using historical information?

2.4.1 Summary measures combining mortality and morbidity

In the BoD study, summary measures are commonly used along with indicators of deaths, including mortality and number of deaths. A summary measure of population health is a single index that combines information on mortality and disability to represent population health. This measure allows for the combination of different health outcomes, the comparison of health status among several populations and the estimation of health trends in one population [118]. The summary measures used by GBD include QALYs (quality-adjusted life years), PYLLs (potential years of life lost), DALYs (disability adjusted life years), DALE (disability-adjusted life expectancy), and HALE (health-adjusted life expectancy).

The method of calculation of summary measures, eg DALYs, has been published although weaknesses and problems still exist. DALY is a health gap measure - the gap between current health status and an ideal situation where everyone lives into old

age, free of disease and disability [119]. One DALY can be thought of as one year of 'healthy' life lost. DALYs are calculated by the sum of years of life lost due to premature mortality (YLL) and the equivalent 'healthy' years of life lost due to disability (YLD) [120].

There have been different opinions about using DALYs. On the one hand, it is a better indicator than other summary measures that ignore the time lived with disability, such as PYLL. Moreover, it has an advantage in an explicit statement of values (choosing disability weights and life expectancy), which is the basis for decision making. In addition to adjusting the value of life years by disability weights and choosing a particular life expectancy, the value of a life year is modified by discounting (the value of a life year now is set higher than the value of future life years) and age weighting (life years of children and old people are counted less) [120]. On the other hand, critical claims about DALYs focus on the ethical issues in their calculation [121]. With ongoing debate and revision, DALYs have value in the estimation of population health for policy makers.

2.4.2 Difficulties in estimating morbidity burden

It is important to include morbidity in burden of disease studies (YLDs), particularly for infectious diseases that have few deaths and high incidence or prevalence, such as diarrhoea. However, it is much more difficult to estimate morbidity burden than mortality burden in terms of choosing weights and discounting used for the calculation of DALYs. Although DALYs have advantages in assessing health burden, the estimation of morbidity burden is always volatile. For example, Kowek argued that DALYs for diarrhoeal diseases may double with consideration of potential long-term morbidity [122].

The estimation of morbidity burden is more complex and difficult, compared to using mortality as the indicator of health status. Rather than simply measuring the number of deaths, there are many ways of measuring the morbidity burden, eg incidence, prevalence or number of days with disability [83]. In addition to age- and sex- specific morbidity data, a review of current knowledge of selected diseases is necessary to obtain incidence, duration and severity of focused diseases to calculate YLDs [110].

2.4.3 Causal attribution analysis

Following descriptive studies of quantitative measures of the burden of disease, evaluations of causal attribution have also been attempted both at global and local levels. In the GBD study 2000, 135 major causes or groups of causes were evaluated [123]. The discussion below focuses only on Environmental Burden of Disease (EBD) study that included a climate change attributed burden.

It is feasible to estimate morbidity burden attributable to risk factors as long as necessary data are available. An assessment of EBD requires the following data for each risk factor:

- the distribution of risk factor exposure within the study population;
- the exposure-response relationship for each risk factor;
- the mortality or morbidity lost to disease for the risk factors of interest.

The approaches conducted in the EBD studies can be generally divided into two categories: exposure-based approaches and scenario-based approaches [124]. When exposure is measured in terms of increasing levels of pollutants, it is called an exposure-based approach. For example, exposure to outdoor air pollution is commonly reported as increases in ambient air pollution. A scenario-based approach, an alternative approach when it is not possible to specify a relationship between the proximal cause of disease and the disease outcome, is to select characteristic exposure scenarios to compare current levels of exposure to the exposure that would occur under an alternative, hypothetical scenario. For example, in the area of water, sanitation and hygiene, there are often no direct measurements of drinking-water quality for the entire population of a country. Therefore, it is appropriate to apply the scenario-based approach to examine the burden of disease due to climate change in the future.

Different methods of estimation can be applied according to the status of previous burden of disease studies in a given country. When a national burden of disease (NBD) study has already been carried out, such as in Australia, the attributable BoD for an environmental risk factor can be obtained by multiplying the attributable disease fraction for the risk factor by the total disease burden for the corresponding disease assessed in the NBD study [124]. When NBD data are unavailable, national or

sub-national mortality and morbidity statistics can be used. If national or local health statistics are limited then it is more difficult. However, it may be possible to estimate the incidence or prevalence of disease by surveys.

2.4.4 Uncertainties

In the field of EBD studies, especially in the estimation of the effects of climate change on population health, considerable uncertainties may be encountered due to natural variability of climate, scenario-based prediction, other co-existing non-climate factors, and the lack of measures of the relationship [109]. Studies conducted among various populations in diverse climatic regions may enhance the validity of the estimation of climate-related burden of disease.

2.5 Conclusion

The Burden of Disease study is trying to use a summary measure, such as DALYs (YLL and YLD), to estimate the regional burden of disease within a global frame and make the results internationally comparable. Australia has conducted a number of burden of disease studies nationally and regionally. No systematic burden of disease study has been conducted in China, which may reflect the lack of reliable data. Years Lost due to Disability (YLD) can be used to estimate the burden of disease in developing countries as long as the necessary data are available.

The WHO reported that a large number of DALYs worldwide are caused by infectious disease. Therefore, it is worth understanding potential attributable risk factors. This is the aim of Environmental Burden of Disease (EBD) studies, which quantify burden attributable to particular risk factors, eg smoking and alcohol. However, climate change is one of the risk factors that have been ignored by previous EBD studies. Indeed, except for the WHO report, there has been no study conducted at a national or sub-national level to investigate the burden attributable to climate change.

In this study, YLD will be used as an indicator to estimate future infectious disease burden from climate change in study areas in Australia and China. This thesis will

add to current knowledge of the future burden of infectious disease related to climate change.

CHAPTER III

STUDY DESIGN

3.1 Introduction

This study is composed of two parts. The first part is an ecological study, which uses a time-series analysis to quantify the relationship between meteorological variables and infectious diseases, including vector-borne diseases and diarrhoeal diseases, in areas with various climatic conditions in Australia and China. The second part projects the burden of selected infectious diseases under various future climate and population scenarios in the study areas in both Australia and China.

This chapter provides a general description of the study design, including aims and objectives, research questions, study regions and target diseases. Due to the different methods used in the two parts of this study, more detailed methods used in each part and the justification for use will be addressed in Chapters Four and Five, respectively.

3.2 Aims and objectives

This study aims to make a contribution to a better understanding of the impact of climate variability on population health, and to provide scientific evidence for policy makers in the development of public health strategies at an early stage in order to prevent or reduce future risks associated with ongoing climate change.

Its objectives are to quantify the relationship between climate variation and vector-borne diseases and enteric infections in different climatic regions in Australia and China and to project the climate-attributable burden of vector-borne diseases and enteric infections in different climatic regions in Australia and China.

3.3 Research questions

- What is the quantitative relationship between climate variation and selected vector-borne diseases and enteric infections in various climatic regions in Australia and China?

- Is there any difference in climate change impact between various climatic regions in Australia and China?

- What might be the burden of target infectious diseases under future climate scenarios in various climatic regions in Australia and China?

3.4 Framework of the study

3.4.1 Selecting study countries

Australia has unique geographic characteristics and diverse climatic regions, which makes it vulnerable to climate change manifested by rising sea levels, floods and droughts [15]. Although many studies have demonstrated the adverse impact of climate variation/climate change in Australia, there are issues that need to be resolved. For instance, the impact of climate variability on various infectious diseases in different climatic regions needs to be studied, as is the projected burden of such diseases due to any future climate change. More research in Australia will provide stronger scientific evidence for policy makers. Accessible high quality surveillance data in Australia will enhance the reliability of the results of this study.

China is the biggest country in the developing world with more than 1.3 billion population. As with Australia, China also has diverse climatic zones and diverse geographic environment. People living in developing countries may well be more vulnerable to climate change compared with those in developed countries. Unfortunately, very few studies have been conducted to examine the impact of climate on population health in developing countries. More research is urgent in such countries to clarify the relationship between climate and health outcomes for better adaptation to and mitigation of future climate change.

It can be seen that both countries have a large area with a range of climatic regions and have experienced vulnerability to the impact of climate change. The other advantage of this integrated study is to examine the relationship between climate variability and infectious diseases in both developed and developing countries, which have different socio-economic status, health services, policies and various cultural backgrounds.

3.4.2 Selecting study diseases

When selecting the target infectious diseases, the following factors were considered:

- Is the disease sensitive to climate variation?
- Is the disease a public health problem affecting local population health?
- Are data about the disease available?

As a result, one vector-borne disease and one enteric infection were selected in each country according to the local occurrence of the diseases (Table 3- 1).

Table 3- 1 Selected infectious diseases in this study

	Selected diseases	Category
Australia	Ross River virus infection	Vector-borne disease
	Salmonellosis	Enteric infection
China	Malaria	Vector-borne disease
	Bacillary dysentery	Enteric infection

Ross River virus (RRV) infection and salmonellosis are the selected infectious diseases in Australia. RRV infection is the most common vector-borne disease in Australia, with 41,000 cases notified during the last decade [73]. Although the relationship between RRV infection and climate in Australia has been addressed by some studies, most of them have been conducted in tropical/subtropical Australia. There has been limited study of the effect of climate variation on RRV infection in South Australia, which has a Mediterranean climate. *Salmonella* is one of the most common agents responsible for enteric infection outbreaks in Australia, with 7,842 cases notified to OzFoodnet in 2004 [125]. There is evidence that the growth and dissemination of the micro-organisms responsible for enteric infections may be influenced by weather [82], and there is a positive association between food poisoning and environmental temperature [126]. The relationship between climate and salmonellosis is far from clear.

Malaria and bacillary dysentery are the selected study diseases in China. Both malaria and dysentery have been legally notifiable diseases in China since the 1950s. The incidence of malaria decreased dramatically during the 19th century in China.

However, there has been an evident re-emergence of malaria since 2000, with more than 740,000 cases occurring in China in 2004. While there are many studies on the impact of climate change on malaria worldwide, few studies have been conducted in China, and little is known about the impact of malaria in temperate areas in northern China. Bacillary dysentery, one of the major diarrhoeal diseases in China, has caused more than 300 deaths per year in the last decade and about 500,000 notified cases in 2005 [11]. Bacillary dysentery commonly occurs in summer, which suggests a potential association with climate variation. The relationship between dysentery and meteorological variables has not been examined by previous studies.

3.4.3 Selecting study regions in both countries

The principles for selecting the target study regions were as follows:

- the selected regions should be from different climatic zones in both countries;
- the selected regions should have necessary data available for the analysis.

Consequently, Adelaide, the capital city of South Australia, with a temperate climate, has been chosen for studying the association between salmonellosis and climate variation. The Murray River regions in South Australia have been selected to examine the relationship between RRV infection and climate variation because most cases of RRV infection in South Australia are from this area. In Queensland, Brisbane, the biggest city in a subtropical area, and Townsville, the biggest city in a tropical area, were selected as target regions for studying RRV infection and salmonellosis associated with climate variation. In China, Jinan, the capital of Shandong province with a temperate climate and Baoan, a special economy district in Guangdong province with a subtropical temperate climate, have been selected to study the association of malaria and bacillary dysentery with climate variation.

Background information about selected study regions is summarised in Table 3- 2 and their location is identified in Figure 3- 1.

Adelaide is the capital city of South Australia. It is located at 34° S and 138° E with a land area of about 1,600 square kilometres and a population of 1.1 million in 2005[127]. It is the driest Australian capital city with relatively little rainfall. The mean

maximum temperature is around 29°C in the warmer months, January and February. Temperatures above 40°C are also recorded [128].

The Murray River regions in South Australia include two areas, upstream Riverland in the north and downstream Murraylands in the south (For detailed map see Figure 4- 1). These two areas along the Murray River with a population of only 68,500 cover more than 48,000 square km. As with Adelaide, these areas have a Mediterranean climate with a hot, dry summer and a mild, humid winter [129].

Brisbane is the capital city of Queensland with a population in excess of 1.6 million in 2005. Brisbane is located at 27° S and 153° E, in the southeast corner of Queensland. It has a hot, humid climate with a summer average maximum temperature around 30^{o}C and average temperatures of around 15^{o}C in winter. Most days in Brisbane are sunny with mean daily hours of sunshine of seven to eight hours. Precipitation is less in winter than in summer, with average monthly rainfall of about 60mm in winter and more than 150mm in summer [128].

The Townsville region lies at 19° S and 146° E with a population of approximately 186,000 in 2005 and an area of about 1,866 km^2. The region experiences two distinct seasons, the 'wet' and the 'dry', running from January through to April, and May through to December respectively. Winter temperatures average 25°C during the day, and summer temperatures rise to around 31°C during the day [130].

Jinan is the capital city of Shandong province, which is in north China. Jinan, with an area of about 2,085 square kilometres, is located at 36°40’ N and 117° E. At the end of 2005 the registered population was 3.28 million. Jinan lies in a temperate, continental, monsoon climatic zone, which has four distinct seasons with plenty of sunshine each year. The average annual temperature is 13.6°C, lowest in January (1.9°C) and highest in July (27°C). Average annual rainfall is about 614 mm [131].

Baoan, the biggest district in Shenzhen, Guangdong province, is a city in one of the Special Economic Zones in China. Baoan is located between 22.27- 22.52° N and 113.46 -114.37° E. The area is 733 square kilometres and there were 3.3 million residents at the end of 2005. Baoan has a subtropical, maritime climate with plenty of

rain and sunshine. It has mild winters and summers. The year's frost-free period can be as long as 355 days. The rainy season lasts from May to September with an annual average rainfall of 1,933.3 mm [132].

Table 3- 2 Background information for selected regions in Australia and China

Regions	Geographic Position	Political Position	Land Area	Population	Climate
Australia					
Adelaide, SA	34° S, 138° E	State capital	1,600 km^2	1.1 million	Temperate climatic zone
Murray River regions, SA	32°~35°S 138°~140°E	Local region	48,210 km^2	68,500	Temperate climatic zone
Brisbane, QLD	17° S, 145 ° E	State capital	4,643 km^2	1.6 million	Subtropical climatic zone
Townsville, QLD	19° S, 146° E	Local region	1,866 km^2	186,000	Tropical climatic zone
China					
Jinan, Shandong	36° N, 117° E	Provincial capital	2,085 km^2	4.3 million	Temperate continental monsoon climatic zone
Baoan, Guangdong	22° N, 113° E	Local region	733 km^2	3.3 million	Subtropical maritime climate

Figure 3- 1 Geography of selected study regions in Australian and China



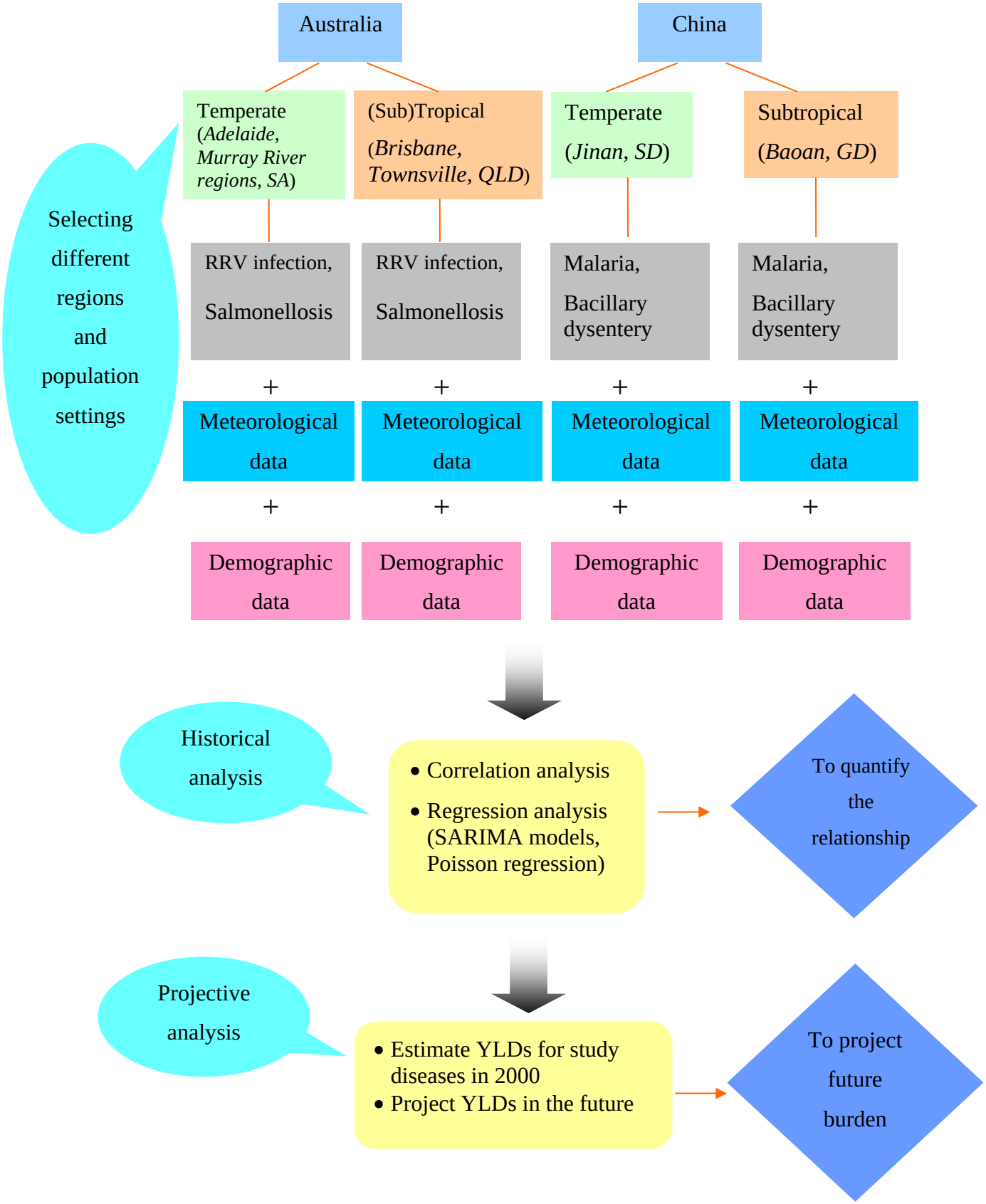


3.4.4 Flowchart describing the framework of this study

The flowchart illustrates the framework of the study, as shown in Figure 3- 2. Data collection includes surveillance data for study diseases (one vector-borne disease and one enteric infection), from selected areas with various climatic conditions in Australia and China, meteorological data and demographic data. The first step uses time-series analysis to quantify the association between climate and study diseases. The data analyses include cross-correlation analysis at various lag times, time-series regression analysis, adjusted Poisson regression and a Seasonal Autoregressive Integrated Moving Average (SARIMA) model, with the control of seasonality, long-term trends, autocorrelation, multillinearity and lag time.

The second step, based on the results from the first step and future climate and population scenarios, uses scenario-based analysis to project the future burden of study diseases in selected climatic regions in each country. The Years Lost due to Disability (YLDs) rather than the DALYs were used as a measure of burden of disease because only the incidence of selected infectious diseases but not the deaths from these diseases has been analyzed along with meteorological variables. Additionally, the mortality from the study infectious diseases is very low in the study regions so that they account for only a very small proportion of the DALYs. The YLDs for the study diseases in 2000 were estimated and projected to 2030 and 2050 in Australia and 2020 and 2050 in China respectively. More detailed methods and justification will be presented in the method sections in the next two chapters.

Figure 3- 2 The framework of the study



CHAPTER IV

RELATIONSHIP BETWEEN CLIMATE VARIATION AND TARGET DISEASES IN SELECTED CLIMATIC REGIONS IN AUSTRALIA AND CHINA

4.1 Introduction

This chapter, addressing the first objective of this thesis, quantifies the relationship between climate variation and vector-borne diseases/enteric infections in different climatic regions in Australia and China.

The methods used in this chapter, including data collection, collation and analysis, are described. Meteorological, health surveillance and demographic data have been collected from relevant local authorities in Australia and China. Study periods for the diseases vary in different regions according to data availability. Descriptive, correlation, and regression analyses have been performed for each study disease in each study region.

The results of the analyses are presented and discussed for each study disease. Due to the different transmission mechanisms of the study diseases, results are presented separately for vector-borne diseases and enteric infections. The discussion examines the relationship between climate variation and the target diseases, suggests possible explanations for the impact, and provides implications for public health practitioners and authorities.

Conclusions are drawn at the end of this chapter about the relationship between meteorological variables and vector-borne diseases/enteric infections. Such conclusions make a contribution to a better understanding of the relationship between climate variation and infectious diseases and provide scientific evidence for consideration by local policy makers and communities to reduce the future impact of climate change on infectious diseases.

4.2 Methods

4.2.1 Data collection

4.2.1.1 Necessary data

Climatic, infectious disease surveillance and demographic data were collected for this study, as shown in Figure 3- 2.

4.2.1.1.1 Meteorological and hydrological data

- Meteorological variables

  In Australia, meteorological data, including daily maximum temperature, minimum temperature, relative humidity (9am and 3pm), rainfall and air pressure, were retrieved from the Australian Bureau of Meteorology. The observations were drawn from local weather stations as summarised in Table 4- 1. The Australian Bureau of Meteorology advised that the records from the weather stations used in this study would be adequate to describe the climate in the local regions during the study period. The Adelaide station is located about 2 km east of the CBD at Kent Town and has more than 30 years of daily weather observations. Loxton Research Centre and Murray Bridge station are local weather stations with more than 20 or 30 years respectively of daily recording. Brisbane station and Townsville station are local weather stations with more than 50 years of daily recording. Records from these weather stations are more than 99% complete [128].

Table 4- 1 Australian weather stations used in this study

Study areas	Weather Stations	Station No.
Adelaide, South Australia	Adelaide (Kent Town) station	23090
Murray River regions, South Australia		
Riverland	Loxton Research Centre station	24024
Murraylands	Murray Bridge station	24521
Brisbane, Queensland	Brisbane Aero station	40223
Townsville, Queensland	Townsville Aero station	32040

In China, meteorological data were obtained from the China Meteorological Administration. The variables include daily maximum temperature, minimum temperature, relative humidity, rainfall and air pressure. The observations were drawn from weather stations in Jinan (No. 54823) and Shenzhen (No. 59493), which are the only local weather stations to have reliable national standard datasets of daily weather recording for more than 40 years.

- River flow and high tides

Daily flows (ML/Day) of the Murray River to South Australia from January 1977 to June 2004 were provided by the Department of Water, Land and Biodiversity Conservation, South Australia.

Daily high tidal data (metres) in Brisbane and Townsville, Queensland, from January 1989 to October 2005 were provided by the Tidal Unit Maritime Safety, Queensland Department of Transport. The tidal station number for Brisbane is 046046A and for Townsville is 055003A.

4.2.1.1.2 Infectious disease surveillance

All selected infectious diseases for this study are legally notifiable diseases in both Australia and China.

In Australia, notified daily cases of Ross River virus infection and salmonellosis were obtained from the South Australian Department of Health and the Queensland Department of Health. The datasets include notification number, date of notification, date of onset, age, sex, address and sources of infection.

In China, notified monthly cases of malaria and bacillary dysentery were obtained from local Centres for Disease Prevention and Control (CDC) in Jinan and Baoan. All clinically diagnosed cases were reported. The datasets include the monthly number of cases and incidence rates by age and sex.

4.2.1.1.3 Demographic data

The total population in each study area with age and sex distributions over the relevant study periods was collected from the Australian Bureau of Statistics (ABS) and the National Bureau of Statistics of China (NBS). The Australian population over the study period was stable. In the study regions in China, the population in Jinan, the temperate city, was relatively stable within the study period, while the population in Baoan, the subtropical city, increased rapidly over the study period.

4.2.1.2 Study periods

The study periods vary for the different target diseases reflecting data availability. The study period for each study disease is summarised in Table 4- 2.

Table 4- 2 Study periods for selected diseases

City	Diseases	Study period	Number of years
Adelaide and Murray River regions, SA	Salmonellosis	1990-2004	15
	RRV infection	1992-2005	13
Townsville and Brisbane, QLD	Salmonellosis	1990-2005	15
	RRV infection	1990-2005	15
Jinan, Shandong, China	Bacillary dysentery	1987-2000	13
	Malaria	1959-1967, 1968-1979*	8 12
Baoan, Shenzhen, China	Bacillary dysentery	1996-2003	8
	Malaria	1995-2003	9

* The study period was divided into two phases due to a wide variation in the number of cases

4.2.2 Data collation

Data collation was conducted before analysis. Detailed summaries of the datasets were performed by Stata 8.2, which generated the smallest number, largest number, percentiles, mean, standard deviation, variances, skewness and kurtosis for each variable. Therefore, if there were abnormal data, they could be easily detected. There were no missing data from the datasets collected for this study. The disease surveillance data, meteorological data and demographic data were merged into one dataset for each disease, on a weekly or monthly basis depending on the number of cases.

4.2.3 Data analysis

The analysis includes descriptive, correlation and time-series regression analyses. Descriptive analysis will provide a description of the time-series characteristics of the study diseases and meteorological variables. Correlation analysis will examine the relationship between meteorological variables and study diseases. Regression analysis will quantify the association of climate variation with selected infectious diseases. The Hockey Stick model [89] was used to detect any potential thresholds of the effect of temperature on disease transmission.

4.2.3.1 Descriptive analysis

A descriptive analysis, including the number of cases of disease in each study region, potential long-term trends or seasonal variation and a summary of meteorological variables over the study period, has been completed for each disease in each study area. Sequential graphs are also presented to provide a background of the following correlation and time-series regression analyses.

4.2.3.2 Correlation analysis

Spearman correlation analysis was performed in this study. Pearson's correlation was not used as this calculation is based on the assumption that both of the variables (X and Y) follow a normal distribution. The Pearson correlation reflects only the degree of linear relationship between two variables [133]. Given that the occurrence of disease may not be normally distributed and the association between meteorological variables and disease may not be a linear relationship, it is appropriate to use a non-parametric Spearman correlation analysis. The calculation of the Spearman coefficients between any two variables X and Y can be given as [134]:

$$r_s = [1 - 6\Sigma D^2]/N(N^2 - 1),$$

where D=X-Y and N is the number of pairs.

Additionally, given the potential lagged effect of the meteorological variables on disease transmission, cross-correlation analysis was also performed with relevant lag values. The maximum correlation coefficients between meteorological variables and disease are presented in the result tables. For example, if maximum temperature is significantly related with the number of cases at 1-, 2- or 3-week lags and the

maximum correlation coefficient is at the 2-week lag, then the maximum coefficient and a lag value of 2 weeks are presented in the result table. The cross correlation coefficient between two series x(i) and y(i) at lag "d" can be calculated by the following formula [134], where *mx* and *my* are the means of x(i) and y(i) respectively.

$$r = \frac{\sum_i [\,(x(i) - mx) * (y(i-d) - my)\,]}{\sqrt{\sum_i (x(i) - mx)^2}\sqrt{\sum_i (y(i-d) - my)^2}}$$

4.2.3.3 Time-series regression analysis

Based on the correlation analysis, the regression models were developed using the variables significantly correlated with disease as explanatory variables, and incidence or the number of cases as the outcome variables. There are several models that can be used to perform the regression analysis, such as Poisson regression, multiple linear regression and Seasonal Autoregressive Integrative Moving Average (SARIMA) models. Classical regression is often insufficient for explaining all of the dynamics of time series data, such as autocorrelation and long-term trends [86, 89, 126]. The SARIMA models have been recently applied in epidemiological studies [87, 135, 136]. In order to decide which model is appropriate to conduct the regression analysis, different regression methods have been compared (and will be published elsewhere [137]). The comparison among standard Poisson regression, adjusted Poisson regression, general linear regression and the SARIMA models has been discussed in this manuscript [137]. The results indicate that the SARIMA model has a better goodness of fit and forecasting ability, compared with the traditional regression models when analysing time series data [137] (Appendix C).

However, the SARIMA models are not suitable for all time-series data. The nature of the data may determine whether or not a particular regression model is valid. For example, if the data are not normally distributed but follow a Poisson distribution then this may invalidate assumptions on which the regression model is based. Moreover, SARIMA modelling often requires the use of differencing and transformations to stabilize the time series. Sometimes, disease series cannot be modified so as to be stationary [138]. Therefore, the SARIMA models, as well as the

autoregressive adjusted Poisson regression (as discussed below), were performed in this study depending on the different characteristics of the time series data.

Based on the results of correlation analyses, maximum temperature and minimum temperature, relative humidity at 9am and 3pm cannot be included in one single model due to the high correlation between them. Therefore, four models have been initially tried for each disease, including maximum temperature and relative humidity at 9am, maximum temperature and relative humidity at 3pm, minimum temperature and relative humidity at 9am and minimum temperature and relative humidity at 3pm. Two models were developed for each disease with consideration of multicollinearity and model diagnosis. The final selected models will be presented in the result section.

4.2.3.3.1 Time-series adjusted Poisson regression

Poisson regression is applied in regression analysis for count data with an assumption of a Poisson distribution rather than a normal distribution. The Poisson distribution has only one parameter, ν, which equals the mean (or variance). The distribution is given by the formula [139]: $\Pr(Y)= \frac{\nu^n e^{-\nu}}{n!}$. However, for time-series data, there are other statistical issues to be considered, including autocorrelation, lag time, potential seasonality and long-term trends.

Autocorrelation. The fact that days of high incidence and similar temperature tend to cluster together is called autocorrelation [22]. To control for the autocorrelation in the outcome variables (Y_t), autoregressive variables (at order d), (Y_{t-1}, Y_{t-2}, …,Y_{t-d}) were included in the regression models. Moreover, lag values were included in order to control for the autocorrelation of the explanatory variables.

Lag time. Lag time refers to the delayed effects on outcome variables because the impact occurs not just on the same day but perhaps weeks or even months later. The lag span differs according to different health outcomes. In this study, up to 4 months (16 weeks) lag values were first detected by cross-correlation analysis, based on a review of previous studies of meteorological variables and infectious diseases. All

significant lags were included in the regression analysis. Stepwise regression methods was used in the analysis as long as there was a significant improvement, determined by the calculation of maximum likelihood [140]. Final parameters of the significant variables of the regression are presented in the results.

Seasonality and long-term trend: seasonality and long-term trends, which vary over time and may be associated with weather conditions, are potential confounders of the relationship between climate variation and diseases. The association between other meteorological variables may not be detected if these co-variables are not controlled in the analysis. Given the potential seasonal distribution of the diseases, a triangular function, $\sin(2\pi t/12)$ (for monthly data) and $\sin(2\pi t/52)$ (for weekly data), was included in the model to control for seasonality [102]. To control for potential long-term trends in the diseases during the study period, a *year* variable was also included in the models.

4.2.3.3.2 SARIMA model

The SARIMA model is developed from the Autoregression and Moving Average (ARMA) model. An ARMA model predicts the outcome variable from the values of the outcome at previous time points [141]. However, it is only suitable for a stationary process where the observations are normally distributed. The SARIMA model allows for trends and seasonal variation. A SARIMA model is classified as an SARIMA(p,d,q)x(P,D,Q) model, which can be generally written as:

$$\Phi_P(B^s)\,\phi(B)\,{}_{,s}\nabla^{D}\,{}_{,}\nabla^{d}x_t = \alpha + \Theta_Q(B^s)\,\theta(B)\omega_t$$

Where, $\phi(B)$ and $\theta(B)$ of orders p and q represent ordinary autoregressive and moving average components and $\Phi_P(B^s)$ and $\Theta_Q(B^s)$ represent seasonal autoregressive and moving average components of orders P and Q. ${}_{,s}\nabla^{D}$ and ${}_{,}\nabla^{d}x_t$ are seasonal difference components.

The autocorrelation function (ACF) and partial autocorrelation function (PACF) were performed to assess the appropriate orders of autocorrelation (AR) and moving average (MA) terms in the model. No extra seasonal variable was defined and included in the model because of the intrinsic components of the SARIMA model.

The seasonal autoregressive and seasonal moving average components of orders P and Q, respectively, with seasonal period 's' (s=12 for monthly data and s=52 for weekly data) can be written as [69]:

$\Phi_P(B^s) = 1- \Phi_1(B^s) – \Phi_2(B^{2s}) - … - \Phi_P(B^{ps})$ and
$\Theta_Q(B^s) = 1+ \Theta_1(B^s) + \Theta_2(B^{2s})+…+ \Theta_Q(B^{Qs})$.

Potential long-term trends in the diseases over the study periods would be controlled by differencing, a function used to smooth the series [69].

4.2.3.3.3 Diagnosis of the regression models

The diagnosis of the time-series adjusted Poisson regression was performed by the calculation of R square, goodness-of-fit, plotting of model residuals and testing of forecasting ability. Goodness of fit is measured by the likelihood ratio, also known as likelihood ratio chi-square, deviance chi-square, or simply G^2 [142]. When the likelihood ratio is not significant, then the model being tested is a good fit to the data because this implies that the parsimonious model is not significantly worse than the well-fitting saturated model. Goodness of fit confirms or not the overall model, whereas residual analysis helps to spot outlier numbers, even if, overall, the model is a well-fitting one as assessed by the likelihood ratio chi-square test [142].

The diagnosis of the SARIMA models was performed by the Aikake Information Criterion (AIC) to compare model fit. The model with the smaller AIC fits the data better. Residual plotting, including scatter figures and partial autocorrelation figures, was performed to identify the distribution and autocorrelation of the model residuals.

In order to test the forecasting ability of developed models, part of the data within the time series were excluded while developing the models. These data were then used to project expected values by the developed models. However, the forecasting ability test could not be performed for each disease because, for some diseases, the time series points over the study periods were insufficient to undertake forecasting. Insufficient time-points decrease the strength of the model development. Consequently, only the models developed with a study period of over 15 years were tested for forecasting. For example, for models developed for Ross River virus

infection in Brisbane and Townsville in Queensland and salmonellosis in all the study regions in Australia, data from 1990 to 2003 were used to develop the regression models and from 2004 onwards data were used to test the forecasting ability of the models. For the models developed for malaria and bacillary dysentery in the study areas in China and for Ross River virus infection in the Murray River regions in South Australia, only goodness-of-fit and residual plotting were performed for model diagnosis.

Detailed formulae and equations for the time-series adjusted Poisson regression and the SARIMA models are presented in Appendices A and B.

4.2.3.4 Detection of a potential threshold temperature

After the regression analysis was conducted of the relationship between meteorological variables and the study diseases, potential threshold effects were detected. The assumption of this analysis is that the association between meteorological variables and infectious diseases may have a threshold effect, thus there may not be significant associations until a threshold is reached. The thresholds may vary in different climatic areas and for different diseases.

To detect a potential threshold for the effect of temperature on enteric infections, a Hockey Stick model was used to estimate a threshold temperature [89]. A natural cubic spline was fitted to explore the shape of the relationship before performing the Hockey Stick model. The assumption of the Hockey Stick model is that temperature has no effect on disease transmission until a threshold value is reached. Autocorrelation variables were included in the models to control for the autocorrelation of the number of cases. Diagnosis of the model was conducted by plotting residuals to check for their normality and homogeneity of variance. The approach is to use the Stata **–nl** hockey- (non-linear hockey) estimation program, which estimates complex linear and non-linear models by least squares [143]. "**nl**" is used to estimate *whether*, and if so *where*, a change in slope occurs in the relationship between two variables by iterative numerical methods [144].

The effect of meteorological variables on vector-borne diseases is rather complex, based on the results of the prior regression analysis. Meteorological variables,

including temperature, rainfall and relative humidity may all have affected the transmission of the vector-borne diseases in an interdependent manner rather than independently. Therefore, there are few practical implications for disease prevention and control in the detection of a threshold for one climatic variable alone. However, in terms of the association between meteorological variables and enteric infections, all the regression models suggest that temperature may be the only meteorological variable that significantly affects the disease transmission. Consequently, potential threshold temperatures were detected only for enteric infections but not for vector-borne diseases in the study areas in Australia and China.

Statistical packages and software, including Excel, SPSS 11.5 [145] and Stata 8.2 [143], were used in the analysis. The significant level α=0.05 was used in all the analyses.

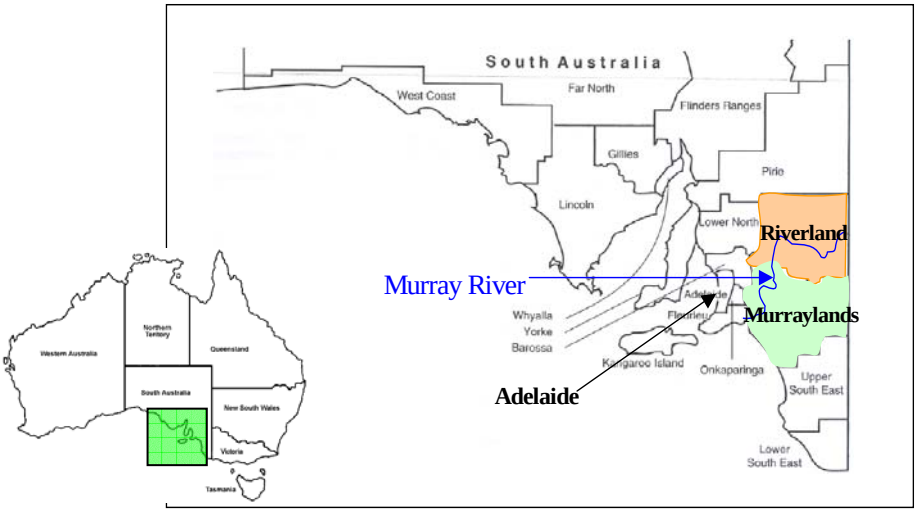
4.3 Results and discussion - Climate variation and vector-borne diseases

4.3.1 Ross River virus infection

4.3.1.1 RRV infection in the Murray River regions, South Australia

RRV infection in the Riverland and the Murraylands has been analysed separately as their different locations along the Murray River may have different effects on mosquitoes and hence influence the transmission of RRV infection. The geographic location of the Riverland and the Murraylands in South Australia is shown in Figure 4- 1.

Figure 4- 1 Index map of Riverland and Murraylands, South Australia



4.3.1.1.A Descriptive analysis

4.3.1.1.A.1 Summary of notified cases of RRV infection in the Murray River regions in South Australia, 1992-2004

Analysis was on a monthly basis due to the relatively small numbers for daily and weekly cases. Over the period 1992 to 2004, there were 1,139 RRV infections in the Murray River regions - 910 RRV infections from the Riverland and 229 RRV infections from the Murraylands, with four epidemics of RRV infection occurring in 1993/94,1997/98, 1999/2000 and 2000/2001 (Figure 4- 2 and Figure 4- 4). Additionally, a clear seasonal distribution of RRV infection was observed with most cases occurring in the summer and autumn (November to May) (Figure 4- 3 and Figure 4- 5).

Figure 4- 2 Number of monthly notified cases of RRV infection in the Riverland in South Australia, 1992-2004

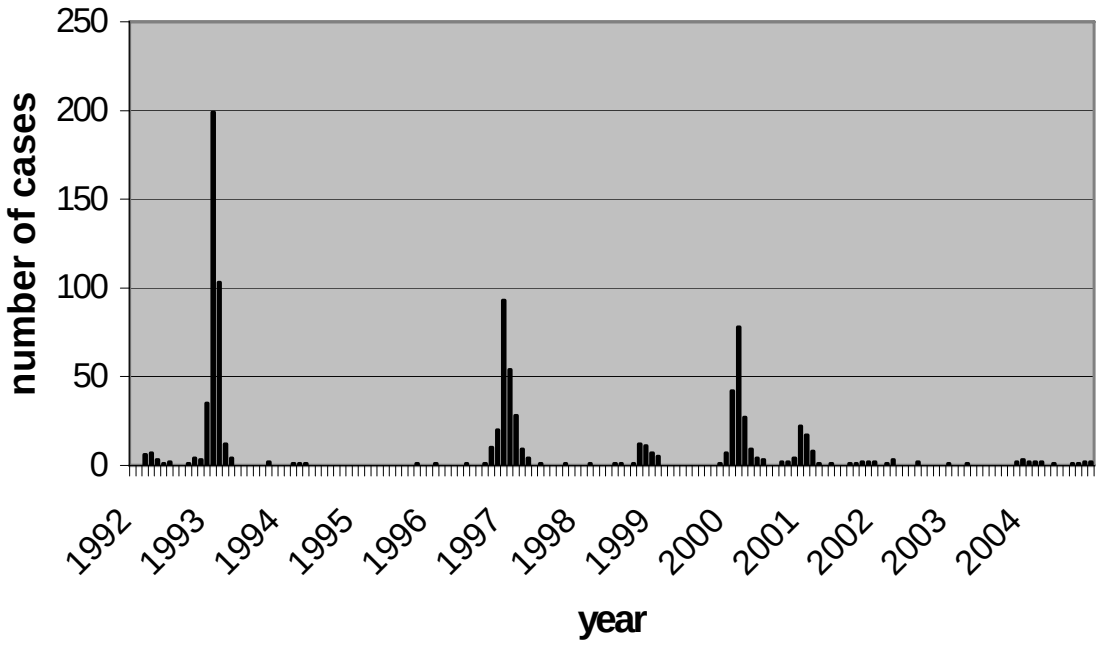


Figure 4- 3 Monthly distribution of notified cases of RRV infection in the Riverland in South Australia, 1992-2004

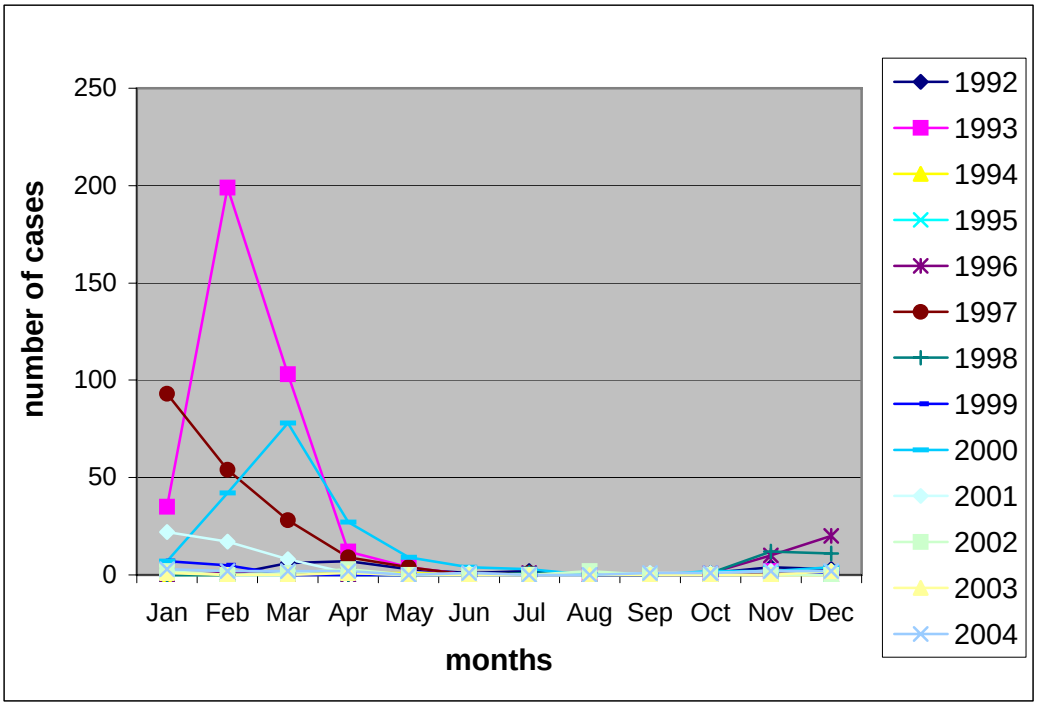


Figure 4- 4 Monthly notified cases of RRV infection in the Murraylands in South Australia, 1992-2004

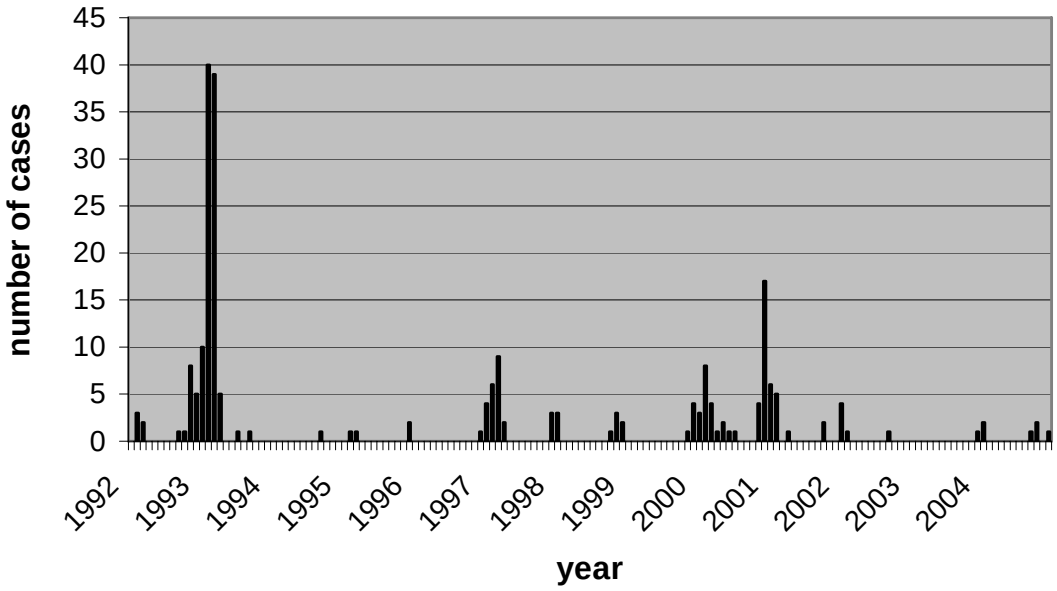
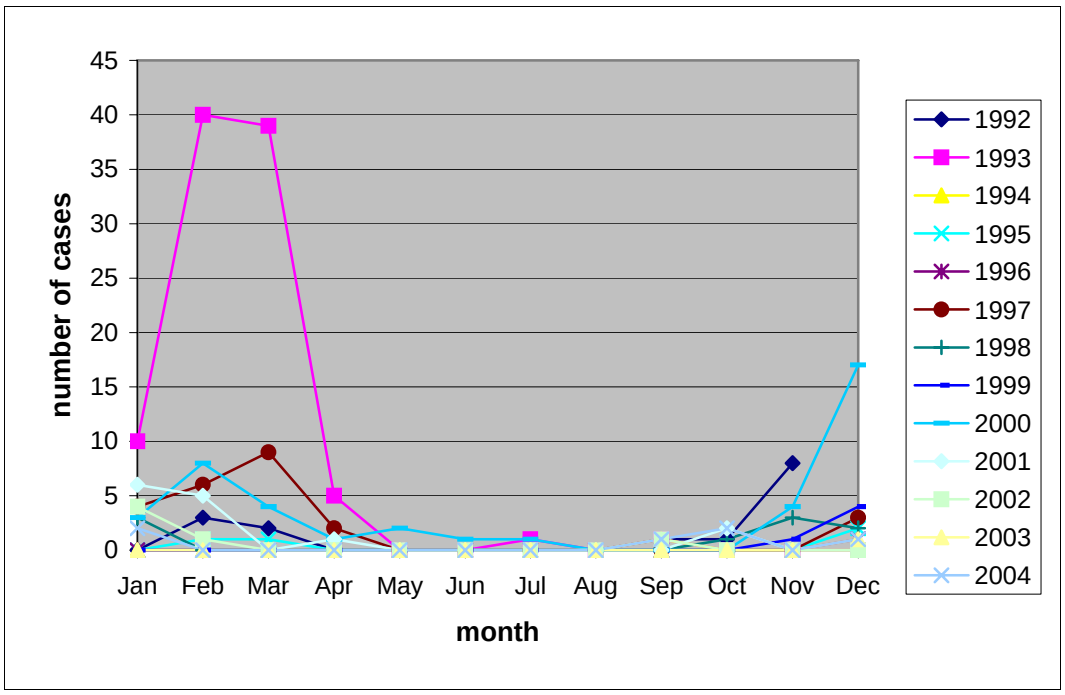


Figure 4- 5 Monthly distribution of notified cases of RRV infection in the Murraylands in South Australia, 1992-2004



4.3.1.1.A.2 Summary of meteorological variables

As shown in Table 4- 3 and 4- 4, the climatic conditions in the Riverland and the Murraylands are slightly different. The range of temperature was narrower in the Murraylands. The monthly flow of the Murray River was slightly higher in the Riverland.

Table 4- 3 Summary of monthly meteorological variables in the Riverland in South Australia, 1992-2004

	Mean	Std. Dev.	Min	Max
Mean min temp (ºC)	8.77	4.03	1.10	18.00
Mean max temp (ºC)	23.69	5.60	14.30	35.70
Total rainfall (mm)	22.14	17.57	0	93.40
Mean humidity 9am (%)	65.19	12.13	42.00	91.00
Mean humidity 3pm (%)	38.63	11.15	18.00	70.00
River flow (GL/month)	461.53	561.10	71.89	3167.00

Table 4- 4 Summary of monthly meteorological variables in the Murraylands in South Australia, 1992-2004

	Mean	Std. Dev.	Min	Max
Mean min temp (ºC)	9.71	3.35	2.90	17.20
Mean max temp (ºC)	22.85	4.62	14.90	32.90
Total rainfall (mm)	31.52	23.24	0	130.40
Mean humidity 9am (%)	72.01	9.64	53.00	92.00
Mean humidity 3pm (%)	46.97	8.74	30.00	72.00
River flow (GL/month)	438.29	545.16	71.89	3167.00

4.3.1.1.B Correlation analysis

Correlation parameters among meteorological variables are reported firstly, followed by the results from Spearman correlation analyses between meteorological variables and RRV infection in the Murray River regions.

4.3.1.1.B.1 Correlation among meteorological variables

There were high correlations among monthly maximum and minimum temperatures (r>0.90) and relative humidity at 9am and 3pm (r>0.80) (Table 4- 5 and Table 4- 6) in the two regions.

Table 4- 5 Correlation coefficients between meteorological variables in the Riverland

	Mean min temp	Mean max temp	Total rainfall	Mean humidity 9am	Mean humidity 3pm	River flow
Mean min temp	1.00					
Mean max temp	0.95	1.00				
	(0.00)					
Total rainfall	-0.04	-0.18	1.00			
	(0.67)	(0.03)				
Mean humidity 9am	-0.67	-0.78	0.20	1.00		
	(0.00)	(0.00)	(0.01)			
Mean humidity 3pm	-0.71	-0.85	0.36	0.91	1.00	
	(0.00)	(0.00)	(0.00)	(0.00)		
River flow	0.10	0.10	0.26	-0.08	0.01	1.00
	(0.23)	(0.23)	(0.00)	(0.36)	(0.94)	

* *p* value in the bracket. Highlighted coefficients demonstrate high levels of correlation.

Table 4- 6 Correlation coefficients between meteorological variables in the Murraylands

	Mean min temp	Mean max temp	Total rainfall	Mean humidity 9am	Mean humidity 3pm	River flow
Mean min temp	1.00					
Mean max temp	0.92	1.00				
	(0.00)					
Total rainfall	-0.20	-0.34	1.00			
	(0.01)	(0.00)				
Mean humidity 9am	-0.60	-0.66	0.24	1.00		
	(0.00)	(0.00)	(0.00)			
Mean humidity 3pm	-0.69	-0.83	0.46	0.82	1.00	
	(0.00)	(0.00)	(0.00)	(0.00)		
River flow	0.12	0.10	0.17	-0.25	-0.11	1.00
	(0.14)	(0.21)	(0.03)	(0.00)	(0.19)	

* *p* value in the bracket. Highlighted coefficients demonstrate high levels of correlation.

4.3.1.1.B.2 Correlation among RRV infection and both meteorological variables and flow of Murray River

All meteorological variables were significantly correlated with RRV infection in the Riverland and the Murraylands with a lag time range from zero to three months. Mean maximum temperature, mean minimum temperature, total rainfall, and the river flow were positively correlated, while relative humidity was negatively correlated with RRV infection (Table 4- 7 and Table 4- 8).

Table 4- 7 Correlation between RRV infection and meteorological variables in the Riverland

	Coefficient (95% CI)	*p*	Lag time
Mean min temp	0.422 (0.402, 0.442)	0.000	1 month
Mean max temp	0.390 (0.36, 0.42)	0.000	1 month
Total rainfall	-0.301(-0.375, -0.227)	0.000	1 month
Mean humidity 9am	-0.322 (-0.388, -0.256)	0.000	1 month
Mean humidity 3pm	0.229 (0.200, 0.458)	0.004	3 months
River flow	0.316 (0.254, 0.378)	0.000	2 months

Table 4- 8 Correlation between RRV infection and meteorological variables in the Murraylands

	Coefficient (95% CI)	*p*	Lag time
Mean min temp	0.451 (0.395, 0.507)	0.000	0
Mean max temp	0.410 (0.360, 0.460)	0.000	0
Total rainfall	-0.317(-0.411, -0.223)	0.000	1 month
Mean humidity 9am	-0.331(-0.381, -0.281)	0.000	0
Mean humidity 3pm	0.244(0.139, 0.349)	0.002	3 months
River flow	0.271 (0.132, 0.410)	0.001	2 months

4.3.1.1.C Regression models for RRV infection in the Murray River regions, South Australia

4.3.1.1.C.1 Regression models for RRV infection in the Riverland

Due to the Poisson distribution of the cases of RRV infection in the Murray River region, two models were developed by adjusted Poisson regression for consideration of multicollinearity. Model 1 has minimum temperature and relative humidity at 3pm, while Model 2 has maximum temperature and relative humidity at 9am. Parameters from the two models (Table 4- 9 and Table 4- 10) were similar, both with R^2 of more than 0.68. Maximum and minimum temperatures with a one-month lag, river flow with a two-month lag, and rainfall with a one-month lag were all positively associated with the transmission of RRV infection in the Riverland. Seasonal variations were significantly included in both models. The number of cases was 1- order autoregressive, which means the number of cases in the current month could be explained by the number of cases in one month prior.

The models suggest that a 1 ºC rise in maximum temperature is related to a 20% (95%CI: 17.8%-22.0%) increase in the number of cases of cases and a 1 ºC rise in minimum temperature is related to about 7.5% (95%CI: 4.5%-10.6%) increase in the number of cases in the Riverland, South Australia. The excellent goodness-of-fit of Model 1 and the randomly distributed residuals are demonstrated in Figure 4- 6. Due to the similarity between Model 1 and Model 2, the diagnostic plotting figures for Model 2 are not presented here.

Table 4- 9 Parameters from adjusted Poisson regression for RRV infection in the Riverland (Model 1)

	Coefficient	Std. Err.	z	P>|z|	[95% CI]	
Lag1 case count*	0.0140	0.0008	16.53	0.000	[0.0124,	0.0157]
Lag2 river flow	0.0002	0.0001	2.23	0.026	[0.0000,	0.0004]
Lag1 min temp	0.0754	0.0155	4.88	0.000	[0.0451,	0.1057]
Lag1 rainfall	0.0182	0.0017	10.53	0.000	[0.0148,	0.0215]
Humidity 3pm	-0.0383	0.0077	-4.94	0.000	[-0.0534,	-0.0230]
Sin(2πt/12)	1.5282	0.1054	14.50	0.000	[1.3216,	1.7349]
Constant	0.0016	0.3642	0.00	0.996	[-0.7121,	-0.7154]

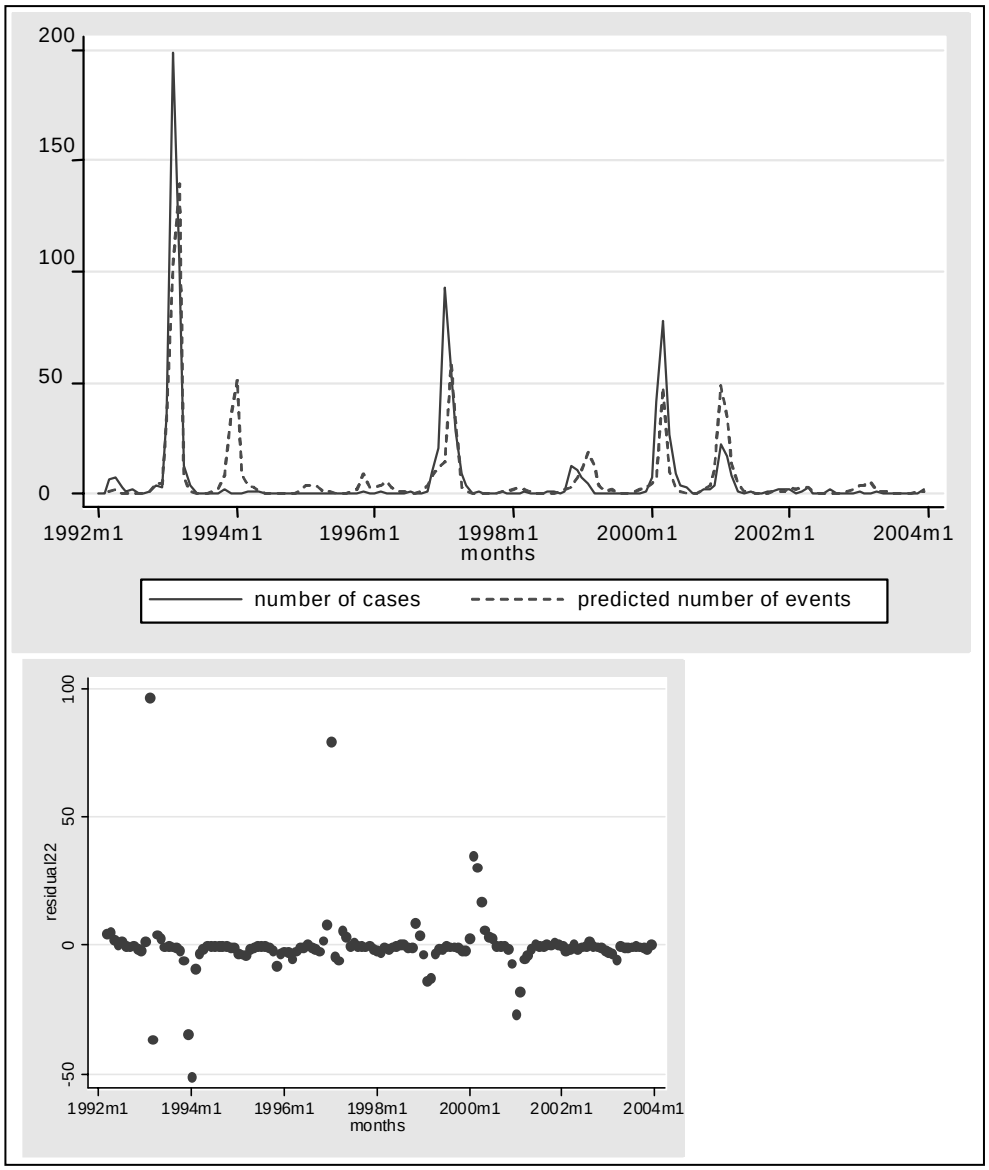
* Lag1 case count: number of cases occurred one month prior.

Table 4- 10 Parameters from adjusted Poisson regression for RRV infection in the Riverland (Model 2)

	Coefficient	Std. Err.	z	P>|z|	[95% Conf. Interval]	
Lag1 case count*	0.0139	0.0008	18.39	0.000	[0.0124,	0.0154]
Lag2 river flow	0.0005	0.0001	6.50	0.000	[0.0003,	0.0006]
Lag1 rainfall	0.0155	0.0017	9.31	0.000	[0.0122,	0.0187]
Lag1 max temp	0.1989	0.0108	18.43	0.000	[0.1778,	0.2201]
Sin(2πt/12)	1.2684	0.1033	12.30	0.000	[1.0659,	1.4709]
Constant	-5.2805	0.3196	-16.52	0.000	[-5.9069,	-4.6541]

* Lag1 case count: number of cases occurred one month prior.

Figure 4- 6 Notified cases vs. model fit cases of RRV infection in the Riverland according to Model 1 and scatter plot of the model residuals



4.3.1.1.C.2 Regression models for RRV infection in the Murraylands

Similar to the results in the Riverland, two models were developed by adjusted Poisson regression for RRV infection in the Murraylands. Parameters of the two models (Table 4- 11 and Table 4- 12) were similar, both with R^2 of more than 0.60. Maximum temperature, minimum temperature, river flow and rainfall were all significantly associated with the transmission of RRV infection in the Murraylands with a lag time from 0 to 2 months.

The models suggest that a 1 ºC rise in maximum temperature is related to an 18.8% (95%CI: 14.7%-22.8%) increase in the number of cases, and a 1ºC rise in minimum temperature is related to a 12.0% (95%CI: 4.1%-19.9%) increase in the number of cases in the Murraylands, South Australia. An excellent goodness-of-fit of Model 1 and the randomly distributed residuals are demonstrated in Figure 4- 7. Due to the high similarity between Model 1 and Model 2, the diagnostic plotting figures for Model 2 are not presented here.

Table 4- 11 Parameters from adjusted Poisson regression for RRV infection in the Murraylands (Model 1)

	Coefficient	Std. Err.	z	P>|z|	[95% Conf. Interval]	
Lag1 case count*	0.0939	0.0060	15.70	0.000	[0.0822,	0.1056]
River flow	0.0003	0.0001	2.66	0.008	[0.0001,	0.0005]
Lag1 min temp	0.1200	0.0402	2.99	0.003	[0.0413,	0.1987]
Lag2 rainfall	0.0253	0.0021	12.29	0.000	[0.0212,	0.0293]
Constant	-4.7369	0.4024	-11.77	0.000	[-5.5256,	-3.9482]

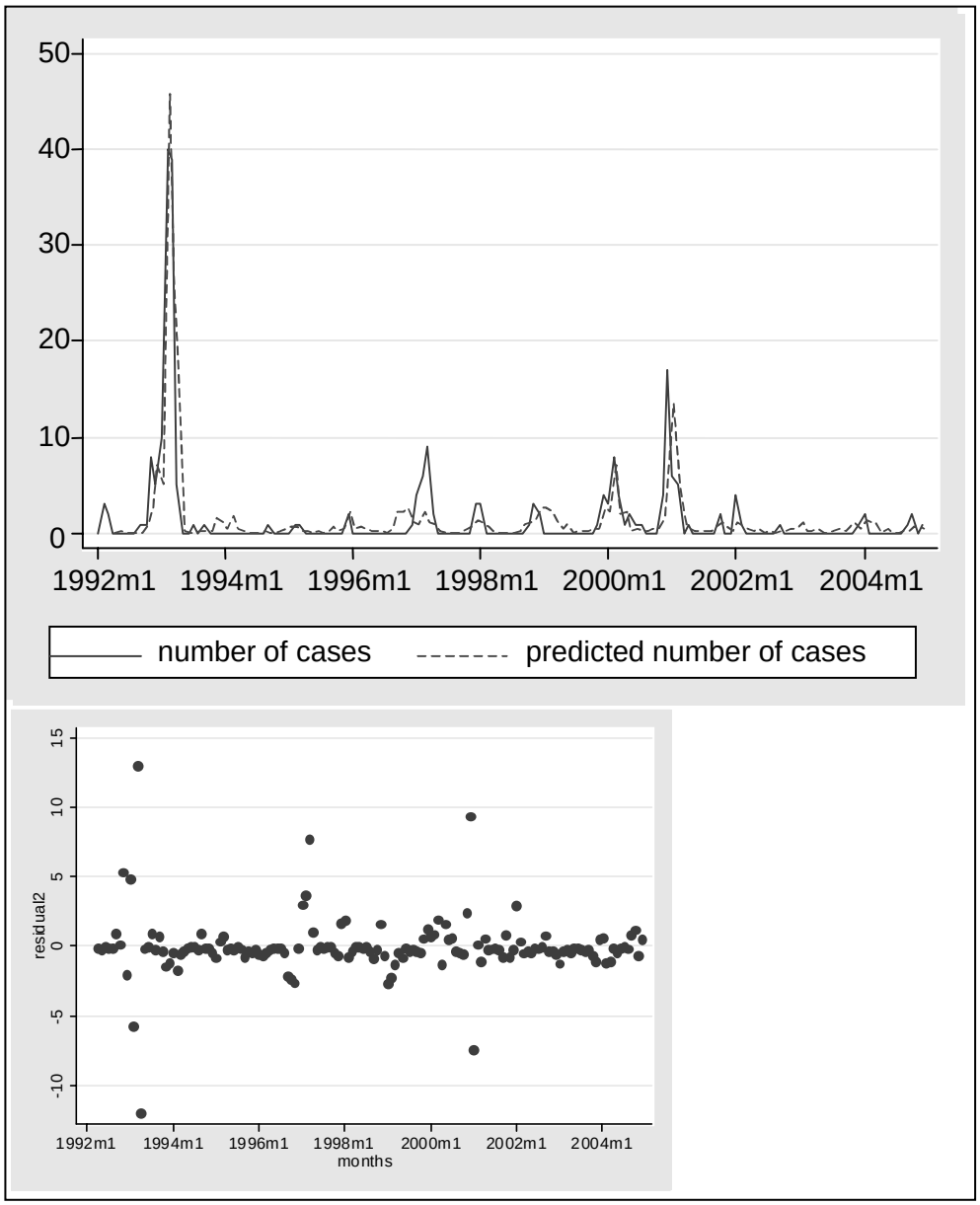
* Lag1 case count: number of cases occurred one month prior.

Table 4- 12 Parameters from adjusted Poisson regression for RRV infection in the Murraylands (Model 2)

	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
Lag1 case count*	0.1004	0.0056	17.90	0.000	[0.0894,	0.1114]
River flow	0.0003	0.0001	2.41	0.016	[0.000049,	0.0005]
Max temp	0.1876	0.0205	9.13	0.000	[0.1473,	0.2279]
Lag2 rainfall	0.0278	0.0020	14.26	0.000	[0.0240,	0.0317]
Constant	-6.1417	0.5613	-10.94	0.000	[-7.2418,	-5.0415]

* Lag1 case count: number of cases occurred one month prior.

Figure 4- 7 Notified cases vs. model fit cases of RRV infection in the Murraylands according to Model 1 and scatter plot of the model residuals



4.3.1.2 RRV infection in Brisbane, Queensland, Australia

4.3.1.2.A. Descriptive analysis

4.3.1.2.A.1 Summary of notified cases of RRV infection in Brisbane, 1990-2005

In total, there were 4,785 RRV infections notified in Brisbane between January 1990 and July 2005, with most cases occurring in summer months. However, the seasonal pattern were not clearly observed in some years such as 1993, 1995 and 2002 (Figure 4- 8 and Figure 4- 9).

Figure 4- 8 Weekly notified RRV infections in Brisbane, January 1990 - July 2005

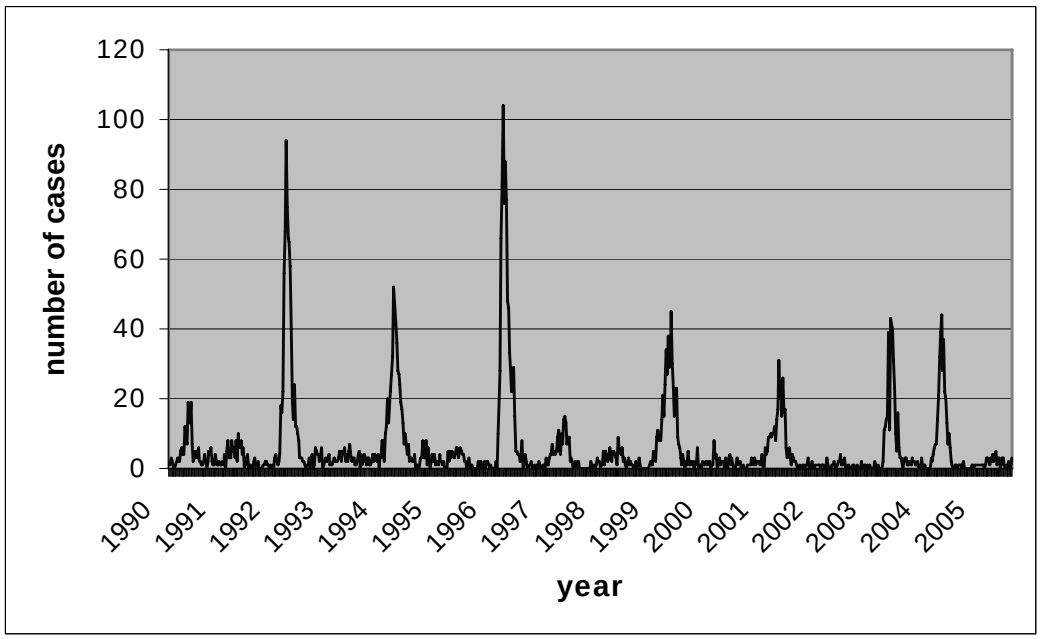
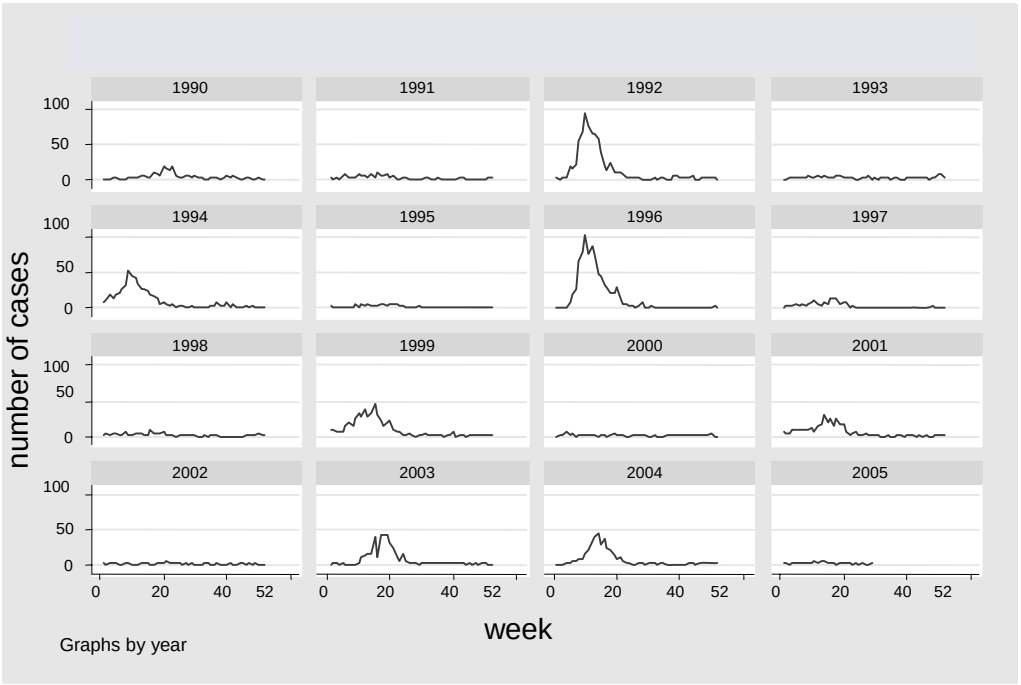


Figure 4- 9 Annual distribution of weekly notified RRV infections in Brisbane January 1990 - July 2005



4.3.1.2.A.2 Summary of meteorological variables

The meteorological variables during the study period in Brisbane are summarised in Table 4- 13. During the study period, the mean maximum and mean minimum temperature were 25.3ºC and 15.3ºC respectively. The weekly total rainfall was less than 20 mm and the average humidity was around 60%. The mean high tide level was 2.02 metres.

Table 4- 13 Summary of weekly meteorological variables in Brisbane, January 1990 - July 2005

	Mean	Std. Dev.	Min	Max
Mean max temp (ºC)	25.33	3.15	17.76	33.10
Mean min temp (ºC)	15.34	4.64	4.57	24.63
Mean humidity 9am (%)	65.22	9.68	27.71	92.71
Mean humidity 3pm (%)	56.44	10.13	26.71	84.57
Total rainfall (mm)	19.64	37.65	0	565.80
High tide (metres)	2.02	0.14	1.61	2.57

4.3.1.2.B Correlation analysis

4.3.1.2.B.1 Correlation among meteorological variables

There were high correlations among weekly mean minimum temperature and maximum temperatures (r=0.88) and relative humidity at 9am and 3pm (r=0.73) in Brisbane over the study period (Table 4- 14).

Table 4- 14 Correlation coefficients between meteorological variables in Brisbane

	Mean max temp	Mean min temp	Mean humidity 9am	Mean humidity 3pm	Total rainfall	High tide
Mean max temp	1.00					
Mean min temp	0.88	1.00				
	(0.00)					
Mean humidity 9am	-0.05	0.30	1.00			
	(0.19)	(0.00)				
Mean humidity 3pm	0.35	0.66	0.73	1.00		
	(0.00)	(0.00)	(0.00)			
Total rainfall	0.12	0.31	0.41	0.48	1.00	
	(0.00)	(0.00)	(0.00)	(0.00)		
High tide	0.02	0.02	0.08	0.02	0.06	1.00
	(0.65)	(0.52)	(0.02)	(0.64)	(0.08)	

* *p* values in the brackets. Highlighted coefficients demonstrate high levels of correlation.

4.3.1.2.B.2 Correlation among RRV infection and both meteorological variables and high tide in Brisbane

The correlation analysis was conducted on a weekly basis. The correlation coefficients and relevant lag values are summarised in Table 4- 15. It can be seen that mean weekly maximum temperature, mean weekly minimum temperature, mean weekly humidity, mean weekly total rainfall and high tidal level were all positively correlated with RRV infection in Brisbane with varying lag time from 4 to 9 weeks.

Table 4- 15 Correlation between weekly RRV infection and meteorological variables in Brisbane

	Coefficient (95% CI)	*p*	Lag time
Mean max temp	0.49 (0.39, 0.59)	0.0000	9 weeks
Mean min temp	0.49 (0.38, 0.60)	0.0000	7 weeks
Mean humidity 9am	0.28 (0.17, 0.39)	0.0000	4 weeks
Mean humidity 3pm	0.25 (0.20, 0.30)	0.0000	7 weeks
Total rainfall	0.21 (0.16, 0.26)	0.0000	8 weeks
High tide	0.16 (0.13, 0.19)	0.0000	4 weeks

4.3.1.2.C Regression models for RRV infection in Brisbane, Queensland

Two regression models were developed for consideration of multicollinearity with Model 1 including maximum temperature and humidity at 9am and Model 2 including minimum temperature and humidity at 3pm. Data from 1990-2003 were used to develop the models and data from 2004 to 2005 were used for forecasting.

The results from Model 1 and Model 2 indicated that, after controlling for seasonal variation, weekly mean minimum temperature (9-week lag), maximum temperature (7-week lag), rainfall (8-week lag), relative humidity at 9am (4-week lag) and 3pm (7-week lag) and the sea high tide (4-week lag) all had a positive association with RRV infection. The number of cases of RRV infection that occurred in one week was also associated with the number of cases in the previous one and two weeks (Table 4-16 and Table 4- 17). The R square values for both models were approximately 0.60. The models suggest that a 1 ºC rise in maximum temperature might bring about a 6.9% (95%CI: 5.3%-8.4%) increase in the number of cases and a 1 ºC rise in minimum temperature is related to a 7.0% (95%CI: 5.7%-8.3%) increase in the number of cases. It also indicates that high tides may play a more important role in the transmission of RRV infection in Brisbane than temperatures and rainfall.

The diagnosis of the models showed randomly distributed residuals. Figure 4-10 illustrates the goodness-of-fit of Model 1, which has the statistical power to estimate peak values in epidemic years. Additionally, these figures indicate that the predictive model based on historic data including meteorological variables may be a good tool to predict potential RRV epidemics in Brisbane. The plotting figures for Model 2 are very similar to those of Model 1. They are not presented here.

Table 4- 16 Parameters from adjusted Poisson regression for RRV infection in Brisbane (Model 1)

	Coefficient	Std. Err.	z	P>|z|	[95% Conf. Interval]	
Lag1 case count*	0.0294	0.0013	22.54	0.000	[0.0268,	0.0319]
Lag2 case count	0.0048	0.0014	3.49	0.000	[0.0021,	0.0075]
Lag9 max temp	0.0688	0.0079	8.74	0.000	[0.0534,	0.0842]
Lag8 rainfall	0.0023	0.0003	8.49	0.000	[0.0018,	0.0028]
Lag4 humidity 9am	0.0109	0.0018	6.02	0.000	[0.0074,	0.0145]
Lag4 high tide	0.3728	0.1116	3.34	0.001	[0.1541,	0.5916]
Sin(2πt/52)	414.9007	29.2169	14.20	0.000	[357.6367,	472.1648]
Constant	-1.5173	0.3401	-4.46	0.000	[-2.1838,	-0.8508]

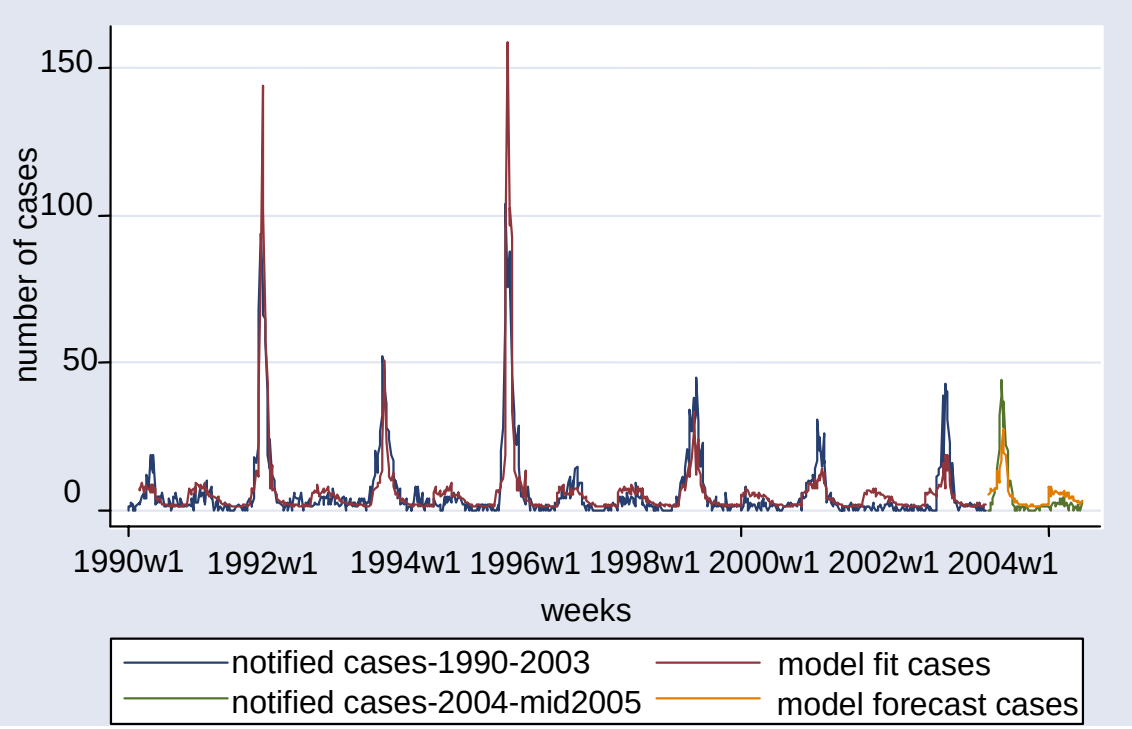
* Lag1 case count: number of cases occurred one month prior.

Table 4- 17 Parameters from adjusted Poisson regression for RRV infection in Brisbane (Model 2)

	Coefficient	Std. Err.	z	P>|z|	[95% Conf. Interval]	
Lag1 case count*	0.0273	0.0013	21.13	0.000	[0.0247,	0.0298]
Lag2 case count	0.0067	0.0013	5.08	0.000	[0.0041,	0.0093]
Lag5 humidity 3pm	0.0084	0.0020	4.23	0.000	[0.0045,	0.0123]
Lag7 min temp	0.0700	0.0066	10.67	0.000	[0.0571,	0.0828]
Lag8 rainfall	0.0020	0.0003	7.04	0.000	[0.0014,	0.0025]
Lag4 high tide	0.3271	0.1117	2.93	0.003	[0.1080,	0.5461]
Sin(2πt/52)	320.2028	30.2679	10.58	0.000	[260.8788,	379.5268]
Constant	-0.6657	0.2847	-2.34	0.019	[-1.224,	-0.1077]

* Lag1 case count: number of cases occurred one month prior.

Figure 4- 10 Notified cases vs. model fit cases (1990-2003) and projected cases (2004-2005) of RRV infection in Brisbane according to Model 1



4.3.1.3 RRV infection in Townsville, northern Queensland, Australia

4.3.1.3.A Descriptive analysis

4.3.1.3.A.1 Summary of notified cases of RRV infection in Townsville, 1990-2005

In total, 3,012 cases of RRV infection were notified in Townsville from January 1990 to July 2005. There was a clear drop in the number of cases after 2001. Most cases occurred in summer and autumn months (Figure 4- 11 and Figure 4- 12).

Figure 4- 11 Monthly notified cases of RRV infection in Townsville, January 1990 - July 2005

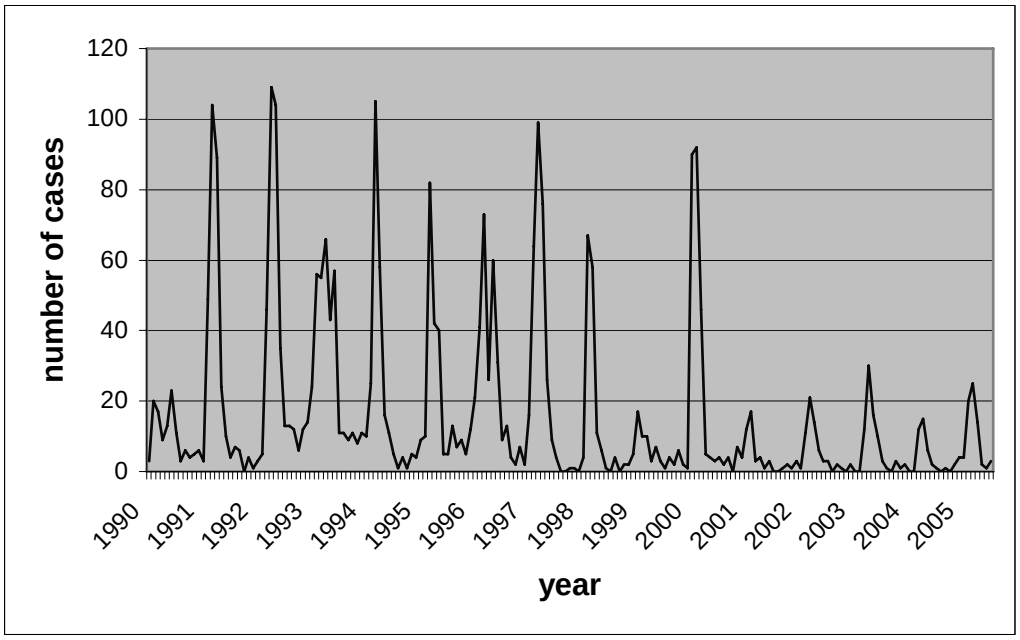


Figure 4- 12 Annual distribution of notified cases of RRV infection in Townsville, January 1990 - July 2005



4.3.1.3.A.2 Summary of meteorological variables in Townsville

Meteorological variables and high tides in Townsville over the study period are summarised in the following table (Table 4- 18). It can be seen that the mean monthly maximum temperature was 29ºC and the mean monthly minimum temperature was 20ºC. The mean humidity was around 60% and the monthly total rainfall was 86 mm. The average monthly high tide was 2.81 metres.

Table 4- 18 Summary of monthly meteorological variables in Townsville, January 1990 - July 2005

Variable	Mean	Std. Dev.	Min	Max
Mean max temp (ºC)	29.36	2.41	24.13	34.30
Mean min temp (ºC)	20.08	4.11	11.00	26.11
Mean humidity 9am (%)	64.33	6.64	49.90	86.06
Mean humidity 3pm (%)	56.37	7.31	39.39	76.83
Total rainfall (mm)	86.14	157.79	0.00	973.80
High tide (metres)	2.81	0.10	2.64	3.10

4.3.1.3.B Correlation analysis

4.3.1.3.B.1 Correlation among meteorological variables

Table 4-19 indicates that there were high correlations among maximum and minimum temperatures (r=0.93) and relative humidity at 9am and 3pm (r=0.84) in Townsville over the study period.

Table 4- 19 Correlation coefficients between meteorological variables in Townsville

	Mean max temp	Mean min temp	Mean humidity 9am	Mean humidity 3pm	Total rainfall	High tide
Mean max temp	1.00					
Mean min temp	0.93	1.00				
Mean humidity 9am	0.24	0.47	1.00			
Mean humidity 3pm	0.48	0.72	0.84	1.00		
Total rainfall	0.28	0.44	0.64	0.71	1.00	
High tide	0.47	0.50	0.41	0.52	0.40	1.00

*All *p* values are less than 0.01. Highlighted coefficients demonstrate high levels of correlation.

4.3.1.3.B.2 Correlation among RRV infection and both meteorological variables and high tide

As shown in Table 4- 20, mean monthly maximum temperature, mean monthly minimum temperature, mean monthly relative humidity, monthly total rainfall and mean monthly high tide were all positively related to RRV infection in Townsville with a relative lag time from one or two months.

Table 4- 20 Correlation between monthly RRV infection and meteorological variables in Townsville

	Coefficient (95% CI)	*p*	Lag time
Mean max temp	0.45 (0.35,0.55)	0.000	2 months
Mean min temp	0.56 (0.41, 0.71)	0.000	2 months
Mean humidity 9am	0.47 (0.17, 0.77)	0.000	2 months
Mean humidity 3pm	0.50 (0.30, 0.70)	0.000	2 months
Total rainfall	0.50 (0.35, 0.65)	0.000	2 months
High tide	0.31 (0.21, 0.41)	0.000	1 month

4.3.1.3.C Regression models for RRV infection in Townsville, Queensland

In Townsville, two models were developed with Model 1 including maximum temperature and humidity at 9am and Model 2 including minimum temperature and humidity at 3pm. Data from 1990 to 2003 were used to develop the regression models and data from 2004 to 2005 were used to test the forecasting ability of the models.

The regression results from Model 1 and Model 2 indicated that, after controlling for seasonality and autocorrelation, monthly mean minimum temperature (2-month lag), maximum temperature (2-month lag), relative humidity (1-month lag), rainfall (2-month lag) and high tides (no lag) all had a positive association with RRV infection. The number of cases of RRV infection that occurred in one month was also related to the number of cases in one month prior (Table 4- 21 and Table 4- 22).

The models suggest that a 1 ºC rise in maximum temperature may bring a 12.0% (95%CI: 9.1%-14.8%) extra cases and a 1 ºC rise in minimum temperature is related to an 8.4% (95%CI: 6.4%-10.5%) increase in the number of cases in Townsville. It

also indicates that high tides may play a more important role in the transmission of RRV infection in Townsville than temperatures. The R square value of both models was 0.54 and there was no autocorrelation among the model residuals. Figure 4- 13 illustrates the goodness-of-fit of the models, which indicates predictive models, including meteorological variables, may be useful to predict potential RRV epidemics in Townsville. The diagnostic plotting for Model 2 was not presented because of the high similarity with Model 1.

Table 4- 21 Parameters from adjusted Poisson regression for RRV infection in Townsville (Model 1)

	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
Lag1 case count*	0.0165	0.0005	27.11	0.000	[0.0134,	0.0155]
Lag2 max temp	0.1199	0.0113	21.17	0.000	[0.2162,	0.2603]
Lag1 humidity 9am	0.0227	0.0040	5.68	0.000	[0.0149,	0.0307]
Lag2 rainfall	0.0002	0.0001	5.92	0.000	[0.0004,	0.0009]
Sin(2πt/12)	399.8398	26.9896	9.65	0.000	[238.5497,	344.3469]
High tide	1.0297	0.2902	3.55	0.000	[0.4610,	1.5985]
Constant	-5.1478	0.8376	-6.15	0.000	[-6.7895,	-3.5062]

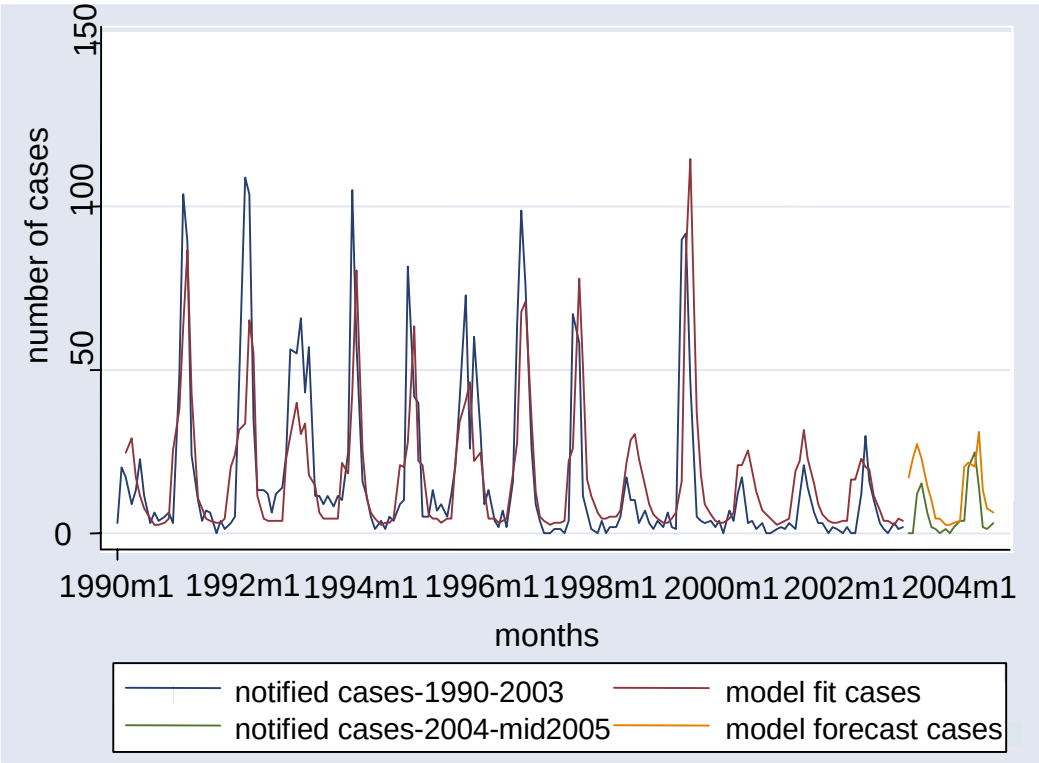
* Lag1 case count: number of cases occurred one month prior.

Table 4- 22 Parameters from adjusted Poisson regression for RRV infection in Townsville (Model 2)

	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
Lag1 case count*	0.0169	0.0005	32.98	0.000	[0.0159,	0.0179]
Lag2 min temp	0.0845	0.0111	7.94	0.000	[0.0636,	0.1053]
Lag1 humidity 3pm	0.0230	0.0033	6.92	0.000	[0.0165,	0.0295]
Lag2 rainfall	0.0012	0.0001	4.92	0.000	[0.0010,	0.0014]
High tide	1.0159	0.2813	3.61	0.000	[0.4645,	1.5672]
Sin(2πt/12)	318.3471	39.5151	8.06	0.000	[240.8991,	395.7952]
Constant	-3.3180	0.6934	-4.97	0.000	[-4.6771,	-1.9590]

* Lag1 case count: number of cases occurred one month prior.

Figure 4- 13 Notified cases vs. model fit cases (1990-2003) and projected cases (2004-2005) of RRV infection in Townsville according to Model 1



4.3.1.4 The relationship between climate variation and RRV infection in Australia

A number of studies have examined the relationship between climate variability and Ross River virus (RRV) infection in different regions of Australia, with most of these studies focused on areas in northern Australia, such as the tropical regions of Queensland, the Northern Territory and Western Australia [75, 77, 79, 90, 98, 100, 146, 147]. Varying regional climatic conditions are likely to influence RRV infection in different ways reflecting variation in ecological characteristics. In coastal regions, for example, sea level plays an important role in the development of the salt-marsh mosquito [66, 100]. There has been no study prior to this on the effect of climate variation on RRV infection in South Australia, where the climate is characterised by warm-to-hot, dry summers, and cool-to-mild winters.

In this study, the effect of meteorological variables on the transmission of RRV infection has been examined in temperate, subtropical and tropical regions in Australia. The results indicate that minimum temperature, maximum temperature,

rainfall and relative humidity have all affected RRV infections in these regions. The positive association between temperature and RRV infection in these regions, with lagged effects from one to two months, is consistent with previous studies elsewhere in Australia [75, 77, 79, 90, 98, 100, 146-148].

Tong et al [75] have conducted a series of studies of RRV infection and climate change in various regions in Queensland. They found a consistent positive associated between temperature and monthly incidence of RRV infection in Queensland. However, different response of RRV to climate variability between coastline and inland cities in Queensland has also been identified [76]. Additionally, the lag times of the effect of temperature on RRV infection could be different in various climatic regions in Australia [77, 78, 79, 80].

Mosquitoes play an important role in the transmission of RRV infection. Therefore, climatic and other environmental factors, contributing to the growth and development of mosquito populations, may affect transmission of the disease. Different mosquito species have been implicated as vectors in different regions of Australia. The major vector in inland regions is the freshwater species *Culex annulirostris*, while in coastal regions *Aedes camptorhynchus* and *Aedes vigilax* are considered the principal vectors [66, 149, 150]. Different mosquito species might have different sensitivity to climate variation.

Increases in temperature, within limits, can lead to a rapid growth in mosquito population, thereby increasing the opportunities for virus transmission because of more rapid development of larvae and shorter incubation for viral infections [152, 153]. Higher temperatures might also change human behaviours, eg more outdoor activities, which result in more opportunities for being bitten by mosquitoes. Furthermore, the increase in minimum temperature might help the larvae survive in winter.

Rainfall also plays an important role in the transmission of RRV, as water is necessary in the bio-development of mosquitoes. The timing and the intensity of rainfall could be of significance. It is reported that in Western Australia, epidemics of RRV infection have been observed following heavy rainfall in late spring and early

summer and after heavy autumn and winter rainfall [152]. In terms of the intensity of the rainfall, very heavy rain can harm mosquito populations by washing eggs and larvae away from the breeding sites. On the contrary, frequent light rain is conducive to mosquito breeding [152].

The strong association between rainfall and RRV infection is consistent with the findings of other studies. For example, in the Northern Territory, summer rainfall was found to be a good predictor of increased risk of RRV infection [153]. An epidemic of RRV infection in Western Australia in 1991/92 followed a dramatic increase in late spring and summer rainfall [79], and in Queensland, rainfall was found to be an important factor in the transmission of RRV infection, particularly in coastal regions [77, 100].

The effects of relative humidity on RRV infection vary across study regions. The results suggest that a positive correlation has been detected in the tropical and subtropical regions in Queensland, while a negative association has been found in the temperate regions of South Australia. This could be due to differences in local climate conditions and the different local types of mosquito vectors.

In addition to these meteorological variables, it was also found that high tides (sea level) in Queensland and the flow of the Murray River (as a surrogate measure of flooding) in South Australia have a positive impact on the transmission of RRV infection in Australia. The results indicate that increased high tides in the future may result in extra cases of RRV infection in coastal areas in Australia. Tidal inundation is the major source of water for breeding of the local vectors of RRV infection - *Ae vigilas* and *Ae camptorhynchus* [151]. High tide is one of the favourite environmental factors for the hatching of mosquito eggs. Large populations of adult mosquitoes can emerge as quickly as eight days after a series of spring tides [151]. The positive effects of high tides on RRV infection are consistent with previous studies [75, 100, 146, 154].

Importantly, this is the first epidemiological report on the effect of river flow on RRV infection. As the principal river in Australia, the Murray River (2,589 km long) crosses three states in Australia - New South Wales, Victoria and South Australia - flowing westwards to the Southern Ocean. It is important to study the impact of

meteorological variables, including the flow of the Murray River, on the transmission of RRV infection in the Murray River regions because of its agricultural importance to Australia. Unlike in coastal areas, river flow plays an important role in the breeding and distribution of the vectors in inland areas in Australia. Higher flow of the Murray River can facilitate the main freshwater mosquito species, *Culex annulirostris,* in South Australia. The finding will help in the understanding of ecological characteristics of the Murray River regions and their impact on population health.

The different impacts of climate variation on RRV infection in tropical, subtropical and temperate region in Australia can be seen in the results. Although maximum and minimum temperatures, rainfall, relative humidity, river flow or high tides were all included in the regression models, the lag times of their effect on RRV infection were different. Across the different study areas, the lag times for maximum temperature range from 0 to 2 months approximately, for minimum temperature from 1 to 2 months approximately, and for rainfall from 1 to 2 months approximately. A one degree increase in maximum or minimum temperature might cause a greater increase in RRV infection (more than 22%) in temperate regions than in subtropical (more than 8%) or tropical regions (more than 14%) in Australia.

The adjusted Poisson regression used in this study has considered the nature of time-series data, including autocorrelation, potential seasonal variation and lag effects, which is appropriate for this analysis. Moreover, reliable disease surveillance data in Australia strengthen the results. For example, these data include the onset date as well as the date of notification of RRV infection, which makes the analysis more accurate. In addition, patients may well be infected away from their place of residence. The place of acquisition of disease (original source of infection) as well as the residential address has been recorded in disease surveillance datasets. This provides an accurate estimation of place of infection, and overcomes the shortcomings in most disease surveillance systems of recording only the place of notification [155]. This is very important for disease control and prevention. Such a refinement in data collection should be applied to relevant disease surveillance systems elsewhere.

One of the limitations of the analysis is regarding to the change of the disease notification system in Australia. The infectious disease notification system has changed from general practitioner (GP) report to laboratory report since 1992. The reason for including data from 1990 is mainly to have as many as time series points in the analysis so as to increase the statistic power of the time series analysis. This change may have an impact on the results. However, RRV infection is the most notified vector-borne disease in Australia and has been included in the notification system for many decades so that GPs should be familiar with this condition. Therefore, there should be no substantial impact of the change of the notification system on this analysis.

It should be acknowledged that the ecology of RRV infection is very complicated. A diverse range of environmental factors, host, animal and human susceptibilities to RRV infection, as well as human behaviours and socio-economic status, all influence mosquito populations and opportunities for contact between humans and vectors, thus affecting the transmission of RRV infection. Research examining these additional factors would be useful to achieve a better understanding of the effect of environmental change on RRV infection.

In summary, meteorological variables, including temperature, rainfall, humidity, river flow and tides have already affected RRV infection in Australia. While temperatures, rainfall, river flow and tides have positive effects on RRV infection, the effects of climate variation, eg lag times, may vary across different climatic regions because of various local climatic conditions and types of mosquitoes. The effects of climate variation on RRV infection may be more serious in temperate regions than in tropical or subtropical regions. Preventive public health action could be initiated by conducting effective measurements to adapt to future climate change.

4.3.2 Malaria

4.3.2.1 Malaria in Jinan, Shandong, northern China

4.3.2.1.A Descriptive analysis

The dataset has been analysed separately in two periods - 1959-1967 and 1968-1979 - due to the considerable change in the number of cases over the study period (i.e. mean and variance vary depending on time *t*) [136] and this un-stationary nature cannot be smoothed by data transformation. The low number of cases in 1967/68 may reflect under-reporting of the disease.

4.3.2.1.A.1 Summary of notified cases of malaria in Jinan, 1957-1967 and 1968-1979

There were 4,489 malaria cases during 1959-1967, and 4,542 cases during 1968-1979 in Jinan, with clear fluctuations in the number of cases over the study period (Figure 4- 14). There was a similar temporal distribution pattern between the periods 1959-1967 and 1968-1979.

Figure 4- 15 demonstrates the annual distribution of the cases of malaria, suggesting most cases occurred in summer.

Figure 4- 14 Notified monthly cases of malaria in Jinan, 1959-1979

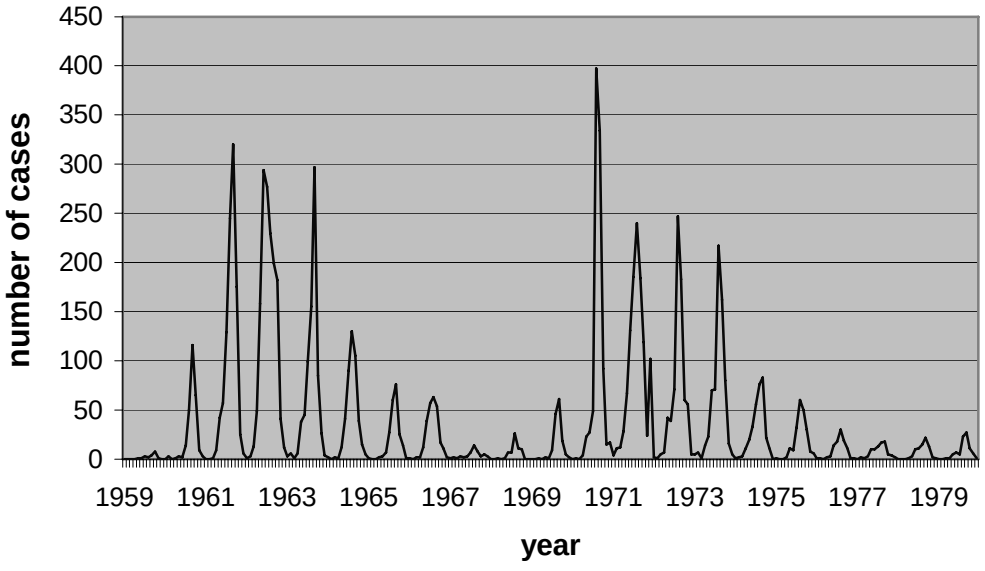
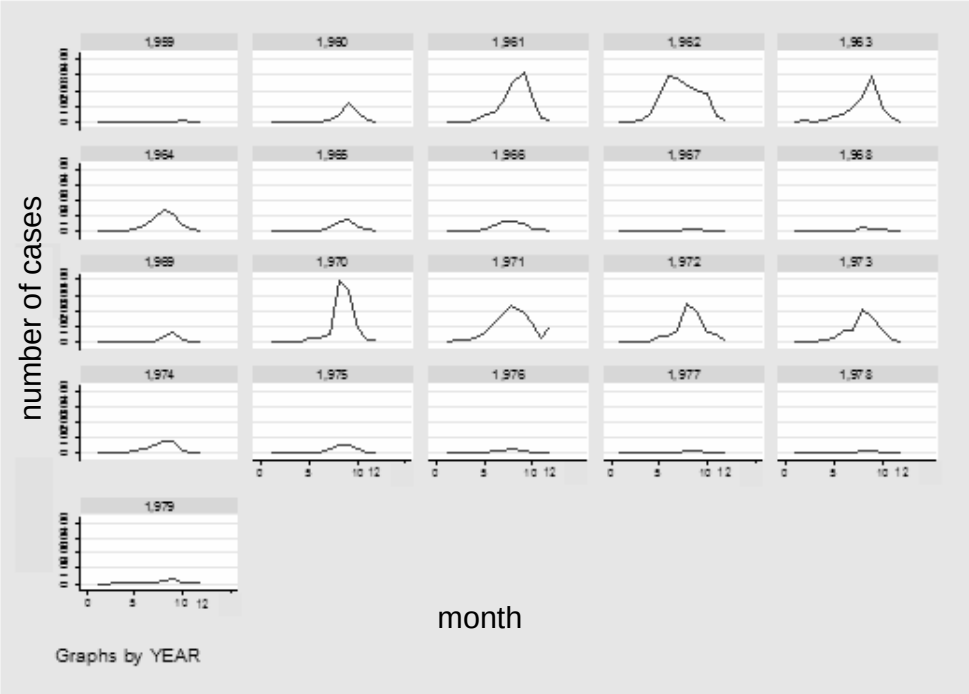


Figure 4- 15 Annual distribution of malaria cases in Jinan, 1959-1979



4.3.2.1.A.2 Summary of meteorological variables in Jinan, 1959-1979

Meteorological variables in Jinan over the study period are summarised in Table 4- 23. It can be seen that the average monthly maximum temperature was approximately 19ºC, the average monthly minimum temperature was approximately 10ºC, the mean monthly humidity was less than 60%, the average monthly total rainfall was approximately 1300 mm with wide variation and the mean air pressure was about 1010 kpa.

Table 4- 23 Summary of monthly meteorological variables in Jinan, 1959-1979

	Mean	Std. Dev.	Min	Max
1959-1967				
Mean max temp (ºC)	19.61	10.50	-0.52	34.46
Mean min temp (ºC)	9.90	10.13	-7.75	24.49
Mean humidity (%)	57.52	13.24	31.26	79.97
Total rainfall (mm)	1351.80	645.40	0.00	2948.78
Mean air pressure (kpa)	1010.28	8.86	995.19	1027.08
1968-1979				
Mean max temp (ºC)	19.20	10.40	0.41	34.59
Mean min temp (ºC)	9.97	9.91	-7.31	24.23
Mean humidity (%)	56.86	12.21	30.04	81.55
Total rainfall (mm)	1256.40	794.80	0.00	3814.55
Mean air pressure (kpa)	1010.07	8.62	994.6	1023.99

4.3.2.1.B Correlation analysis

4.3.2.1.B.1 Correlation among meteorological variables in Jinan

As shown in Table 4- 24, there was positive correlation between maximum and minimum temperatures (r=0.99) and negative correlation between air pressure and both maximum and minimum temperatures ($|r| \geq 0.94$) in Jinan.

Table 4- 24 Correlation coefficients between meteorological variables in Jinan, 1959-1979

	Mean max temp	Mean min temp	Mean humidity	Total rainfall	Mean air pressure
1959-1967					
Mean max temp	1.00				
Mean min temp	0.99	1.00			
	(0.00)				
Mean humidity	0.27	0.38	1.00		
	(0.01)	(0.00)			
Total rainfall	0.12	0.15	0.28	1.00	
	(0.23)	(0.13)	(0.00)		
Mean air pressure	-0.95	-0.95	-0.29	-0.16	1.00
	(0.00)	(0.00)	(0.00)	(0.09)	
1968-1979					
Mean max temp	1.00				
Mean min temp	0.99	1.00			
	(0.00)				
Mean humidity	0.31	0.41	1.00		
	(0.00)	(0.00)			
Total rainfall	-0.15	-0.13	0.15	1.00	
	(0.08)	(0.13)	(0.08)		
Mean air pressure	-0.94	-0.94	-0.34	0.03	1.00
	(0.00)	(0.00)	(0.00)	(0.69)	

*p values in the brackets. Highlighted coefficients demonstrate high levels of correlation.

4.3.2.1.B.2 Correlation between meteorological variables and malaria in Jinan

Table 4- 25 suggests that maximum temperature, minimum temperature, relative humidity and rainfall were all positively correlated, while air pressure was negatively correlated with malaria cases in Jinan, with one month lag time for each meteorological variable (Table 4- 25).

Table 4- 25 Correlation between monthly malaria cases and meteorological variables in Jinan

	1959-1967		1968-1979	
	Coefficient (95% CI)	Lag values	Coefficient (95% CI)	Lag values
Mean max temp	0.54 (0.50, 0.58)**	1 month	0.59 (0.57, 0.61)**	1 month
Mean min temp	0.59 (0.53, 0.65)**	1 month	0.65 (0.61, 0.69)**	1 month
Mean air pressure	-0.25 (-0.29, -0.21)**	2 month	-0.30 (-0.33, -0.27)**	1 month
Mean humidity	0.33 (0.0.30, 0.36)*	0 month	0.42 (0.39, 0.45)*	1 month
Total rainfall	0.12 (-0.03, 0.27)#	2 month	0.19 (-0.02, 0.40)#	1 month

** $p<0.01$, * $p<0.05$, # $p>0.05$

4.3.2.1.C Regression models for malaria in Jinan

For consideration of multicollinearity, monthly mean maximum temperature and monthly minimum temperature were put into separate models. After controlling for autocorrelation and seasonal distribution, four SARIMA models were developed for the two periods in Jinan. The significant meteorological variables included in the regression models were maximum/minimum temperatures with one-month lag (Table 4- 26 to Table 4- 29). Other meteorological variables including rainfall, humidity and air pressure were not included in the SARIMA models. The 1-order moving average was included in the model to smooth the time series. The models indicated that the numbers of cases were 1- order autoregressive (AR1), that is, the number of cases that occurred in the current month could be explained by the number of cases occurring one month prior. In addition, the seasonal variation was significantly included in all the models and no significant long-term trend was detected.

The models suggest that a 1ºC rise in maximum temperature is related to a 4.2% to 13.9% increase in the number of cases of malaria. A 1ºC rise in minimum temperature may bring approximately 6.8% to 14.8% increase in malaria cases in Jinan. The goodness of fit of Model 1, including maximum temperature for the two study periods, is demonstrated in Figure 4- 16 and Figure 4- 17 respectively. There is no autocorrelation among the model residuals with an Aikake Information Criterion

(AIC) approximately 750 of the two models. The diagnostic figures for Model 2 with minimum temperature are not presented here due to the similarity with results obtained with Model 1.

Table 4- 26 Parameters from SARIMA Model 1 for malaria in Jinan, 1959-1967

	Coefficient	Std. Err.	z	p
AR1	0.766	0.063	12.196	0.000
Seasonal AR1	0.379	0.105	3.601	0.001
Lag1 max temp	0.082	0.020	4.156	0.000
Constant	0.411	0.636	0.646	0.520

AR1= 1-order autoregressive.

Table 4- 27 Parameters from SARIMA Model 2 for malaria in Jinan, 1959-1967

	Coefficient	Std. Err.	z	p
AR1	0.771	0.063	12.309	0.000
Seasonal AR1	0.289	0.113	2.548	0.013
Lag1 min temp	0.108	0.019	5.622	0.000
Constant	0.985	0.486	2.025	0.076

AR1= 1-order autoregressive.

Table 4- 28 Parameters from SARIMA Model 1 for malaria in Jinan, 1968-1979

	Coefficient	Std. Err.	z	p
AR1	0.969	0.026	37.892	0.000
MA1	0.715	0.074	9.632	0.000
Seasonal AR1	0.203	0.100	2.037	0.044
Lag1 max temp	0.124	0.008	15.111	0.000
Constant	-0.607	0.624	-0.973	0.332

AR1= 1-order autoregressive, MA1=1-order moving average.

Table 4- 29 Parameters from SARIMA Model 2 for malaria in Jinan, 1968-1979

	Coefficient	Std. Err.	z	p
AR1	0.973	0.022	44.88	0.000
MA1	0.684	0.074	9.20	0.000
Seasonal AR1	0.213	0.103	2.017	0.040
Lag1 min temp	0.134	0.007	19.31	0.000
Constant	0.473	0.584	0.811	0.419

AR1= 1-order autoregressive, MA1=1-order moving average.

Figure 4- 16 Notified cases vs. model fit cases of malaria in Jinan (1959-1967) according to Model 1

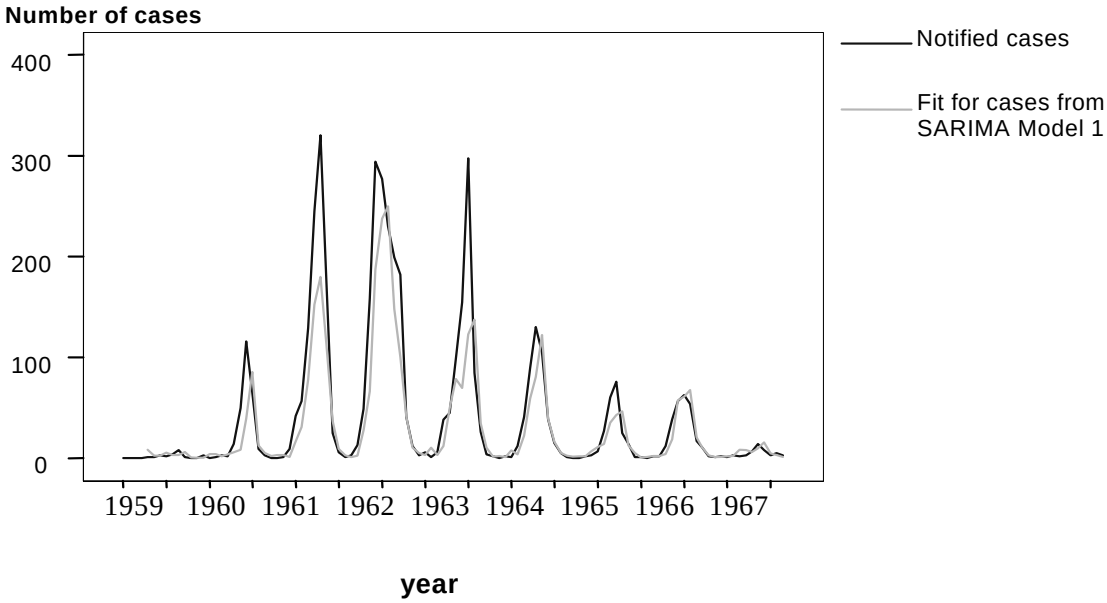
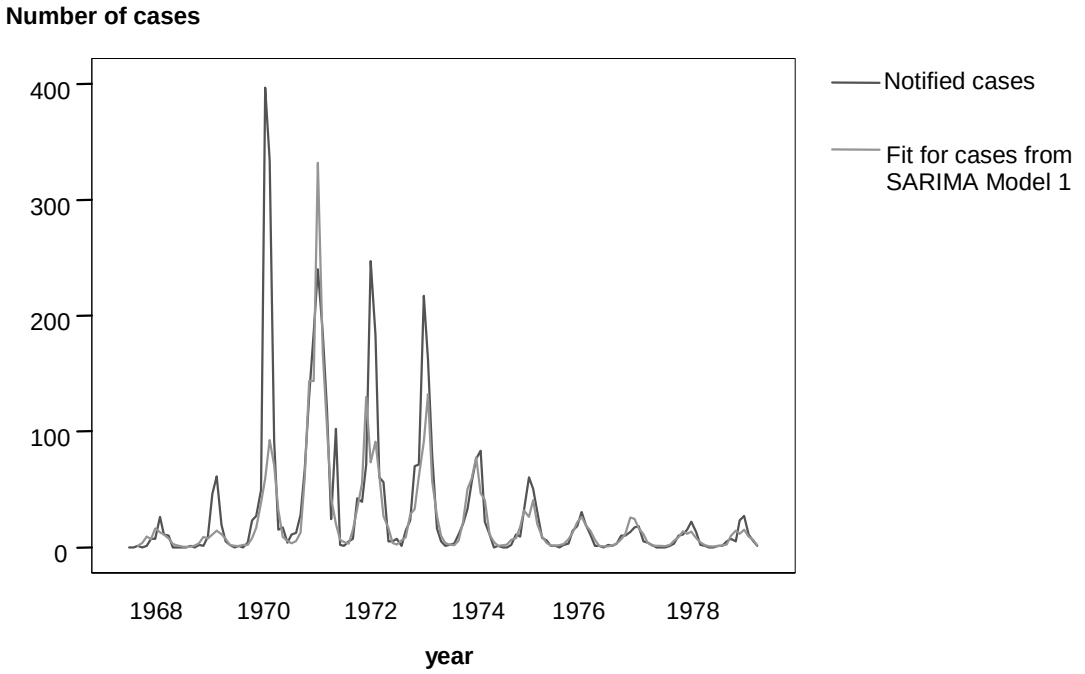


Figure 4- 17 Notified cases vs. model fit cases of malaria in Jinan (1968-1979) according to Model 1



4.3.2.2 Malaria in Baoan, Shenzhen, southern China

4.3.2.2.A Descriptive analysis

4.3.2.2.A.1 Summary of notified cases of malaria in Baoan, 1995-2003

In total, there were 2,032 cases reported in Baoan from 1995 to 2003 with an average monthly incidence of 1.60/100,000 (Figure 4- 18). A declining trend was observed over the period. There was a clear seasonal distribution with more cases occurring in summer months (Figure 4- 19).

Figure 4- 18 Monthly incidence of malaria in Baoan, 1995-2003

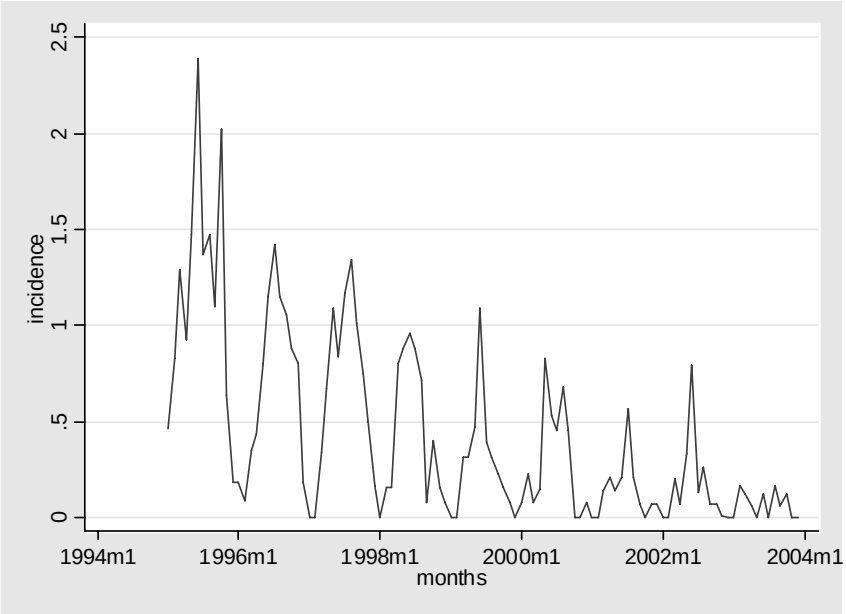
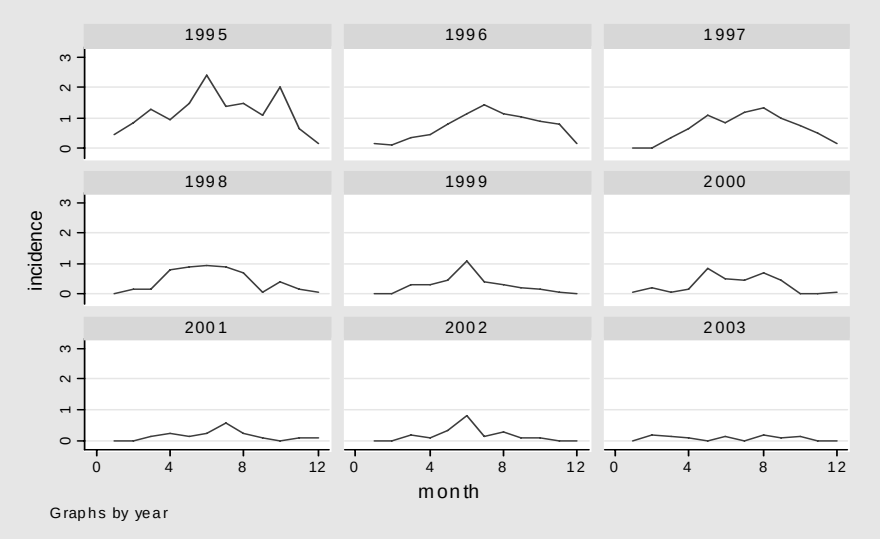


Figure 4- 19 Annual distribution of monthly incidence of malaria in Baoan, 1995-2003



4.3.2.2.A.2 Summary of meteorological variables in Baoan

The meteorological variables in Baoan over the study period are summarised in Table 4- 30. The average monthly maximum and minimum temperatures were 27ºC and 20ºC respectively. The average monthly total rainfall was more than 1000 mm, the mean monthly humidity was 76%, and the mean air pressure was 1010 kpa.

Table 4- 30 Summary of monthly meteorological variables in Baoan, 1995-2003

	Mean	Std. Dev.	Min	Max
Mean max temp (ºC)	26.90	4.99	15.97	33.96
Mean min temp (ºC)	19.95	5.38	9.03	27.49
Mean air pressure (kpa)	1010.08	6.23	998.59	1022.62
Mean humidity (%)	76.11	7.13	53.81	88.58
Total rainfall (mm)	1086.52	614.34	82.06	3274.08

4.3.2.2.B Correlation analysis

4.3.2.2.B.1 Correlation among meteorological variables

Table 4- 31 shows that among the meteorological variables in Baoan, there was high positive correlation among maximum and minimum temperatures (r = 0.97) and reverse correlation between air pressure and temperatures ($|r| \geq 0.77$).

Table 4- 31 Correlation coefficients between meteorological variables in Baoan

	Mean max temp	Mean min temp	Mean air pressure	Mean humidity	Total rainfall
Mean max temp	1.00				
Mean min temp	0.97	1.00			
	(0.00)				
Mean air pressure	-0.79	-0.77	1.00		
	(0.00)	(0.00)			
Mean humidity	0.37	0.45	-0.66	1.00	
	(0.00)	(0.00)	(0.00)		
Total rainfall	0.09	0.11	-0.23	0.26	1.00
	(0.40)	(0.27)	(0.02)	(0.01)	

* *p* values in the brackets. Highlighted coefficients demonstrate high levels of correlation.

4.3.2.2.B.2 Correlation between malaria and meteorological variables in Baoan

Table 4- 32 shows that maximum temperature, minimum temperature, air pressure and humidity all significantly correlated to the number of malaria cases in Baoan. However, a statistically significant correlation between rainfall and malaria cases was not detected.

Table 4- 32 Correlation between malaria and meteorological variables in Baoan

	Coefficient (95% CI)	*p*	Lag time
Mean max temp	0.506 (0.456, 0.556)	0.000	0 month
Mean min temp	0.472 (0.402, 0.0.49)	0.000	0 month
Total rainfall	0.175 (-0.015, 0.365)	0.072	2 months
Mean air pressure	-0.608 (-0.658, -0.558)	0.000	0 month
Mean humidity	0.611 (0.543, 0.679)	0.000	1 month

4.3.2.2.C Regression models for malaria in Baoan

Time series adjusted Poisson regression was performed for malaria in Baoan. After controlling for seasonality, autocorrelation and the declining trend in malaria cases, maximum and minimum temperatures were significantly associated with malaria cases in Baoan (Table 4- 33 and Table 4- 34). Other meteorological variables were not significant in the models. The regression models suggest that a 1ºC rise in maximum temperature is related to a 15.5% (95%CI: 13%-18%) increase in the number of cases, and a 1 ºC rise in minimum temperature is related to a 14.4% (95%CI: 12.1%-16.7%) increase in malaria cases in Baoan. Both models have a R^2 of approximately 0.48. There is no autocorrelation among the model residuals observed. The goodness of fit of Model 1 is demonstrated in Figure 4- 20.

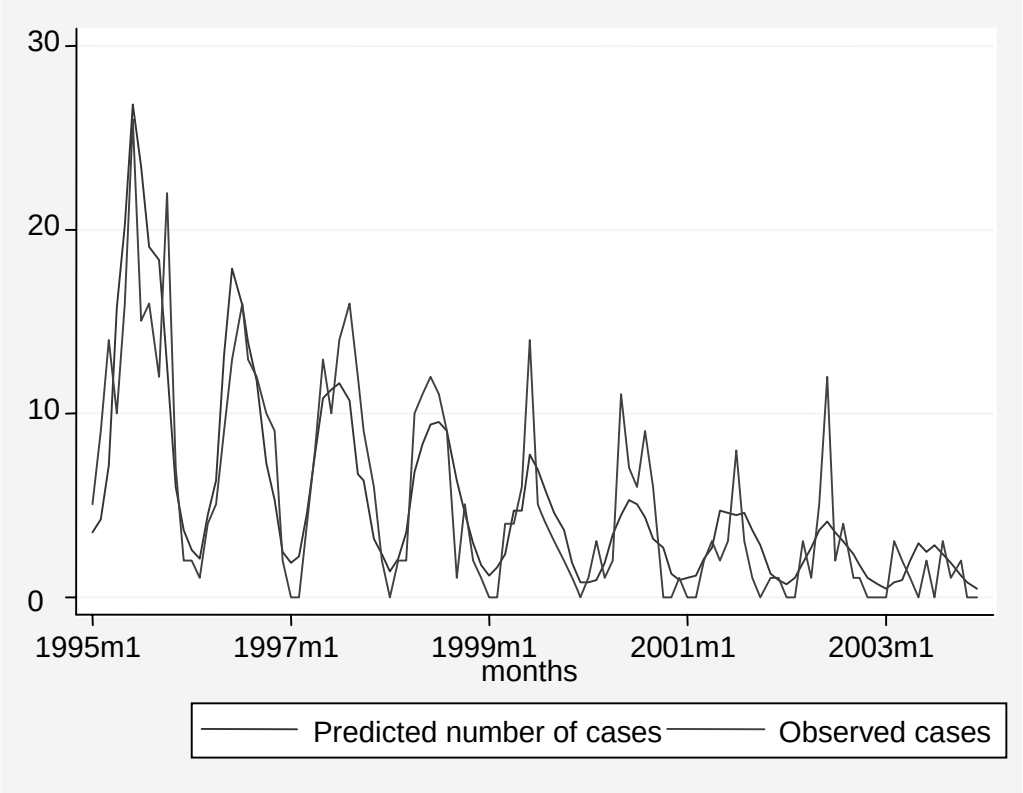
Table 4- 33 Parameters from adjusted Poisson for malaria in Baoan (Model 1)

	Coefficient	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Mean max temp	0.155	0.013	12.26	0.000	[0.130,	0.180]
Sin(2πt /12)	0.364	0.077	4.72	0.000	[0.213,	0.515]
Year	-0.283	0.019	-15.22	0.000	[-0.320,	-0.247]
Constant	563.351	37.151	15.16	0.000	[490.537,	636.165]

Table 4- 34 Parameters from adjusted Poisson for malaria in Baoan (Model 2)

	Coefficient	Std. Err.	z	P>|z|	[95% Conf. Interval]
Mean min temp	0.144	0.012	12.41	0.000	[0.121, 0.167]
Sin(2πt /12)	0.268	0.073	3.69	0.000	[0.126, 0.410]
Year	-0.288	0.018	-15.98	0.000	[-0.324, -0.253]
Constant	574.903	36.032	15.96	0.000	[504.282, 645.524]

Figure 4- 20 Notified cases vs. model fit cases of malaria in Baoan according to Model 1



4.3.2.3 The relationship between climate variation and malaria in China

Malaria is still a serious public health problem in most developing countries. In China, the re-emergence of malaria has been observed since 2000, with more than 740,000 cases occurring in 2004. However, only limited studies about the impact of meteorological variables on malaria have been conducted in China. This study is the first epidemiological study examining the association between climate variation and malaria in both subtropical and temperate climatic regions in China. The results suggest that temperature rather rainfall or humidity plays an important role in the transmission of malaria in China.

The transmission of malaria is complicated, and climate variability may well a risk factor for the re-emergence of malaria [156,157]. Being a mosquito-borne disease, malaria is strongly influenced by climatic factors because of the climate-sensitive mosquito vector species. Meteorological variables play an important role in the geographical distribution and seasonal abundance of these vector species [158,159]. Anticipated changes in climate, such as temperature, precipitation, humidity and wind patterns, may directly affect the reproduction, development and longevity of mosquito species [160]. However, each vector specie has different seasonal distributions, habitats, biting, resting behaviours and vectorial capacities [161], so that the impact of climate variability on malaria varies between regions.

In addition to the effects on mosquitoes, climate variation also affects the transmission of malaria by altering human behaviours. Increasing temperature may cause people to wear fewer clothes during outdoor activities, which increases the opportunity of exposure to mosquito bites, resulting in a greater risk of infection. Effective mosquito control programs or health education activities, including informing local communities about self- protection methods during outdoor activities (e.g. wearing long sleeved clothes and using insect repellent spray), could significantly reduce the chance of getting malaria.

This study demonstrates that both maximum temperature and minimum temperature have a positive association with malaria transmission, and could be used as a predictor of malaria cases in the temperate and subtropical regions in China. The association between temperature and malaria has been investigated in many studies,

particularly in tropical and subtropical areas. The results from this study are consistent with previous studies in other regions in the world [46, 50, 160, 162-163]. The lagged effects of temperature on malaria cases roughly estimated by this study are one month in the temperate region with no lag time detected in the subtropical region. This is consistent with the development of the parasites within the reservoir, the growth of mosquitoes, and the period of incubation.

A clear association between rainfall and malaria has not been detected in this study in either subtropical or temperate regions in China. Results from previous studies on the association between rainfall and malaria are not consistent. One study argued that rainfall rather than temperature may be the primary force behind malaria transmission in Africa [51]; one study detected a positive relationship between rainfall and malaria in India [164]; another claimed an inverse correlation in Africa [48], while other studies observed no relationship or only a weak association in south Asia [52, 55]. There is no clear explanation for this heterogeneity, which may reflect the different local climatic conditions or the types of local mosquitoes. One study, in a Chinese county, suggested a positive impact of rainfall on malaria [50]. However, this study has investigated the potential effects of meteorological variables on the transmission of malaria in metropolitan areas rather than in rural areas. Given the large, diverse geographic area of China, further studies should be conducted in other regions to gain a better understanding of the impact of rainfall on malaria.

The regression models suggest that the number of malaria cases in the temperate city is correlated with the number of cases one month prior. In the subtropical city, there is no autocorrelation of the number of malaria cases, suggesting that the number of cases may vary from month to month in this region. Moreover, given the short lag time for the effect of meteorological variables in the subtropical region, faster and more effective public health responses and measures are required in that region than in the temperate region in China to prevent and control the risk of malaria. There is no clear long-term trend of malaria observed in the analysis due to the large variation of the number of cases. The potential risk of the increase in malaria cases caused by future temperature should be acknowledged by the Chinese government.

There are some limitations in this analysis. Firstly, under-reporting of malaria cases over the study period, caused by the disease notification system in China, weakens the strength of the analysis. In addition, data quality during the late 1960s in Jinan might not be reliable due to national political activities ("The Greater Cultural Revolution"), reflecting very low numbers of notified malaria cases over that period. The large variation in the number of cases makes the time series analysis difficult. However, in order to minimize the impact of this data defect on the results, data analysis has been performed by dividing the Jinan malaria dataset into two parts. Great caution should be given to interpret the result based on the data over that period. Secondly, availability of weekly data and the date of onset rather than the date of report (often different to onset date) would increase the accuracy of the analysis, particularly for the estimation of lag times. Thirdly, socio-economic factors and other potential confounders, such as local mosquito control programs which affect the transmission of malaria, have not been included in this analysis due to the unavailability of the data. Last but not least, different time-series regression techniques have been applied in the two study areas. Although the SARIMA model has advantages in dealing with time-series data, the adjusted Poisson regression was applied in the subtropical area (Baoan) because no transformation could effectively smooth the time series data. However, both the SARIMA and the adjusted Poisson regression have considered the nature of time-series data, including autocorrelation, seasonal distribution, lag effect and long-term trends, which make the results comparable.

Recent increasing epidemics of malaria in developing countries, including China, are a threat to populations worldwide. It is worthwhile investigating the possible underlying causes for this situation. Climate change may be one of the forces leading to more cases and to an extension in the geographic distribution from tropical or subtropical areas to temperate areas. Although the history of malaria control in Africa indicates successes for vector control, the greatest threat of resurgent epidemics may result from more frequent and intense climate variability [161]. Roll Back Malaria, a new global initiative against malaria, has been founded on the implementation of malaria control in the African region [165]. Therefore, this study may provide scientific evidence to policy makers to help prevent and control the potential future risk of malaria in other regions similar to China.

4.3.3 Relationship between climate variation and vector-borne diseases – summary and implications

Climate variation has already affected vector-borne disease in various climatic regions in Australia and China. Climate variation may play a role in the potential increasing trend in RRV infection in temperate regions in Australia and the resurgence of malaria in China. Maximum and minimum temperatures, rainfall and humidity, river flow and high tides have made significant contributions to the transmission of RRV infection in local areas. Temperatures also may be used to predict malaria cases in metropolitan areas in both temperate and subtropical areas of China.

A difference in the impact of climate variation on vector-borne diseases in Australia and China has been demonstrated. The key climatic variables that may affect vector-borne disease transmission vary across different climatic regions. River flow or tides could affect the transmission of RRV infection in Australia. Although temperatures may have effects on both RRV infection in Australia and malaria in China, the impact of rainfall and humidity on malaria transmission in China has not been clearly detected in this study. The impact of rainfall, particularly heavy rainfall, on the transmission of vector-borne diseases needs further study. The potential reasons for the difference may be local climatic conditions, uneven distribution of socio-economic status, availability of health care, and species of local mosquitoes as well as data quality.

Given the predictions of a warming trend in both Australia and China, this study has very important public health implications for the prevention and control of vector-borne diseases in both countries. First, the availability of high quality surveillance data is essential and will provide the foundation for further studies and monitoring the impact of any prevention strategies. Infectious disease surveillance should include additional relevant information beyond the occurrence of disease. For instance, the site of infection and onset date will provide important information for accurate estimation for decision making. Furthermore, in addition to health outcomes, other related factors, including socio-economic status and vector information (see more detail next page) that may affect the transmission of infectious

diseases should be integrated in a comprehensive surveillance system. Effective information sharing systems have been installed in most developed countries, such as the National Notifiable Diseases Surveillance System (NNDSS) in Australia, which provides online data access to public health practitioners, researchers and communities. Such information sharing and exchange are highly desirable in developing countries to establish reliable datasets for effective monitoring, prevention and control of infectious diseases, especially for a regional and global health problem such as dealing with the consequence of climate change.

Closer monitoring of meteorological factors could help to enhance relevant infectious disease prevention mechanisms. Local meteorological variables, river flow and tides, should be included in infectious disease surveillance systems for RRV infection in Australia. Monitoring local meteorological variables, particularly any increase in temperature, could benefit malaria prevention and control in China. In this way, the accuracy of predicting future risks of climate change on vector-borne diseases could be improved. Therefore, there is a requirement for collaboration, cooperation, co-ordination and information exchange among different organisations. For example, routine meetings among various government organisations, especially before the epidemic season are crucial for vector-borne disease control and prevention. This is extremely important for developing countries.

A long-term, systematic mosquito monitoring system is highly recommended, although there is a long way to go both in Australia and China. A diverse range of environmental factors, host, animal and human susceptibility and human behaviours all influence mosquito populations and exposure opportunities between human beings and vectors. Systematic monitoring and data collection will provide important information for health prevention and intervention for vector-borne diseases. In Australia, mosquito monitoring in certain risk areas has been complemented by the Australian Quarantine Inspection Service (AQIS), which intensively monitors for and controls the importation of foreign mosquito species through sea and air-ports. The AQIS is mainly responsible for preventing the introduction of exotic mosquitoes. Some States in Australia, including Western Australia, New South Wales, Queensland, Victoria and the Northern Territory, have established mosquito surveillance programs. Local city councils have also conducted vector investigations.

However, there are no national mosquito surveillance strategies and no systematic and reliable data available on mosquito distribution [166]. For an increased understanding of the impact of climate variation on vector-borne diseases, more studies incorporating additional variables, such as the density of vectors over the long-term, are necessary in this research field, especially in China with its large geographic area and diverse climatic conditions.

To prepare for the re-emergence of malaria or the emergence of new and unfamiliar diseases related to climate change, effective and prompt public health response systems and mechanisms should be developed, such as providing relevant advice for travellers and those who are living in high risk regions. Uneven geographic distribution of the impacts of weather on vector-borne diseases should be addressed by public health interventions. In addition to tropical and subtropical areas, vector-borne diseases in temperate areas may be an emerging serious problem due to climate change.

Preventive public health action could also be initiated by warning and educating public and local communities to conduct relevant health promotion campaigns, and to change behaviours such as increasing awareness of the potential risks of climate variation on health, health safety warnings for travellers to high risk regions, and promoting self-protection measures, such as wearing long sleeve clothing or using insect repellent to prevent mosquito bites, and using mosquito nets at night and screen doors and windows where appropriate.

Clinicians play a role in health education, especially among patients. Clinic waiting rooms and hospital information units should be used for such education. In addition, hospitals and doctors should prepare for extra health burdens from vector-borne diseases when high temperature or heavy rainfall is forecast.

Collaboration beyond health sectors is also important to control infectious diseases. For example, cooperation with the meteorological department, which monitors the weather variables, river flow or sea level rise, may reduce pubic health department response time in preventing potential emergencies of infectious diseases. Moreover, education departments' involvement is vital to increase public awareness, especially

among school students. Community participation is important in education, provision of facilities, administration, and feedback to researchers and governments. Therefore, the role that local community will play in reducing future risk of climate change is crucial.

4.4 Results and discussion - Climate variation and enteric infections

4.4.1 Salmonellosis

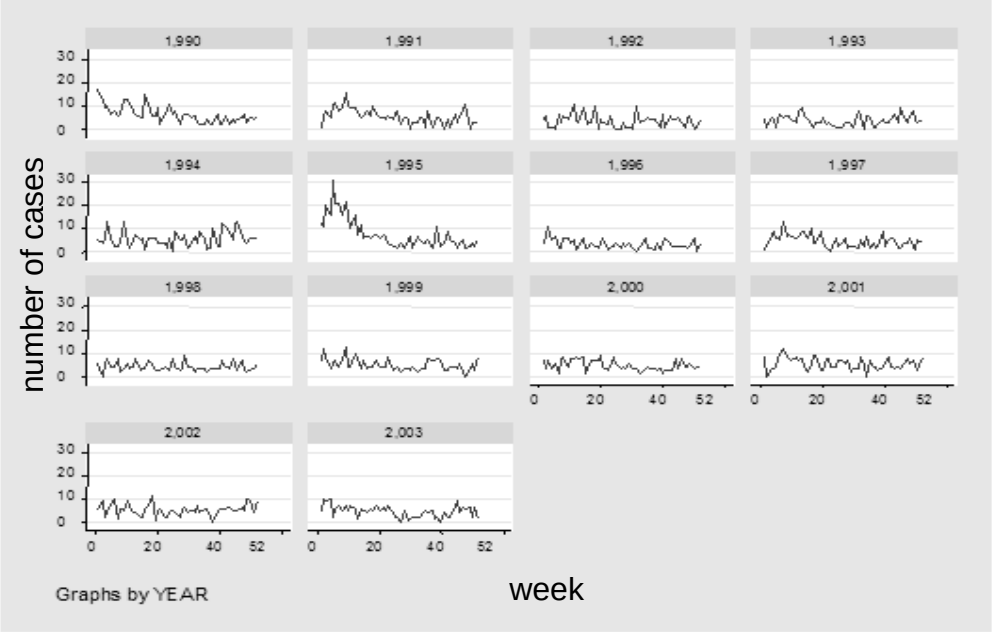
4.4.1.1 Salmonellosis in Adelaide, South Australia

4.4.1.1.A Descriptive analysis

4.4.1.1.A.1 Summary of notified cases of salmonellosis in Adelaide, 1990-2003

In total, 3,628 sporadic cases of salmonellosis were notified during 1990 to 2003 in the Adelaide metropolitan area. Figure 4- 21 demonstrates the annual temporal distribution of the number of cases of salmonellosis. There was no consistent seasonal distribution of the cases over the study period.

Figure 4- 21 Annual distribution of weekly salmonellosis cases in Adelaide, 1990-2003



4.4.1.1.A.2 Summary of meteorological variables

Meteorological variables in Adelaide over the study period are summarised in Table 4- 35. The mean weekly maximum and minimum temperature was 22ºC and

12ºC respectively. It should be noted that the mean weekly total rainfall was only 1.55mm.

Table 4- 35 Summary of weekly meteorological variables in Adelaide, South Australia, 1990-2003

	Mean	Std. Dev.	Min	Max
Mean max temp (ºC)	22.04	5.44	12.99	37.49
Mean min temp (ºC)	12.17	3.89	4.04	23.67
Total rainfall (mm)	1.55	2.01	0	13.06
Mean humidity 9am (%)	63.04	12.59	29.43	93.14
Mean humidity 3pm (%)	47.98	12.05	19.71	76.29
Mean air pressure (kpa)	1017.84	5.02	1004.57	1035.4

4.4.1.1.B Correlation analysis

4.4.1.1.B.1 Correlation among meteorological variables in Adelaide

Table 4- 36 indicates that there were high positive correlations among maximum and minimum temperatures (r=0.93) and humidity at 9am and 3pm (r=0.89).

Table 4- 36 Correlations coefficients between meteorological variables in Adelaide

	Mean max temp	Mean min temp	Total rainfall	Mean humidity 9am	Mean humidity 3pm	Mean air pressure
Mean max temp	1.00					
Mean min temp	0.93	1.00				
	(0.00)					
Total rainfall	-0.42	-0.25	1.00			
	(0.00)	(0.00)				
Mean humidity 9am	-0.77	-0.65	0.50	1.00		
	(0.00)	(0.00)	(0.00)			
Mean humidity 3pm	-0.81	-0.63	0.59	0.89	1.00	
	(0.00)	(0.00)	(0.00)	(0.00)		
Mean air pressure	-0.41	-0.53	-0.21	0.23	0.15	1.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	

* *p* value in the brackets. Highlighted coefficients demonstrate high levels of correlation.

4.4.1.1.B.2 Correlation between salmonellosis and meteorological variables in Adelaide

Table 4- 37 indicates that maximum and minimum temperatures with a two-week lag were positively associated with salmonellosis, while rainfall and relative humidity were negatively correlated with the weekly occurrence of salmonellosis in Adelaide over the study period.

Table 4- 37 Correlation between weekly salmonellosis and meteorological variables in Adelaide

	Coefficient (95% CI)	*p*	Lag time
Mean max temp	0.32 (0.25, 0.39)	0.000	2 weeks
Mean min temp	0.31(0.24, 0.38)	0.000	2 weeks
Total rainfall	-0.18 (-0.25, -0.11)	0.001	0
Mean humidity 9am	-0.22 (-0.27, -0.17)	0.000	0
Mean humidity 3pm	-0.25 (-0.32, -0.18)	0.000	0

4.4.1.1.C Regression models for salmonellosis in Adelaide

The SARIMA models for data from 1990 to 2003 suggest that the number of cases were 4-order autoregressive, which means the number of cases in one week may be correlated with the number of cases occurring one to four weeks prior. Additionally, the seasonal distribution was significant. After controlling for the autocorrelation, only maximum or minimum temperature had a positive effect on salmonellosis transmission (Table 4- 38 and Table 4- 39).

The models suggest that a 1ºC rise in maximum temperature is related to an 8.2% (95%CI: 6.1%-11.4%) increase in the number of cases and a 1ºC rise in minimum temperature may lead to a 15.1% (95%CI: 10.8%-19.2%) increase in the number of cases in Adelaide. The Aikake Information Criterion (AIC) values of the models were approximately 210. Figure 4- 22 and Figure 4- 23 show randomly distributed residuals without autocorrelation among them.

The 2004 data for salmonellosis were used to test the forecasting ability of the models. The observed and predicted cases by Model 1 are presented in Figure 4- 24, demonstrating the goodness-of-fit.

Table 4- 38 Parameters from SARIMA for salmonellosis in Adelaide (Model 1)

	β	Std. Err.	p
AR1	0.258	0.037	0.000
AR2	0.132	0.036	0.001
AR3	0.171	0.038	0.000
AR4	0.128	0.037	0.000
Seasonal AR1	0.076	0.038	0.046
Lag2 mean max temp	0.082	0.032	0.010
Constant	3.292	0.791	0.000

AR1-4: 1-4 order autoregressive; SeasonalAR1: 1-order seasonal autoregressive; Lag2 mean max temp: mean maximum temperature occurred two weeks prior.

Table 4- 39 Parameters from SARIMA for salmonellosis in Adelaide (Model 2)

	β	Std. Err.	p
AR1	0.253	0.037	0.000
AR2	0.127	0.038	0.001
AR3	0.176	0.038	0.000
AR4	0.131	0.037	0.000
Seasonal AR1	0.085	0.038	0.027
Lag2 mean min temp	0.151	0.042	0.000
Constant	3.246	0.632	0.000

AR1-4: 1-4 order autoregressive; SeasonalAR1: 1-order seasonal autoregressive; Lag2 mean max temp: mean maximum temperature occurred two weeks prior.

Figure 4- 22 Notified cases vs. model fit cases of salmonellosis in Adelaide (1990-2003) according to Model 1

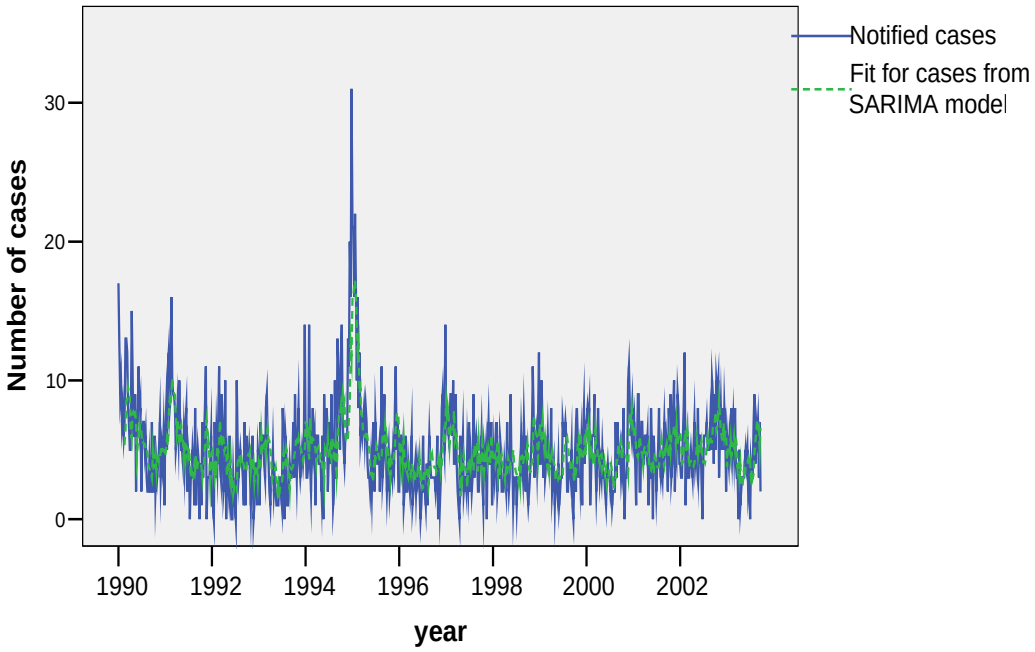


Figure 4- 23 Diagnoses of the residuals from Model 1 for salmonellosis in Adelaide

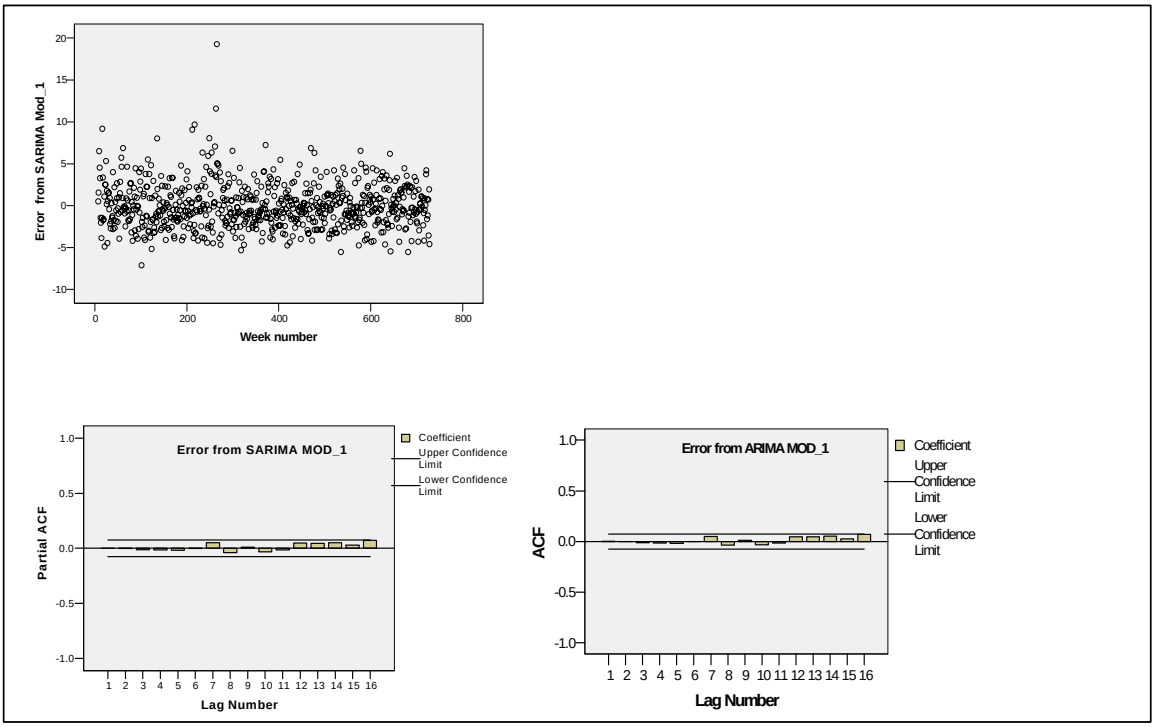
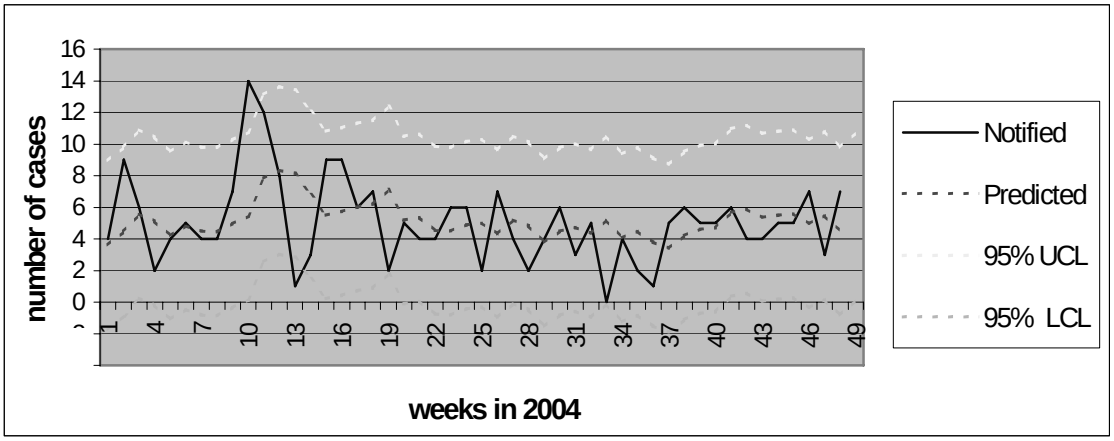


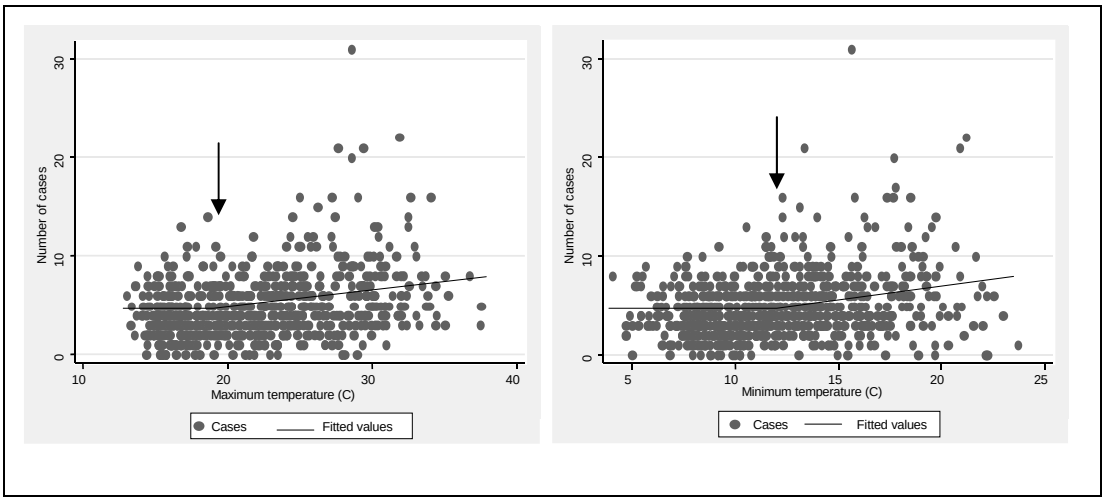
Figure 4- 24 Notified cases vs. predicted cases of salmonellosis in Adelaide (2004) according to Model 1



4.4.1.1.D Detection of threshold temperatures

A threshold of 19.5ºC for the effect of maximum temperature and a threshold of 12.1ºC for minimum temperature on salmonellosis in Adelaide were detected by the Hockey Stick model, as demonstrated in Figure 4- 25.

Figure 4- 25 Thresholds for the effect of temperatures on salmonellosis in Adelaide, South Australia



4.4.1.2 Salmonellosis in Brisbane, southern Queensland, Australia

4.4.1.2.A Description of notified cases of salmonellosis in Brisbane, 1990-2005

In total, 5,294 cases from January 1990 to July 2005 were notified in Brisbane with an increasing trend. A seasonal distribution of cases was observed with most occurring in summer (Figure 4- 26 and Figure 4- 27).

Figure 4- 26 Weekly salmonellosis in Brisbane, January 1990 - July 2005

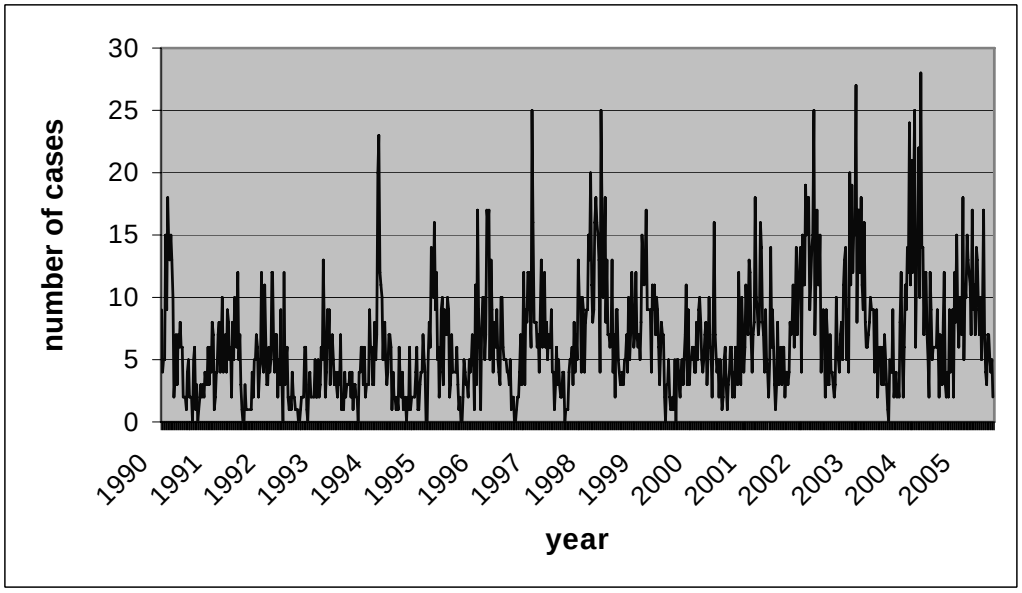
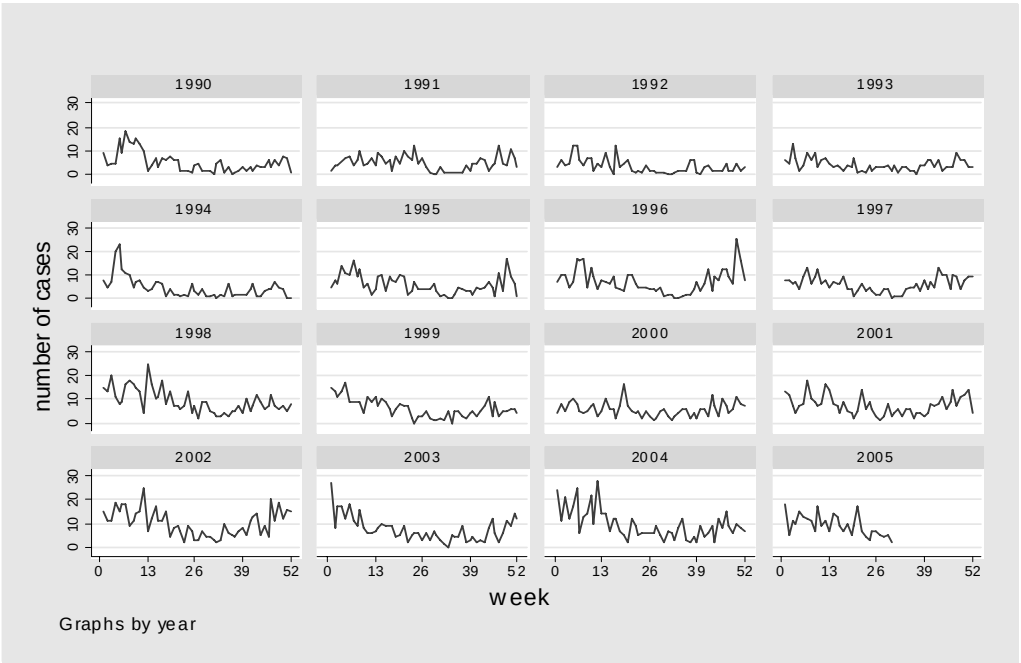


Figure 4- 27 Annual distribution of weekly salmonellosis cases in Brisbane, January 1990 - July 2005



4.4.1.2.B Correlation analysis

As shown in Table 4- 40, maximum and minimum temperatures, relative humidity and rainfall were all correlated with the weekly number of cases of salmonellosis in Brisbane with relevant lag times from zero to two weeks.

Table 4- 40 Correlation between meteorological variables and salmonellosis in Brisbane

	Coefficient (95% CI)	*p*	Lag time
Mean max temp	0.57 (0.51, 0.63)	0.000	2 weeks
Mean min temp	0.56(0.49, 0.63)	0.000	2 weeks
Mean humidity 9am	0.09 (0.03, 0.15)	0.015	0
Mean humidity 3pm	0.12 (0.06, 0.18)	0.010	2 weeks
Total rainfall	0.23 (0.19, 0.27)	0.000	2 weeks

4.4.1.2.C Regression models for salmonellosis in Brisbane

The adjusted Poisson regression for data from 1990 to 2003 suggests that the number of cases were 2-order autoregressive with a significant seasonal distribution. The 'year' was included in the models indicating an increase in the cases over the study period. After controlling for the autocorrelation, seasonality and the increasing trend in the number of cases, maximum or minimum temperature and rainfall, with two week lags, had a positive association with the cases of salmonellosis in Brisbane (Table 4- 41 and Table 4- 42).

The models suggest that a 1 ºC rise in maximum temperature is related to an 8.8% (95%CI: 7.6%-10.0%) increase in the number of cases, and a 1 ºC rise in minimum temperature may lead to a 5.8% (95%CI: 5.0%-6.7%) increase in the number of cases in Brisbane. The observed cases, model fit cases, and predicted cases for data from 2004 to 2005 by Model 1 are demonstrated in Figure 4- 28. Diagnostic plotting of Model 2 is not presented here due to its similarity to the plots for Model 1.

Table 4- 41 Parameters from adjusted Poisson regression for salmonellosis in Brisbane (Model 1)

	Coefficient	Std. Err.	z	*p*	[95% Conf.	Interval]
Lag1 case count	0.0279	0.0037	7.48	0.000	[0.0206,	0.0352]
Lag2 case count	0.0163	0.0037	4.35	0.000	[0.0090,	0.0236]
Lag2 max temp	0.0881	0.0062	14.31	0.000	[0.0760,	0.1001]
Lag2 rainfall	0.0020	0.0003	6.28	0.000	[0.0014,	0.0026]
Sin(2πt /52)	27.3695	16.2749	1.68	0.033	[4.5288,	50.2102]
Year	0.0367	0.0041	8.96	0.000	[0.0287,	0.0447]
Constant	-74.0947	8.1962	-9.04	0.000	[-90.1590,	-58.0304]

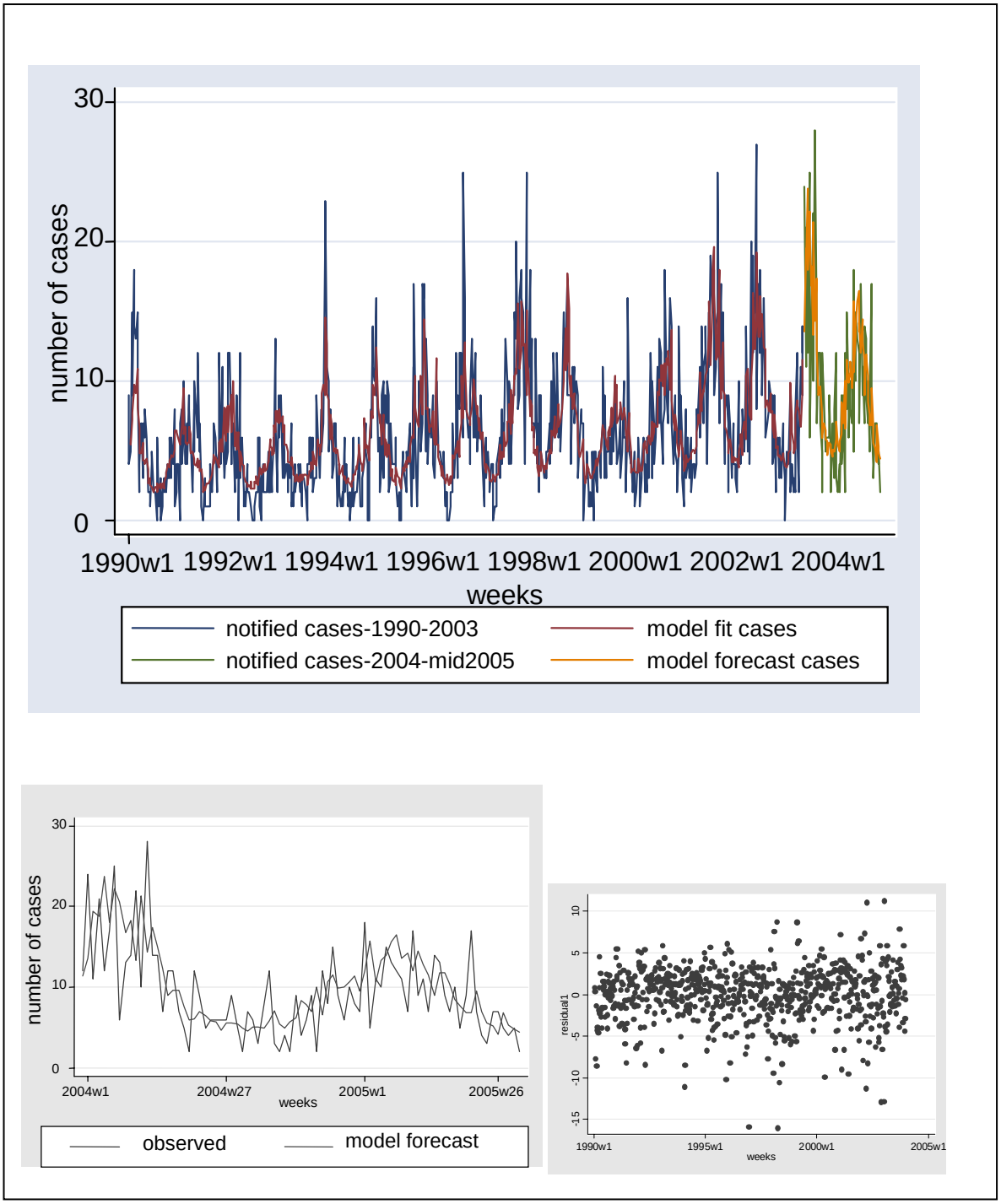
Lag1 case count: number of cases occurred one month prior.

Table 4- 42 Parameters from adjusted Poisson regression for salmonellosis in Brisbane (Model 2)

	Coefficient.	Std. Err.	z	p	[95% Conf.	Interval]
Lag1 case count	0.0311	0.0037	8.41	0.000	[0.0239,	0.0384]
Lag2 case count	0.0162	0.0038	4.31	0.000	[0.0088,	0.0235]
Lag2 min temp	0.0583	0.0044	13.36	0.000	[0.0498,	0.0669]
Lag2 rainfall	0.0013	0.0003	3.85	0.000	[0.0006,	0.0019]
Sin(2πt /52)	34.7144	16.2028	2.14	0.032	[2.9574,	66.4713]
Year	0.0380	0.0041	9.24	0.000	[0.0299,	0.0460]
Constant	-75.2489	8.2116	-9.16	0.000	[-91.3434,	-59.1545]

Lag1 case count: number of cases occurred one month prior.

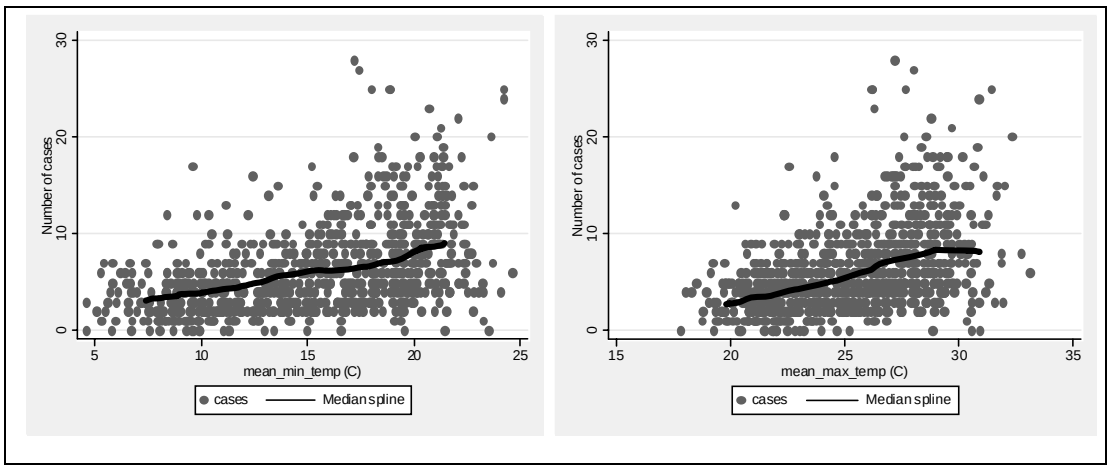
Figure 4- 28 Notified cases vs. model fit cases (1990-2003) and predicted cases of salmonellosis (2004-2005) in Brisbane according to Model 1 and scatter plot of the model residuals



4.4.1.2.D Detection of threshold temperatures

No threshold for the effects of maximum temperature and minimum temperature on salmonellosis was detected in Brisbane. The spline curves of the relationship between cases of salmonellosis and temperature are presented in Figure 4- 29.

Figure 4- 29 Relationship between temperature and salmonellosis in Brisbane, Queensland



4.4.1.3 Salmonellosis in Townsville, northern Queensland, Australia

4.4.1.3.A Description of notified cases of salmonellosis in Townsville, 1990-2005

In total, 1,170 cases of salmonellosis were notified in Townsville over the study period with a trend to increasing numbers (Figure 4- 30). Most cases occurred in summer months but the seasonal pattern was not clear for every year over the study period (Figure 4- 31).

Figure 4- 30 Monthly notified cases of salmonellosis in Townsville, January 1990 - July 2005

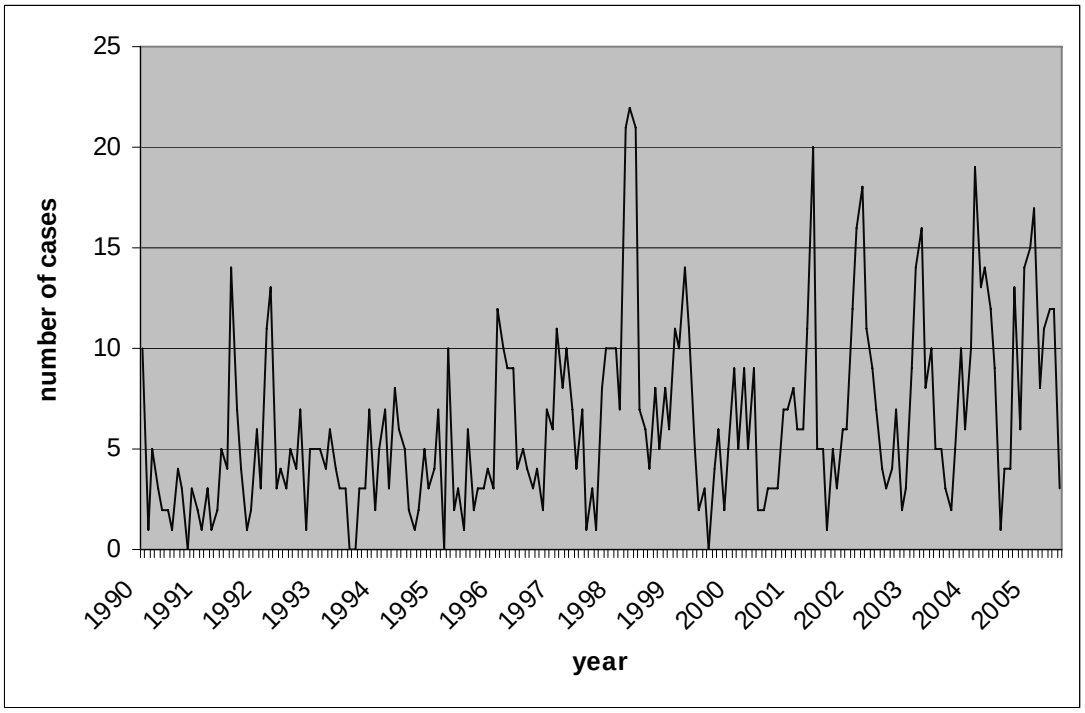
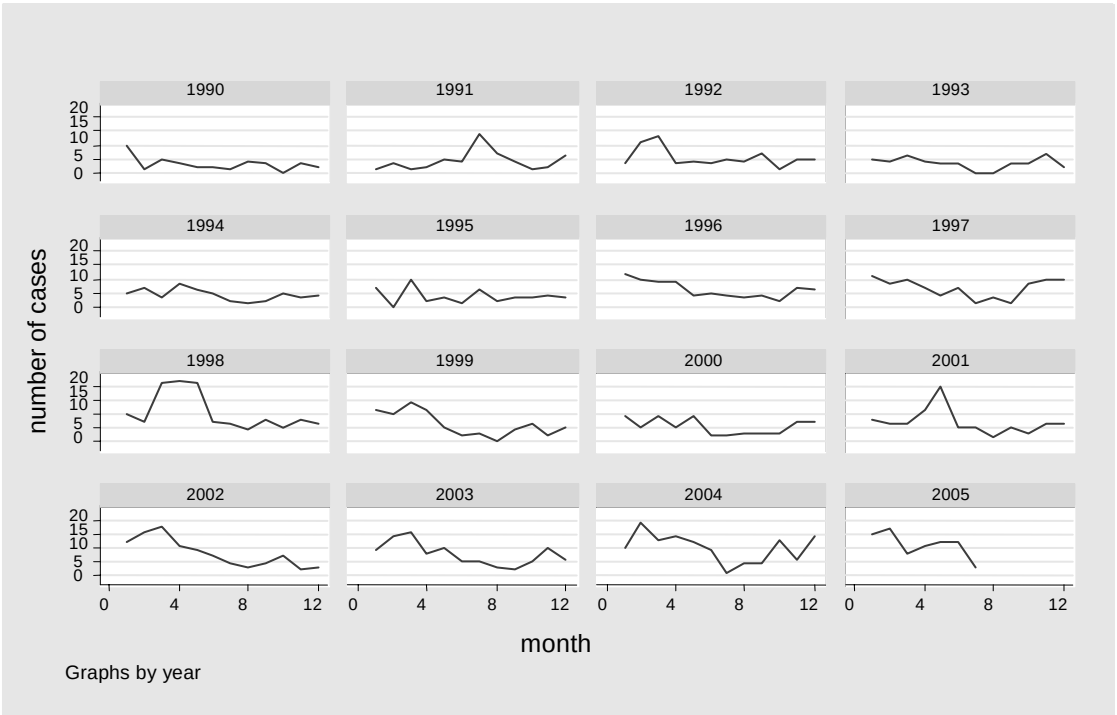


Figure 4- 31 Annual distribution of notified salmonellosis in Townsville, January 1990 - July 2005



4.4.1.3.B Correlation analysis

Table 4- 43 shows that maximum and minimum temperatures, relative humidity and rainfall were all positively correlated with monthly salmonellosis cases in Townsville with 2-month lags for each climatic variable.

Table 4- 43 Correlation between meteorological variables and salmonellosis in Townsville

	Coefficient (95% CI)	*p*	Lag time
Mean max temp	0.54 (0.50, 0.58)	0.000	2 months
Mean min temp	0.50 (0.43, 0.57)	0.000	2 months
Mean humidity 9am	0.21 (0.14, 0.28)	0.000	2 months
Mean humidity 3pm	0.35 (0.30, 0.40)	0.000	2 months
Total rainfall	0.40 (0.34, 0.46)	0.001	2 months

4.4.1.3.C Regression models for salmonellosis in Townsville

Two models were developed by adjusted Poisson regression. The regression models indicate that the number of salmonellosis cases was 2-order autoregressive and had a significant seasonal distribution. The included 'year' variable suggested an increase in the number of cases over the period. After controlling for the autocorrelation, seasonality and secular trend in the number of cases, temperature and rainfall were significantly associated with salmonellosis transmission in Townsville (Table 4- 44 and Table 4- 45). The models suggest that a 1 ºC rise in maximum temperature is related to an 11.9% (95%CI: 8.7%-15.1%) increase in the number of cases of salmonellosis and a 1 ºC rise in minimum temperature is related to a 5.9% (95%CI: 4.0%-7.8%) increase in the number of cases in Townsville. The goodness of fit and the forecasting ability for Model 1 are demonstrated in Figure 4- 32, which indicate the developed models have the statistical power to project future number of salmonellosis cases in Townsville.

Table 4- 44 Parameters from adjusted Poisson regression for salmonellosis in Townsville (Model 1)

	Coefficient	Std. Err.	z	P>|z|	[95% Conf. Interval]
Lag1 case count	0.0439	0.0082	5.36	0.000	[0.0278, 0.0599]
Lag2 case count	0.0266	0.0088	3.02	0.002	[0.0094, 0.0439]
Mean max temp	0.1188	0.0162	7.33	0.000	[0.0870, 0.1505]
Lag3 rainfall	0.0006	0.0002	3.19	0.001	[0.0002, 0.0009]
Year	0.1501	0.0231	8.70	0.000	[0.1050, 0.1952]
Sin(2πt /12)	99.5097	38.381	2.59	0.010	[24.2833, 174.7360]
Constant	0.2059	0.2500	0.85	0.382	[-0.2841, 0.6959]

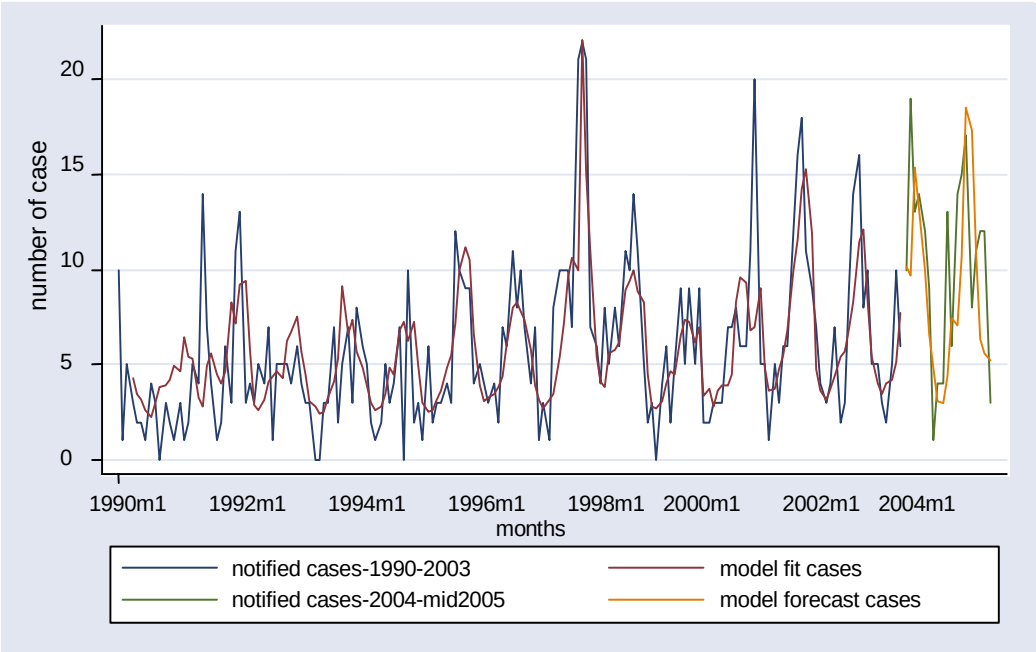
Lag1 case count: number of cases occurred one month prior.

Table 4- 45 Parameters from adjusted Poisson regression for salmonellosis in Townsville (Model 2)

	Coefficient	Std. Err.	z	P>|z|	[95% Conf. Interval]
Lag1 case count	0.0470	0.0082	5.73	0.000	[0.0309, 0.0631]
Lag2 case count	0.0249	0.0089	2.80	0.005	[0.0075, 0.0423]
Mean min temp	0.0587	0.0096	6.09	0.000	[0.0398, 0.0776]
Lag3 rainfall	0.0005	0.0002	2.79	0.005	[0.0001, 0.0008]
Year	0.1567	0.0198	7.82	0.000	[0.1250, 0.1884]
Sin(2πt /12)	110.4626	38.8100	2.85	0.004	[34.3964, 186.5289]
Constant	0.2186	0.2500	0.87	0.382	[-0.2712, 0.7085]

Lag1 case count: number of cases occurred one month prior.

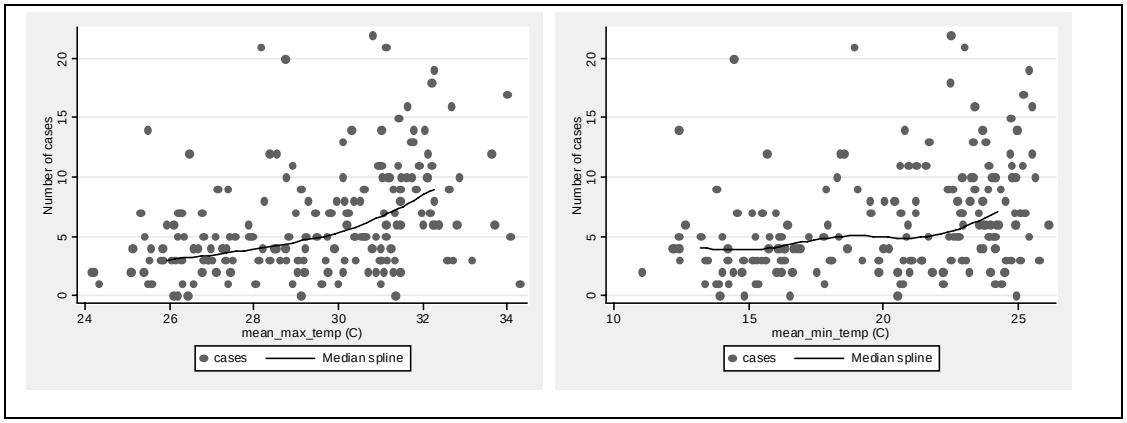
Figure 4- 32 Notified cases vs. model fit cases (1990-2003) and predicted cases (2004-2005) of salmonellosis in Townsville according to Model 1



4.4.1.3.D Detection of threshold temperatures

No threshold for the effect of maximum and minimum temperatures on salmonellosis was detected in Townsville. The spline curves of the relationship between cases of salmonellosis and temperatures are presented in Figure 4- 33.

Figure 4- 33 Relationship between temperatures and salmonellosis in Townsville, Queensland



4.4.1.4 The relationship between climate variation and salmonellosis in Australia

Salmonellosis is one of the most common and widely distributed enteric infection, with millions of cases being reported worldwide every year [167]. In Australia, *Salmonella* is one of the most common agents responsible for food-borne disease outbreaks [9]. This was a 10 percent increase compared with the previous four-year period. Recent estimation indicated that *Salmonella* may be the cause of 92,000 cases of gastroenteritis annually in Australia [168].

This is the first systematic study of the effect of climate variation on salmonellosis in various climatic regions in Australia, including temperate, subtropical and tropical, using historical disease surveillance datasets. The results from this study indicate that both maximum and minimum temperatures have a positive impact on salmonellosis in all the study regions in Australia, with a lagged effect of two weeks to two months. The results are similar to other recent publications, including studies in Europe, North America and Asia, which studied salmonellosis [40, 86], Hepatitis A [87], campylobacteriosis [39, 88, 89, 106] and other enteric infections [30, 96, 102-105, 126].

The control of salmonellosis is still a challenge and it is worthwhile understanding the underlying causes, including climate variation [169]. Although enteric infection is multi-causal, the growth and spread of the responsible microorganisms are influenced by climate variation [82, 96]. Temperature may affect the transmission of enteric infections via several causal pathways, such as direct effects on bacterial proliferation and indirect effects on eating habits during hot days. The optimum temperature for the growth of S*almonellae* is between 35°C and 37°C. The growth is greatly reduced at less than 15°C [170]. *Salmonella* can survive a long time in food and on surfaces. For example, *Salmonellae* can survive for 28 days on the surfaces of vegetables under refrigeration. Given the large number of different serotypes of salmonella species, some serotypes are significantly more heat resistant than the others [171]. Although not all salmomellosis cases in Australia are food-borne, more than 70% cases are transmitted by food [9]. Thus, ambient temperature might also influence the development of *Salmonellae* at various stages in the food chain, including bacterial loads on raw food production, transport and inappropriate storage. Temperature might also affect the exposure of individuals to *Salmonellae* through seasonal changes in eating patterns and behaviors.

Both maximum and minimum temperatures have a positive impact on the occurrence of salmonellosis in all the study regions in Australia. The two-week lagged effect of temperatures on salmonellosis might include the incubation period of the disease and the propagation of the pathogen. The results also demonstrate that a 1°C increase in temperature might cause an approximately 10% increase in the number of salmonellosis cases in all the study regions in Australia. This is similar to results of previous studies. For example, a 1°C increase in temperature was related to a 5% increase in the risk of severe diarrhoea among Peruvian children [30] and a 1°C rise in temperature has been found to correspond to a 5 % increase in the number of reported cases of campylobacteriosis in England [39].

The potential thresholds for the effect of temperature on salmonellosis have been investigated in this study. The results indicate that only the temperate region in South Australia has a threshold for the effect of both maximum and minimum temperatures (19.5ºC and 12.1ºC, respectively). The threshold temperatures detected in South Australia are consistent with other studies conducted in Europe and Australia investigating the relationship between temperature and salmonellosis [40, 86]. The detection of such thresholds suggests that there may be extra cases in the future should the temperature go above a certain level (the threshold). This has significant implications for public health practitioners and policy makers. No threshold temperature has been detected in the subtropical and tropical regions in Queensland. This may reflect the different local climate conditions, with a narrow range of temperatures in these regions.

In addition to the difference in the temperature thresholds, the effects of the meteorological variables on salmonellosis vary in the study areas. Lag times of maximum and minimum temperatures are shorter in Townsville (tropical) than in Brisbane and Adelaide (subtropical and temperate). Moreover, the effects of rainfall and humidity on salmonellosis are different. These different impacts of climate variation on salmonellosis may be attributable to local weather conditions. Further studies conducted in other areas are needed to have a better understanding of such relationship.

In the study regions, the association between other meteorological variables, including rainfall and relative humidity, and salmonellosis, is not as clear as the relationship with temperatures. In the temperate region of South Australia, rainfall is not significant in the regression models, while in the subtropical and tropical regions of Queensland rainfall is positively associated with the number of salmonellosis cases. Relative humidity is not significantly included in the regression models, although it is significant in the correlation analysis. Actually, rainfall, especially heavy rainfall events, may affect the frequency and level of contamination of drinking water, and hence enteric infection. A strong association between drinking water quality, precipitation and gastroenteritis in New Zealand has been described [171]. However, the highly urbanised population and well-managed water treatment system and reticulation in the metropolitan area of South Australia may conceal any relationship between rainfall and salmonellosis.

Relative humidity is negatively correlated with salmonellosis in the temperate region but positively correlated with salmonellosis in the tropical and subtropical regions in Australia. This may reflect the reverse association between relative humidity and temperature in the temperate weather region. This is consistent with recent studies [39, 40, 86, 89], but does not imply that relative humidity has not had any impact on the transmission of enteric infection. The effect of humidity may not be independent because it is often related with other meteorological variables, including temperature and rainfall. Further studies are needed to understand the effect of humidity on enteric infection.

The high quality of disease surveillance data in Australia enhances the research strength of this study. In the Australian study regions the disease surveillance records, including onset of disease, are used in the analysis rather than notification dates. The onset date is more closely correlated with the date of infection. Therefore, as discussed by Kovats et al [40], the use of the onset date overcomes the shortcoming of recording only the date of notification in most disease surveillance systems, which generally entails a delay of approximately one week for diarrhoeal diseases. This is very important for the epidemiology of enteric infection when considering

prevention and control. Such a refinement should be applied to strengthen relevant disease surveillance systems and related research power.

The analysis is on a weekly basis in Adelaide, South Australia, and Brisbane, Queensland, but on a monthly basis in Townsville, Queensland, for consideration of sample size (to avoid many zeros in the time series). While monthly data might not provide an accurate estimation for enteric infection, there were only a few cases every week in Townsville (reflecting the size of the region). It is strongly recommended that weekly data be used in similar studies if surveillance data are available.

Under-reporting is an important issue in disease surveillance systems, especially for enteric infections. Generally only those patients with severe symptoms go to see the doctor and are notified to relevant authorities. It is reported that only approximately one in fifteen cases of enteric infection is notified in Australia [172]. Under-reporting obviously has an impact on the study results. However, there is no reason to believe that the trend in under-reporting varies over the study period. The other limitation of the analysis is the change of infectious disease notification system in Australia after 1992. In order to have enough time series points to guarantee the statistical power for the time series analysis, it is assumed there is no considerable difference between GP report and laboratory report of salmonellosis caused by the change of the notification system.

There are more than 2,000 serotypes of *Salmonellae* in natural environment, which might have different sensitivity to climate variation [169]. This study did not distinct different serotypes of salmonellosis, which is one disadvantage of this study. The transmission of *Salmonellae* to humans is a complex ecological process. Meteorological variables are a component of a causal network neither necessary nor sufficient for the transmission of the infection. Warmer temperature, in combination with differences in eating behaviour, may therefore contribute to enteric infections including salmonellosis. Furthermore, many factors including socioeconomic factors may play a significant role in enteric infection, thus such measures should be included in regression models. Additional systematic studies on the impact of climate

variation on host/reservoirs, patients and bacterial survival, as well as socioeconomic status, are necessary in future.

4.4.2 Bacillary Dysentery

4.4.2.1 Bacillary dysentery in Jinan, northern China

4.4.2.1.A Descriptive analysis

4.4.2.1.A.1 Summary of notified cases of bacillary dysentery in Jinan, 1987-2000

In total, 312,584 cases were notified over the period of 1987-2000 in Jinan with most cases occurring in summer months (Figure 4- 34 and Figure 4- 35).

Figure 4- 34 Monthly notified cases of bacillary dysentery in Jinan, 1987-2000

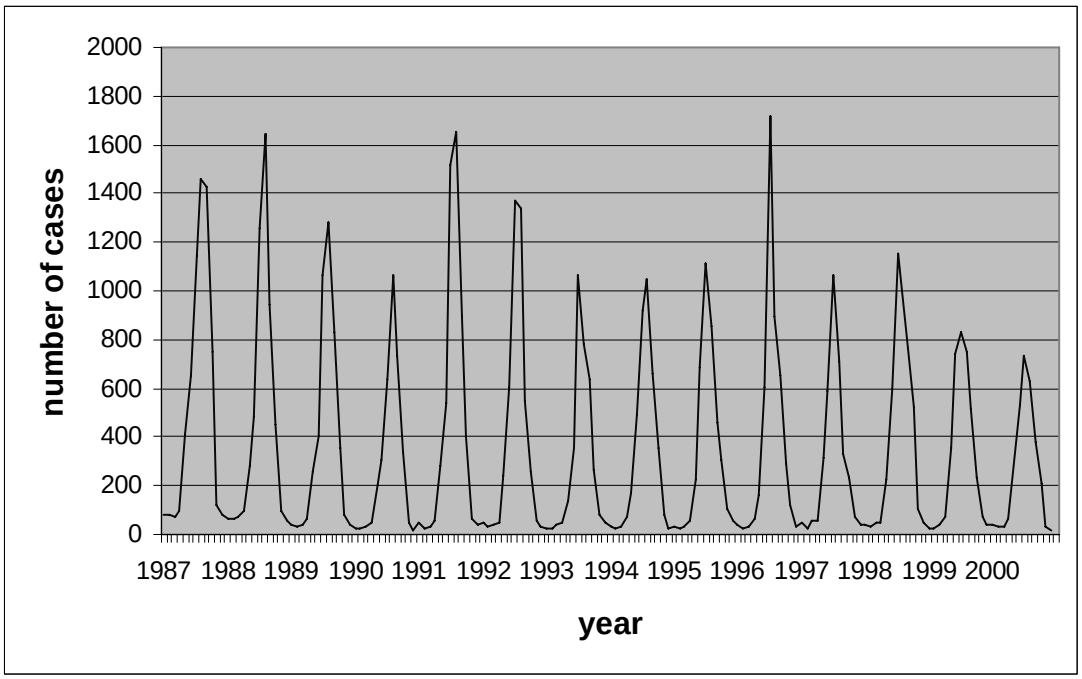


Figure 4-35 Monthly distribution of bacillary dysentery in Jinan, 1987-2000

NOTE: This figure is included on page 127 of the print copy of the thesis held in the University of Adelaide Library.

4.4.2.1.A.2 Summary of meteorological variables in Jinan The meteorological variables in Jinan from 1987-2000 are summarised in Table 4- 46. The mean monthly maximum temperature and mean monthly minimum temperature were 19.8ºC and 10.93ºC respectively. The mean monthly humidity was 57%; mean monthly total rainfall was 871.96mm, and the mean monthly air pressure was 1008 kpa.

Table 4- 46 Summary of monthly meteorological variables in Jinan, 1987-2000

	Mean	Std. Dev.	Min	Max
Mean max temp (ºC)	19.80	10.01	0.55	34.93
Mean min temp (ºC)	10.93	9.52	-6.07	26.41
Mean humidity (%)	57.24	11.13	36.07	81.97
Total rainfall (mm)	871.96	620.53	0.00	2967.80
Mean air pressure (kpa)	1008.30	9.71	984.05	1023.50

4.4.2.1.B Correlation analysis

4.4.2.1.B.1 Correlations among meteorological variables

Table 4- 47 shows that there were high positive correlations between maximum and minimum temperatures (r=0.99) and negative correlation between air pressure and temperatures (r>-0.8) in Jinan over the period 1987 to 2000.

Table 4- 47 Correlation coefficients between meteorological variables in Jinan

	Mean max temp	Mean min temp	Mean air pressure	Mean humidity	Total rainfall
Mean max temp	1.00				
Mean min temp	0.99	1.00			
	(0.00)				
Mean air pressure	-0.83	-0.82	1.00		
	(0.00)	(0.00)			
Mean humidity	0.39	0.47	-0.37	1.00	
	(0.00)	(0.00)	(0.00)		
Total rainfall	0.41	0.43	-0.38	0.29	1.00
	(0.00)	(0.00)	(0.00)	(0.00)	

* *p* value in the brackets. Highlighted coefficients demonstrate high levels of correlation.

4.4.2.1.B.2 Correlations between bacillary dysentery and meteorological variables

Monthly mean maximum and minimum temperature, rainfall and humidity were positively related, while air pressure was negatively related to bacillary dysentery in Jinan with relevant lag times (Table 4- 48).

Table 4- 48 Correlation between monthly bacillary dysentery and meteorological variables in Jinan

NOTE: This table is included on page 128 in the print copy of the thesis held in the University of Adelaide Library.

4.4.2.1.C Regression models for bacillary dysentery in Jinan

After controlling for the 2-order autocorrelation and seasonal variation of bacillary dysentery cases, only maximum and minimum temperatures were significantly included in the SARIMA models (Table 4- 49 and Table 4- 50) with the Aikake Information Criterion (AIC) values approximately195. The models suggest that a 1°C rise in maximum temperature may be related to an 11% (95%CI: 7%-14%) increase in the number of cases of bacillary dysentery, and a 1 °C rise in minimum temperature may be related to a 12% (95%CI: 9%-15%) increase in the number of cases of bacillary dysentery in Jinan. The plotting of the residuals is demonstrated in Figure 4- 36, which indicates no autocorrelation among the residuals.

Table 4- 49 Parameters from SARIMA for bacillary dysentery in Jinan (Model 1)

NOTE: This table is included on page 129 in the print copy of the thesis held in the University of Adelaide Library.

Table 4- 50 Parameters from SARIMA for bacillary dysentery in Jinan (Model 2)

	B	Stand. Err.	*z*	*p*
AR2	-0.1897	0.0623	-4.306	0.032
SMA1	-0.3750	0.0794	-4.726	0.000
Lag1 min temp	0.1244	0.0068	18.289	0.000
Constant	-0.0129	0.0317	-0.407	0.684

AR2: 2- order autoregressive; SMA1: Seasonal 1-order moving average.

Figure 4- 36 Notified cases vs. model fit cases of bacillary dysentery in Jinan according to Model 1 and plot of the model residuals

NOTE: This figure is included on page 130 of the print copy of the thesis held in the University of Adelaide Library.

4.4.2.1.D Detection of threshold temperatures

A threshold of 17.0°C for the effect of maximum temperature and a threshold of 8.0°C for the effect of minimum temperature on cases of bacillary dysentery were detected in Jinan (Figure 4- 37).

Figure 4- 37 Thresholds for the effect of temperatures on bacillary dysentery in Jinan

NOTE: This figure is included on page 130 of the print copy of the thesis held in the University of Adelaide Library.

4.4.2.2 Bacillary dysentery in Baoan, southern China

4.4.2.2.A Description of notified cases of bacillary dysentery in Baoan, 1996-2003

In total, there were 2,032 cases of bacillary dysentery notified in Baoan over the study period with an average monthly incidence of 1.60/100,000 (Figure 4- 38). The seasonal pattern in the number of cases was not significant (Figure 4- 39).

Figure 4- 38 Monthly incidence of bacillary dysentery in Baoan, 1996-2003

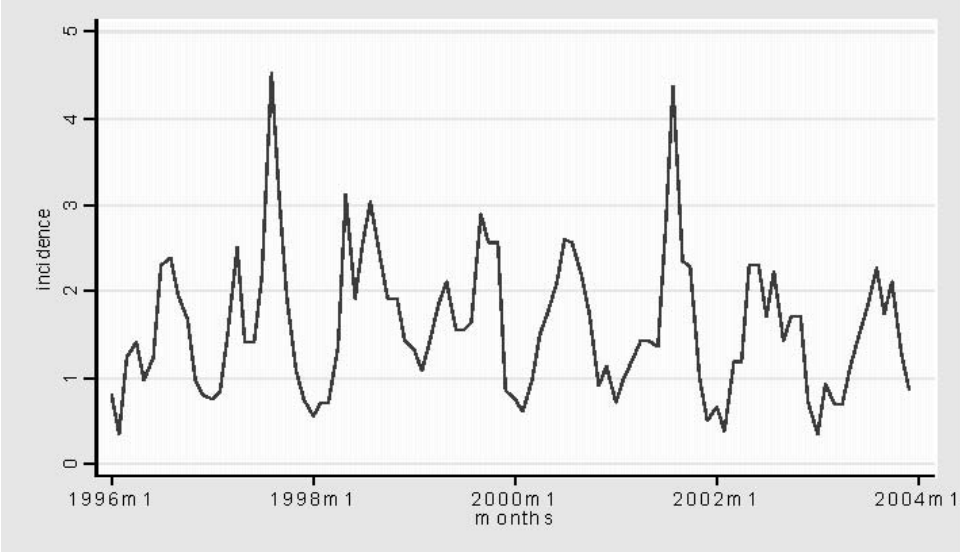


Figure 4- 39 Annual distribution of bacillary dysentery in Baoan, 1996-2003

NOTE: This figure is included on page 132 of the print copy of the thesis held in the University of Adelaide Library.

4.4.2.2.B Correlation analysis Table 4- 51 indicates that monthly mean maximum and minimum temperatures, rainfall and humidity were positively correlated while air pressure was negatively correlated with bacillary dysentery in Baoan with relevant lag times (Table 4- 51).

Table 4- 51 Correlation between meteorological variables and bacillary dysentery in Baoan

	Coefficient (95% CI)	*p*	Lag time
Mean max temp	0.82 (0.69, 0.89)	0.000	0
Mean min temp	0.79 (0.71, 0.89)	0.000	0
Total rainfall	0.21 (0.46, 0.52)	0.045	2 months
Mean humidity	0.50 (0.61, 0.71)	0.000	2 months
Mean air pressure	-0.69 (-0.89, -0.72)	0.000	1 month

4.4.2.2.C Regression models for bacillary dysentery in Baoan The results of the SARIMA models indicate that the number of bacillary dysentery cases in Baoan was 1-order autoregressive without a significant seasonal distribution.

The Aikake Information Criterion (AIC) values of the models were approximately 210. The only meteorological variables significantly included in the SARIMA models were maximum or minimum temperature (Table 4- 52 and Table 4- 53).

The models suggest that a 1 °C rise in maximum temperature is related to a 16% (95%CI: 13%-19%) increase in the number of cases of bacillary dysentery, and a 1°C rise in minimum temperature is related to a 14% (95%CI: 10%-18%) increase in the number of cases of bacillary dysentery in Baoan. The goodness of fit of Model 1 is demonstrated in Figure 4- 40, which also shows randomly distributed residuals without autocorrelation among them.

Table 4- 52 Parameters from SARIMA for bacillary dysentery in Baoan (Model 1)

NOTE: This table is included on page 133 in the print copy of the thesis held in the University of Adelaide Library.

Table 4- 53 Parameters from SARIMA for bacillary dysentery in Baoan (Model 2)

	B	Stand. Err.	*z*	*P*
AR1	0.289	0.098	2.947	0.04
Lag1 min temp	1.442	0.169	8.556	0.000
Constant	-7.595	3.494	-2.174	0.032

AR1: 1-order autoregressive.

Figure 4- 40 Notified cases vs. model fit cases of bacillary dysentery in Baoan according to Model 1 and plot of the model residuals

NOTE: This figure is included on page 134 of the print copy of the thesis held in the University of Adelaide Library.

4.4.2.2.D Detection of threshold temperatures

A threshold for the effect of temperatures on bacillary dysentery was not detected in Baoan, as shown in Figure 4- 41.

Figure 4- 41 Relationship between temperatures and bacillary dysentery in Baoan

NOTE: This figure is included on page 135 of the print copy of the thesis held in the University of Adelaide Library.

4.4.2.3 The relationship between climate variation and bacillary dysentery in China

Bacillary dysentery, caused by *Shigella* bacteria, is a bacterial infection of the intestines resulting in severe diarrhoea. Patients who are infected with *Shigella* often develop bloody diarrhoea, fever, and stomach cramps with an incubation of one or two days173. While most cases of bacillary dysentery are mild and do not require drastic treatment, excessive dehydration can be fatal in a severe attack if treatment is unsuccessful 174. The infection is spread from person to person via oral-faeces, food or drinking water. Epidemics are frequent in overcrowded populations with poor sanitation and most cases occur in summer and autumn.

This is the first epidemiological study examining the impact of climate on bacillary dysentery in various climatic/geographic areas in China. Our results indicate that temperatures are the key climatic indicator of the transmission of bacillary dysentery in the regression models. Laboratory evidence shows that *Shigella* can growth from a minimum 6-7◦C to a maximum of 45-47◦C. The survival time of *Shigella* is only a few minutes if the temperature is above 60◦C 175. The growth and survival of *Shigella* vary in different environmental conditions. Moreover, temperature is not the only factor that can influence the growth and survival of the pathogen, other environmental factors, such as humidity, can also play a role. However, high

temperatures may cause more cases by influencing factors that favour the transmission of bacillary dysentery, such as human eating habits in hot weather (when cold or insufficiently cooked food is more likely to be eaten), food storage, transportation and food processing. A potential 1°C increase in temperature is associated with a more than 10% increase in bacillary dysentery cases in the study regions in China, if other affecting factors remain constant. This result is consistent with other research on the effects of temperature on enteric infections [30, 39].

In addition to temperature, other meteorological variables, such as rainfall, relative humidity and air pressure, may contribute to the transmission of enteric infection. The association between other climatic conditions and enteric infections is far from clear. Some studies claim that rainfall does not affect transmission of enteric infection [40, 86], while other studies report inconsistent results [102, 176, 177]. In this study, although there was a significantly positive association in the correlation analysis, rainfall did not enter the regression models. Relative humidity and air pressure are correlated with the number of cases of bacillary dysentery but are not significantly included in the regression models. This does not mean that these meteorological variables do not affect the transmission of bacillary dysentery. Indeed, all the climatic variables may work together to have an effect on diseases. More studies in other climatic areas are needed to further understand the association between these meteorological variables and enteric infections.

The threshold for the effect of temperature varies in different climatic zones. In the northern city, Jinan, with a temperate climate, thresholds for maximum and minimum temperature have been detected. The detection of such thresholds suggests that there may be more cases expected in the future once temperature increases above the threshold. This has significant implications for public health practitioners and policy makers. No threshold was detected in the southern city, Baoan, where there is a narrow range of temperature within a subtropical zone. This result is similar to other studies conducted in Europe and Australia investigating the relationship between temperature and salmonellosis [40, 86].

The order of auto-correlation of the number of cases and the lag effects of the meteorological variables vary in the two cities. The number of bacillary dysentery

cases is auto-correlated with the number of cases occurring two months prior in the northern city, but it is only one month autoregressive in the southern city, which reflects the reduced temperature variation in the southern city compared to the northern city. The lag time for temperature was one month in the northern city, however no lag effect for temperature was detected in the southern city, which suggests that climate variation may have a more rapid impact on diarrhoeal diseases in southern than in northern areas. This result is consistent with other studies on climate and enteric infections [88, 102].

The varying impacts of climate variation on bacillary dysentery in these two regions may be attributed to local climatic characteristics in temperate and subtropical zones. Therefore, local climate conditions should be considered when attempting to ameliorate the impact of future climate change. Due to the short lag effect and no threshold for temperatures in the southern city, Baoan, a disease surveillance system with high quality and rapid response is particularly desirable in subtropical regions with similar climatic conditions.

Socio-economic status plays an important role in the transmission of diarrhoeal diseases. Improvement in socio-economic status could lead to a secular change in the number of dysentery cases, which may be one of the most important reasons for the higher incidence of dysentery in Jinan than in Baoan - a young and relatively well-developed city. In this study, although a measure of socio-economic status has not been included in the analyses, a trend function has been used in the ARIMA model to control for the effect of secular trend, which may control for the effect of socio-economic factors. Further studies, including additional climate zones and predictive studies using mathematical models, need to be conducted for better understanding of the relationship between climate change and enteric infection and to prepare for the potential risks inherent in future climate change.

The quality and availability of data is another important issue in studying the association between meteorological variables and infectious diseases, especially for enteric infection. Firstly, under-reporting is inevitable. The influence of under-reporting is assumed consistent over the study period (according to the report from internal data audit of the Jinan Municipal Centre of Disease Prevention and Control).

Secondly, onset dates rather than notified dates of diseases, which would be more suitable for such analysis, may result in a better estimation of lag values. Thirdly, some notified cases of bacillary dysentery may not have a laboratory test. However, given that bacillary dysentery is a very common disease in China, it is not difficult for doctors to make a correct clinical diagnosis. Fourthly, weekly data rather than monthly data may produce a more accurate estimation of effects. However, only monthly surveillance data were available for this study. Obviously, improvements in disease surveillance systems and health information sharing need to be seriously addressed, particularly in developing countries.

4.4.3 Relationship between climate variation and enteric infections – summary and implications

Maximum and minimum temperatures have affected the transmission of enteric infections in various climatic regions in Australia and China. Moreover, although there may have been different patterns of seasonal distribution of cases in various climatic regions in Australia and China, the quantitative relationship between temperature and the number of cases is similar. Thresholds of temperature have been detected in temperate regions but not in subtropical or tropical regions in both countries.

The association among other meteorological variables, including rainfall, humidity and air pressure, and enteric infections is not fully clarified by this study. While rainfall does affect the number of salmonellosis cases in the subtropical and tropical regions in Australia, an effect of rainfall on salmonellosis in the temperate region has not been detected. Additionally, no significant association has been detected between rainfall and bacillary dysentery in the temperate and tropical regions in China. The difference in the impact of climate variation on enteric infection in Australia and China may reflect differences in climatic conditions, environmental hygiene, food industry standards, food chain and human behaviour as well as different socioeconomic status. Moreover, it should be acknowledged that these meteorological variables do not act independently, but interact with each other.

Local climatic conditions play an important role in the transmission of enteric infections. Early warning systems for enteric infections can be developed by

integrating local meteorological variables, particularly temperature, with local disease surveillance data, especially before the epidemic season. The detection of threshold temperatures in different climatic regions has policy implications for local disease control and prevention in both Australia and China.

Global warming has brought about challenges to public health and infectious disease control and prevention systems, including those for salmonellosis, given the prediction of temperature change in much of Australia [3]. Therefore, public health action should be initiated by educating producers of food, managers of commercial food outlets, and the public about the increased risks of infection in hot weather, and the importance of hygiene, correct storage, appropriate temperature control during food preparation and production, and changing eating patterns and behaviors. Moreover, preventive measures should be included in education programs, eg simple things like a dilute bleach solution can effectively prevent salmonellosis. In addition, education of school children about healthy food and eating habits and washing hands before eating could be one of the main tasks.

The food and livestock industries have responsibility to form integrated trade standards, which allow for response to climate variation in order to prevent or reduce food and water contamination. Local public health practitioners should enforce supervision over food industries and food retailers, especially when high temperatures are predicted, and educate food producers, industries and communities about the increased risk of enteric infection in hot weather. This is very important for small business. Restaurants and food retailers should not be neglected in the prevention of food-borne diseases. Early warning of occurrence of food-borne diseases related to climate variation should be distributed in a timely manner.

Hospitals and doctors should prepare for a large number of cases which may occur in a short time when the temperature is above the threshold. Additional attention should be paid to vulnerable populations, such as children, the elderly, aboriginal people or people living in rural areas. Clinical guidelines for doctors should incorporate the potential risks of climate change on population health. Education for clinicians about research findings on climate change impacts would be helpful.

Research findings should be distributed widely and in a timely manner to appropriate audiences. This will require communication and collaboration between public health practitioners, clinicians, researchers and government agencies. In Australia, for example, the National Enteric Pathogens Surveillance Scheme (NEPSS) has partly collected, analysed and disseminated data on human enteric infections since 1980. Laboratory diagnosed *Salmonella* is reported quarterly by NEPSS [178]. Another Australian government collaborative initiative on enteric infection in Australia is OzFoodNet - a health network established in 2000 to enhance the surveillance of food-borne diseases [179]. These government agencies link research with practice, which is an effective channel of information sharing and communication. It is greatly hoped that these successful networks can be emulated by developing countries with modifications based on local conditions, including the attitude of local communities, governments and health authorities.

To reduce the risk of climate variation on enteric infections will be more difficult in China. Problems that will be encountered include but are not limited to less reliable data quality, relatively slow infectious disease notification system, unsystematic monitoring of food industries or restaurants, shortages of health care services, lack of health education and health promotion programs, and the urgent need for economic development. Therefore, it is a real challenge for policy makers and practitioners to adapt to and mitigate climate change in China.

4.5 Conclusions regarding the relationship between climate variation and selected infectious diseases in study regions

This study suggests that climate change may alter the ecology of vector-borne diseases and enteric infection. Climate variation, particularly increases in temperatures, has affected the transmission of both vector-borne diseases and enteric infections in various climatic regions in Australia and China. Either maximum or minimum temperature could be used as an indicator of the number of cases with consideration of lag time, seasonality, autocorrelation and long-term trends.

This study has confirmed the impact of climatic factors, especially temperature, on vector-borne diseases. Climate variation may play a role in a potential increase in RRV infection in temperate regions in Australia and in the resurgence of malaria in China. However, the impact of rainfall on vector-borne diseases may be more complicated and more difficult to clarify. A significant association between rainfall and RRV infection has been detected in Australia, while no relationship between rainfall and malaria in China has been detected in this study.

In terms of the relationship between climate variation and enteric infections, the results suggest that the effects of an increase in temperatures on enteric infections may not be less than those on vector-borne diseases. The effects of temperatures on enteric infections have been documented in all the regions selected in Australia and China in this study. Moreover, threshold temperatures have been demonstrated in temperate regions but not in subtropical and tropical regions in both countries. However, the effects of the other meteorological variables, such as rainfall and humidity, on such diseases have not been clearly identified and the effects may vary cross different climatic regions.

The potential reasons for the different impacts of climate variation on the infectious diseases may be due to the different local climatic conditions, various types of vectors and pathogens, local environmental hygiene and socio-economic status. Further studies are necessary to explore the underlying causes of the uneven distribution of the impact of climate variation on population health.

These results have implications for governments at all levels, local public health practitioners, clinicians, local communities, and industries. Education should play an essential role in preventing and reducing risks of climate variation on population health. Effective and timely public health response depends on communication and collaboration between all relevant sections and reliable data and information sharing. Policies with consideration of the relationship between climate variation and population health should be developed at an early stage.

CHAPTER V

PROJECTION OF THE BURDEN OF SELECTED INFECTIOUS DISEASES ASSOCIATED WITH FUTURE CLIMATE CHANGE

5.1 Introduction

The identification of disease determinants is essential in disease prevention and control. As a determinant, climate change contributes to adverse health impact at a population level. Identifying the health burden attributed to climate change can help prioritize actions for preventing or reducing the impact and assist in planning for future preventive action [180]. It will also aid health research prioritization, infrastructure establishment, and development of disaster response mechanisms. While the Environmental Burden of Disease (EBD) studies conducted by the World Health Organization (WHO) have analyzed the global burden of disease from 26 risk factors including climate change [107], few quantitative studies have been performed to predict future climate-related burden at national and sub-national levels. Such studies are fundamental to provide evidence for local policy makers on the identification of risks, and for adaptation and mitigation actions.

It is of great significance for both Australia and China to estimate the climate-related health burden for the coming decades. Although Australia completed its first national burden of disease study in 1999 [113], and since that time sub-national burden of disease studies have been conducted in several Australian states, including Queensland [115] and South Australia [181], climate change as a risk factor has not been investigated in these studies. According to the recently released World Energy Outlook (WEO) 2006 report, by 2030, China will be emitting more than seven billion tons of carbon dioxide each year and surpassing the US as the world's largest emitter [182]. However, few studies have been conducted on the health impact of climate change in China.

This chapter addresses the second objective of the thesis, to project the burden of target diseases, measured in terms of Years Lost due to Disability (YLDs), under future scenarios for climate and population change in different climatic regions in Australia and China. Given the considerable assumptions and uncertainties in the methodology in all burden of disease studies, these scenario-based projections aim to estimate potential trends in the morbidity burden of targeted diseases. The purpose is

to provide scientific evidence for policy makers and local communities in order to reduce future risks of climate change and take relevant action when necessary.

5.2 Methods

In order to estimate the future burden of target diseases under climatic and population scenarios, measured in terms of the YLDs, the methods used in this chapter are based on the framework of the Global Burden of Disease (GBD) study [107] and the Australian National Burden of Disease study [113]. In Australia, the tropical region, Townsville, in far northern Queensland, could not be included in this part of the thesis due to the lack of essential data, such as projected age- and sex-distribution of the population. Moreover, because of the uncertainty in estimating the burden of disease in small areas [183] and the unavailability of essential data from the Murray River region in South Australia, the YLDs were projected for the whole of South Australia. Therefore, South Australia, the temperate region, and Brisbane, the subtropical region, were the study areas used to project future burden of disease related to climate change in Australia. In China, Jinan, the temperate city, and Baoan, the subtropical city, were the study areas used for the projection of future burden related to climate change.

This projection of future morbidity burden of disease related to climate change does not include all climate-related diseases, only those target diseases analyzed in Chapter Four. The relationship between exposure and diseases is based on the regression models developed in Chapter Four. The future increase in temperature was used as a proxy for all future climate scenarios because temperature is the only climatic variable included in all the regression models developed for study diseases, and there are large variations in the predictions for other meteorological variables, such as rainfall and relative humidity.

5.2.1 Assumptions

In addition to the assumptions associated with the original methods used in the GBD studies which have been described in detail in previous publications [107, 113], other assumptions need to be addressed in this analysis.

Firstly, the quantitative associations between climate variation and target diseases were assumed to be maintained in the future, despite potential changes in the impact of other factors, such as socio-economic status, on disease transmission. These quantitative relationships were then applied to future climate and population growth scenarios. This assumption might introduce significant uncertainty to the projections.

Secondly, in order to calculate the YLDs in South Australia, it was assumed that the quantitative relationship between meteorological variables and RRV infection in the Murray River regions, and the relationship between meteorological variables and salmonellosis in Adelaide, represent the corresponding relationship for South Australia in its entirety. Given that more than 60% of cases of salmonellosis were from Adelaide and more than half the cases of RRV infection were from the Murray River regions in South Australia, this assumption is believed to be reasonable.

Thirdly, temperature is the key weather factor influencing the transmission of the target diseases. Other climatic factors, such as rainfall, may also influence disease transmission. In this study, the effects of other meteorological variables on infectious diseases have been assumed to be constant.

Fourthly, any future change in the vulnerability of population to climate change was not taken into account. Moreover, adaptation to and mitigation of climate change were assumed unchanged. For example, non-climatic factors, such as exposure to vectors or contaminated food, which affect the transmission of infectious diseases, have not been included in this projection on the assumption that they would remain constant over the study period.

Given the assumptions and the consequent uncertainties, this study attempts to generate only a broad picture to indicate possible trends in the morbidity burden from study diseases associated with future climate change.

5.2.2 Calculation of the YLDs

The estimation of mortality burden, using a measure such as the Years of Life Lost (YLLs), has quite reliable calculation methods, based on available death registrations. Estimated YLDs however can be volatile due to (i) the parameters used in the

calculation; (ii) difficulties in defining "disability"; and (iii) the observed variations in the incidence rate of infectious diseases.

The methods used to calculate the YLDs in this study are similar to those used in the GBD studies, using similar age groups, disability weights, discounting and age weighting [107]. The calculation of the YLDs from the target diseases in Australia was aided by the use of data from the Australian National Burden of Disease study and the previous South Australia and Queensland burden of disease studies [113,115, 181]. However, this was not the case in China, where such studies have not been conducted and few existing data from previous studies could be used. The calculation of the YLDs in Chinese areas followed the procedure of the GBD studies using data collected from relevant local authorities.

5.2.2.1 Necessary data

- Demographic data

Age- and sex-specific demographic data were needed to calculate the YLDs. The age groups are not exactly the same between Australia and China, reflecting the data availability in the two countries. The age groups used in this thesis for both sexes are as follows:

For the Chinese population: 0~, 5~, 10~, 15~, 20~, 30~, 40~, 50~, 60+;

For the Australian population: 0~, 5~, 15~, 25~, 35~, 45~, 55~, 65~, 75+.

- Age- and sex- specific incidence rates

In order to calculate the YLDs, detailed information about the study diseases is essential. Age- and sex- specific incidence rates of each study disease were collected from local authorities for each study region in both countries.

- Disability weights

The calculation of summary measures of population health, including YLDs, involves several explicitly social value choices including disability weights. Initially, these preference weights were derived using a Person Trade Off method with groups of health experts [184]. No comparable study has yet been undertaken to determine local weights for the range of health states relevant to Australian and China. Severity and duration of each study disease was determined based on a literature review of

previous GBD studies and National Burden of Disease studies. The Dutch weights [185] used in the Australian national burden of disease study [113] and weights used in the GBD study [186] were used in this analysis (Table 5- 1). The weights for salmonellosis and bacillary dysentery could not be identified from any previous studies because they had been included in the category of "diarrhoeal disease" in previous burden of disease studies. Therefore, the weights used for the category "diarrhoeal disease" were used in this assessment. The average severity and duration for each disease used in this calculation are summarised in Table 5- 1. Case definitions were derived from the GBD study conducted in 2002 [186].

5.2.2.2 Discounting and age weighting

Social values, including discount rate and age weights, have been incorporated into the calculation of the Disability Adjusted Life Years (DALYs). The discount rate, which addresses the difference in value of current versus future health benefits, is commonly used in cost-effectiveness analyses. A 3% discount rate was applied in this study to calculate the YLDs to ensure consistency with the measurement of health outcomes in other analyses [107, 120].

Table 5- 1 Parameters used to calculate the YLDs for each study disease

			Average disability weights	Average duration (year)	Sources
Australia	RRV infection	Acute	0.12	0.08	Australian BoD study[113]
		Chronic	0.14	0.80	
	Salmonellosis	Uncomplicated	0.09	0.01	
		Complicated	0.42	0.04	
China	Malaria	Episode	0.21	0.47	GBD 2002[186]*
	Bacillary dysentery	Episode	0.09	0.04	

* In the WHO defined Western Pacific regions WproB1 including China.

Age weight, where a year of healthy life lived at one age is valued differently from that at another age, is the most controversial value built into the methodology of the Global Burden of Disease study [120]. There was no compelling evidence for the particular form of age weighting used by the GBD study; no non-uniform age weighting was applied in the Australian burden of disease studies [113, 115, 181] ,and any age weights would need recalibrating for the Chinese population. For this study to have international comparability, uniform age weighting has been adopted.

Although different discounting and age weighting could be used in burden of disease studies, such as no discounting and non-uniform age weighting - YLD(0,0) - or 3% discounting and non-uniform age weighting - YLD(3,1) - these discounting measures and weights would not affect the potential trends between observed and projected burden of disease based on linear regression. Therefore, only 3% discounting without age weighting were used for the calculation of the YLD (3,0) in this study, as used in most burden of disease studies [107, 113].

5.2.2.3 Formula to calculate the YLDs

The formula used to calculate the YLDs in this study, with a 3% discounting and no age weighting, is presented below [107]:

$$\text{YLD} = \frac{I \times DW \times \left(1 - e^{-rL}\right)}{r}$$

Where:

I=incidence rate

DW=disability weight

L=average duration of disability (years)

r=discount rate (0.03)

5.2.3 Projections of future YLDs for target diseases

The climate-related health outcomes included in this estimation of morbidity burden include Ross River virus infection and salmonellosis in Australia, and malaria and bacillary dysentery in China. The associations between temperature and the selected vector-borne diseases and enteric infections were quantified in the previous chapter and then used as the basis for the projections. Climatic and demographic changes were considered in the projections.

5.2.3.1 Timeframe

The YLDs for the study diseases in 2000 were chosen as the baseline for the projection. The reasons for choosing 2000 as baseline include: (i) the burden of disease studies have been conducted in the Australian study areas and the up-to-date results are in 2000, which can be used to validate the estimate by this study; (ii) year 2000 is the latest year in the collected dataset from Jinan, the temperate city in China; (iii) in order to make possible comparison across the study areas, it is necessary to select a same baseline time for all the study areas.

Projections from that baseline were then conducted for 2030 and 2050 in Australia, and 2020 and 2050 in China. The different time periods of the projections are due to the availability of data on future climate scenarios and demographic changes in each country.

5.2.3.2 Climate scenarios

Due to a consistent positive relationship being detected only between temperature and the selected infectious diseases, the temperature-based scenarios are used as a proxy for future exposure to climate change. The projections for the increase in temperature in the Australian regions were obtained from the latest Commonwealth Scientific and Industrial Research Organization (CSIRO) report [3], and the corresponding projections in Chinese regions were obtained from the IPCC reports in 2001 [187]. The ranges of the projections of temperatures in temperate and subtropical regions in both countries are summarised in Table 5- 2.

Table 5- 2 Future temperature scenarios - range of increases in temperature (°C)

	Australia		China	
	2030	2050	2020	2050
Temperate regions (South Australia and Jinan)	0.3-1.3	0.6-2.2	0.3-2.4	0.8-4.6
Subtropical regions (Brisbane and Baoan)	0.3-2.0	0.5-3.2	0.3-3.6	1.8-5.0

5.2.3.3 Future population structures

In addition to the change in temperature, changes in future population structures were taken into account to project the future YLDs for the study diseases. The scenarios for future population structures in each country were collected from the Australian Bureau of Statistics (ABS) and the National Bureau of Statistics of China (NBSC), respectively. The demographic changes in the study areas of Australia and China are summarized in Table 5- 3 and Table 5- 4.

Table 5- 3 Future demographic changes in study regions in Australia

Australia	South Australia			Brisbane		
	2000	2030	2050	2000	2030	2050
Population (thousands)	1505.0	1648.5	1586.2	1689.1	2723.8	3328.0
Population sex ratio (males per 100 females)	97.7	98.8	99.2	97.8	99.7	99.9
Percentage aged 0-4 (%)	6.2	4.8	4.4	6.7	5.3	4.9
Percentage aged 5-14 (%)	13.3	10.2	9.4	13.8	11.2	10.4
Percentage aged 15-24 (%)	13.1	10.7	10.3	15.6	11.8	11.2
Percentage aged 65 or over (%)	13.5	26.2	29.8	10.9	21.3	25.2

Table 5- 4 Future demographic changes in study regions in China

China	Jinan			Baoan		
	2000	2020	2050	2000	2020	2050
Population (thousands)	5602.122	6270	5720	2736	4680	4305
Population sex ratio (males per 100 females)	103.6	101.3	99.5	104.3	103.1	101.5
Percentage aged 0-4 (%)	3.33	3.15	2.79	1.66	1.35	1.14
Percentage aged 5-14 (%)	10.62	9.98	8.41	5.18	3.81	3.26
Percentage aged 15-24 (%)	29.96	27.89	26.35	20.45	17.01	14.55
Percentage aged 60 or over (%)	12.29	18.7	25.5	7.44	12.53	20.84

5.2.3.4 Uncertainty estimate

This study has two major uncertainties, as has all other research on health effects of climate change. One is the uncertainty in the assessment of the quantitative relationship between meteorological variables and diseases. The other is the uncertainty in the projections of future scenarios. For the first uncertainty, as it is not yet feasible to quantify the relationship based on observed long-term effects of climate change [188], the appropriate time-series regression was applied to quantify a shorter-term exposure-effect relationship. In terms of uncertainty in the scenarios, particularly climate scenarios, projections are limited by largely unpredictable factors both within the climate system itself, and in the interaction between climate and human behaviours, including population growth and economic development [3]. Therefore, a range of the morbidity burden under various scenarios rather than point estimation is presented to incorporate the quantifiable uncertainties.

5.3 Results and discussion - Projected burden of selected vector-borne diseases associated with climate change

5.3.1 Ross River virus infection

5.3.1.1 Projected YLDs for RRV infection in South Australia

The YLDs for RRV infection in South Australia in 2000 and the projected ranges for YLDs in 2030 and 2050 are presented in Table 5- 5. The total YLDs for RRV infection in 2000 in South Australia were 83, with 43 from males and 40 from females. It can be seen that the burden of RRV infection is similar between males and females. In addition, the projected YLDs in 2030 and 2050 have a clear increasing trend compared to the YLDs in 2000.

Figure 5- 1 demonstrates the increased trend in the projected YLDs for RRV infection. If only the temperature scenarios are considered, the YLDs for RRV infection in South Australia would increase by up to 40% by 2030 and 80% by 2050. With consideration of both temperature and future population change, the YLDs for RRV infection in South Australia would increase by up to 66% by 2030 and 92% by 2050, if other factors remain constant.

Figure 5- 2 shows the age-specific YLDs in South Australia in 2000 and projected YLDs for RRV infection in 2030 and 2050, considering both climatic and population scenarios. It demonstrates that middle-aged persons are the most affected by RRV infection. In addition, the burden of RRV infection in elderly people may have a higher rate of increase due to the future ageing of the population.

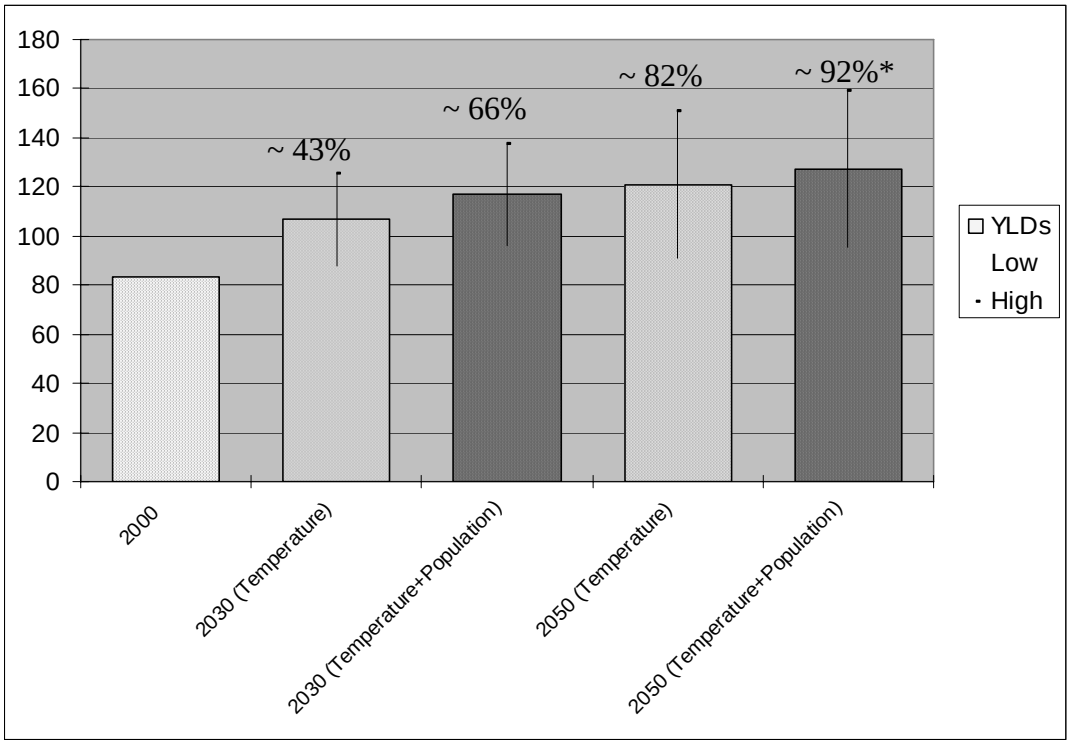
Table 5- 5 The YLDs for RRV infection in South Australia: 2000, 2030 and 2050

		Total	Male	Female
2000		83	43	40
2030	Projection A*	88~126	45~65	42~61
	Projection B^	96~138	50~72	46~66
2050	Projection A*	91~151	47~78	44~73
	Projection B^	96~159	50~83	46~76

* Projection A considers future change in temperature

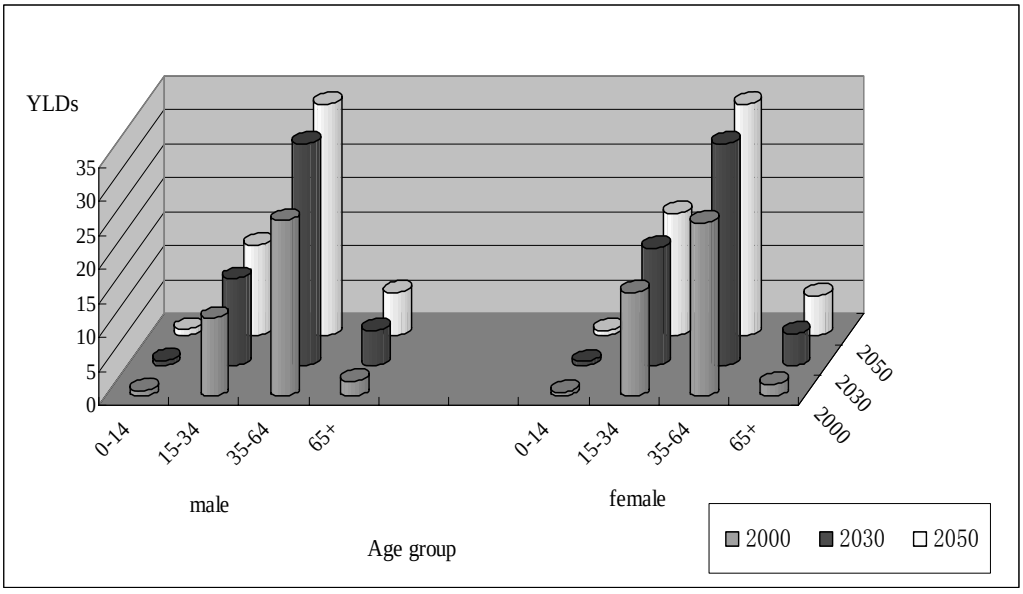
^ Projection B considers future change in both temperature and population growth

Figure 5- 1 Projected YLDs for RRV infection in South Australia



*The figures show the estimated highest percentage increase in YLDs

Figure 5- 2 Projected YLDs for RRV infection by age and sex in South Australia



5.3.1.2 Projected YLDs for RRV infection in Brisbane, southern Queensland, Australia

Table 5- 6 shows the estimated YLDs for RRV infection in Brisbane, Queensland, in 2000, and the projected ranges for YLDs in 2030 and 2050. In 2000, the total YLDs for RRV infection were 36, with 16 from males and 20 from females. A consistent increasing trend in the YLDs has been projected by 2030 and 2050 for both females and males.

Figure 5- 3 demonstrates the projected increasing trend in the total YLDs for RRV infection in 2030 and 2050, compared to 2000. The YLDs for RRV infection in Brisbane would increase by up to 66% by 2030 and 90% by 2050 if there is an increase in temperature. When considering both future climate and demographic change, the YLDs for RRV infection would increase by 86% by 2030 and by 94% by 2050, if other factors remain constant.

Figure 5- 4 shows the age-specific YLDs in Brisbane in 2000 and projected YLDs for RRV infection in 2030 and 2050, considering both climatic and population scenarios. It indicates that, as with South Australia, middle-aged persons are the most affected by RRV infection, and the burden of RRV infection in the elderly group

may increase more than in other age groups due to future changes in population structure.

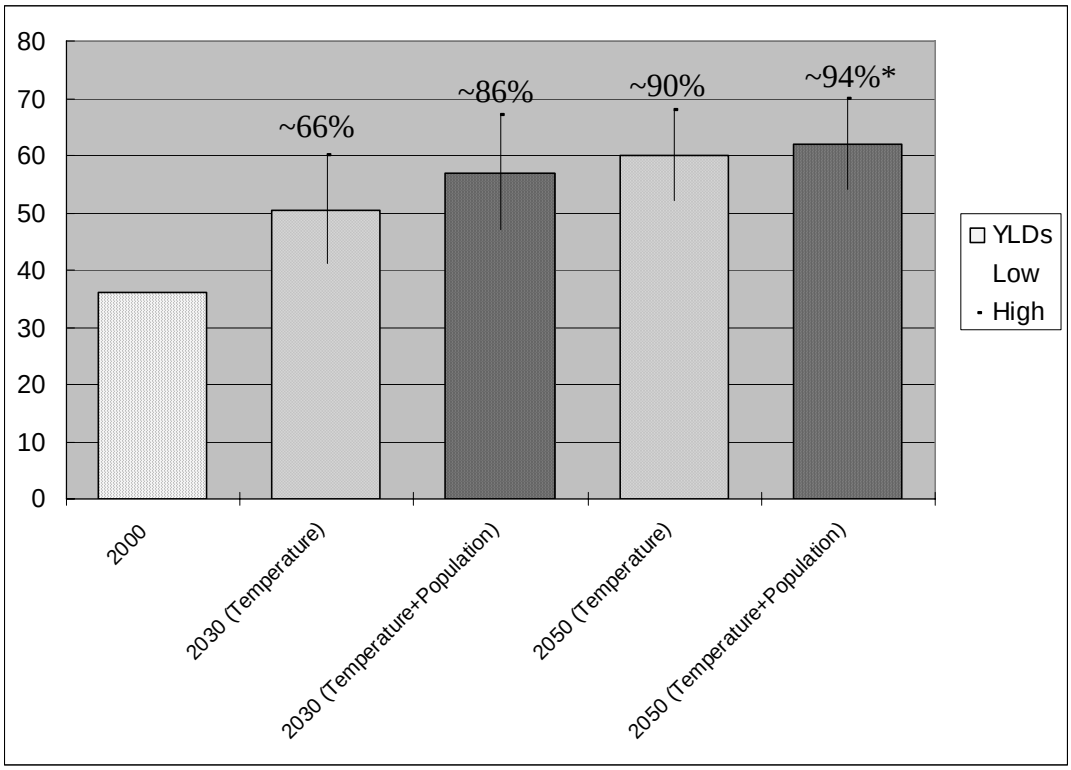
Table 5- 6 The YLDs for RRV infection in Brisbane: 2000, 2030 and 2050

		Total	Male	Female
2000		36	16	20
2030	Projection A*	41~60	19~27	22~33
	Projection B^	47~67	21~30	26~37
2050	Projection A*	53~68	23~30	30~38
	Projection B^	59~70	22~42	37~58

* Projection A considers future change in temperature

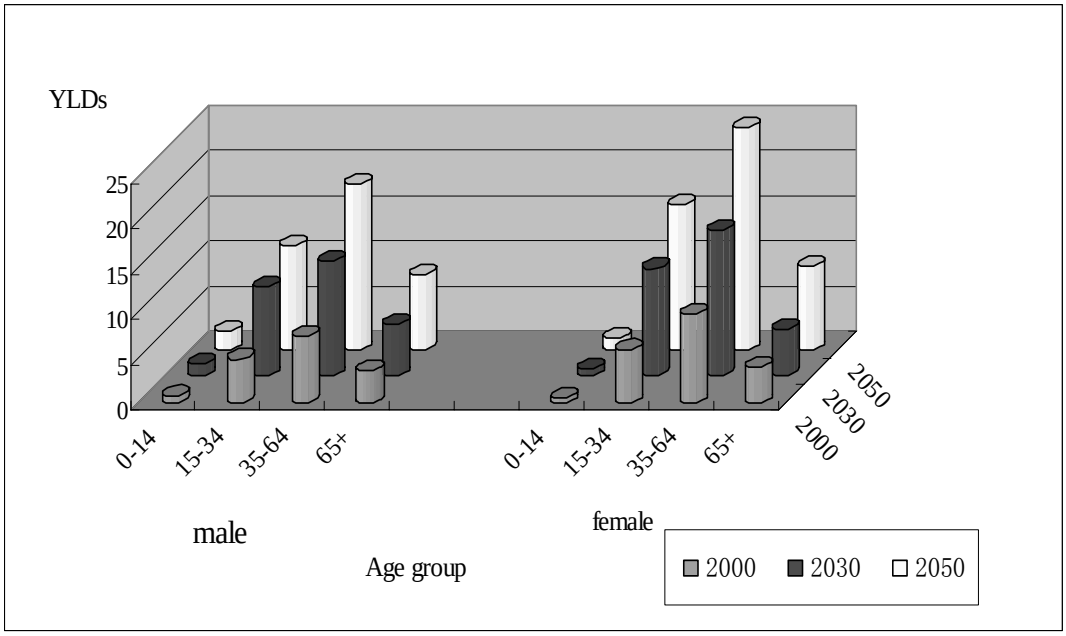
^ Projection B considers future change in both temperature and population growth

Figure 5- 3 Projected YLDs for RRV infection in Brisbane



*The figures show the estimated highest percentage increase in YLDs

Figure 5- 4 Projected YLDs for RRV infection by age and sex in Brisbane



5.3.2 Malaria

5.3.2.1 Projected YLDs for malaria in Jinan, northern China

Table 5- 7 shows the estimated YLDs for malaria in 2000 and projected YLDs for malaria under different scenarios in 2020 and 2050 in Jinan. It can be observed that the estimated total YLDs for malaria in 2000 were 59, with 32 from males and 27 from females. It also suggests that there may be an increase in the morbidity burden from malaria in Jinan due to a future rise in temperature and demographic changes. The projected YLDs for malaria are slightly higher in males than in females.

Figure 5- 5 demonstrates the potential increasing trend in the burden of malaria in Jinan under scenarios of both climate change and population growth. It indicates that if temperature scenarios only are considered, the YLDs for malaria might increase by up to 61% by 2020 and 108% by 2050 compared to 2000, if other factors remain constant. When considering future changes in both climate and population structure, however, the YLDs for malaria in Jinan would increase by up to 116% by 2020 and 170% by 2050, if other factors remain constant.

Figure 5- 6 demonstrates the age- and sex- specific YLDs for malaria in Jinan in 2000 and the projected YLDs for malaria, under the scenarios with greatest

temperature increase and population change, indicating that middle-aged adults account for the largest proportion of the burden. Moreover, the burden of malaria among people over 60 may have the greatest increase, compared with other age groups, due to future ageing of the population.

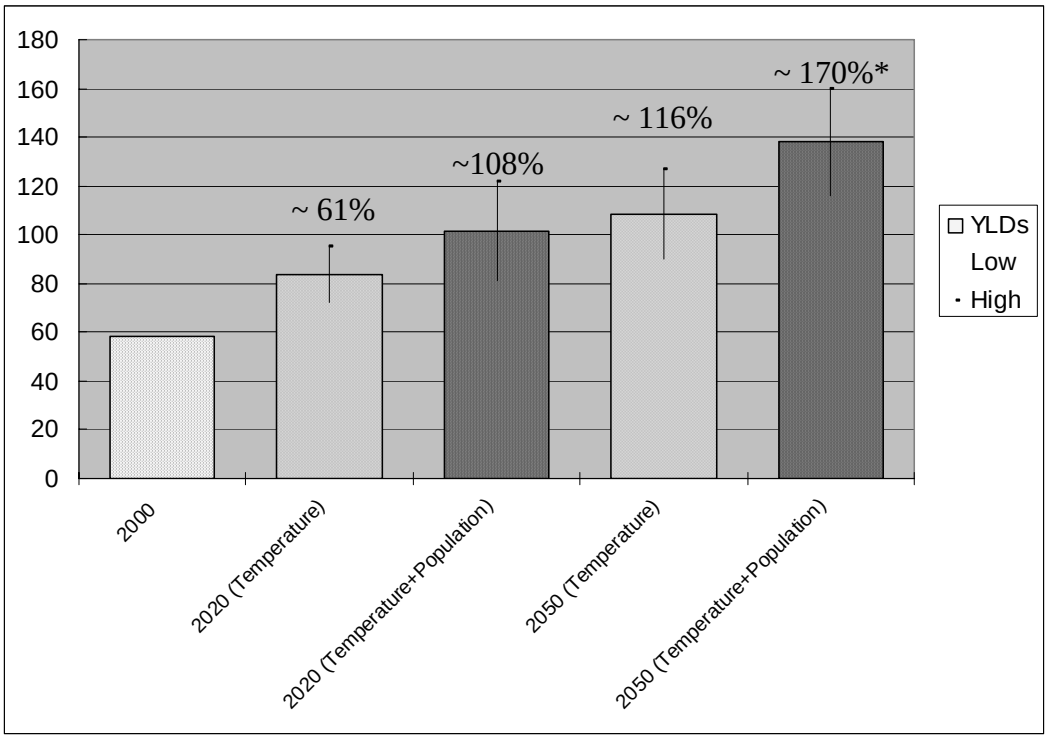
Table 5- 7 The YLDs for malaria in Jinan: 2000, 2020 and 2050

		Total	Male	Female
2000		59	32	27
2020	Projection A*	72~95	39~53	33~42
	Projection B^	81~122	49~67	42~55
2050	Projection A*	90~127	54~70	46~57
	Projection B^	116~160	79~86	57~74

* Projection A considers future change in temperature

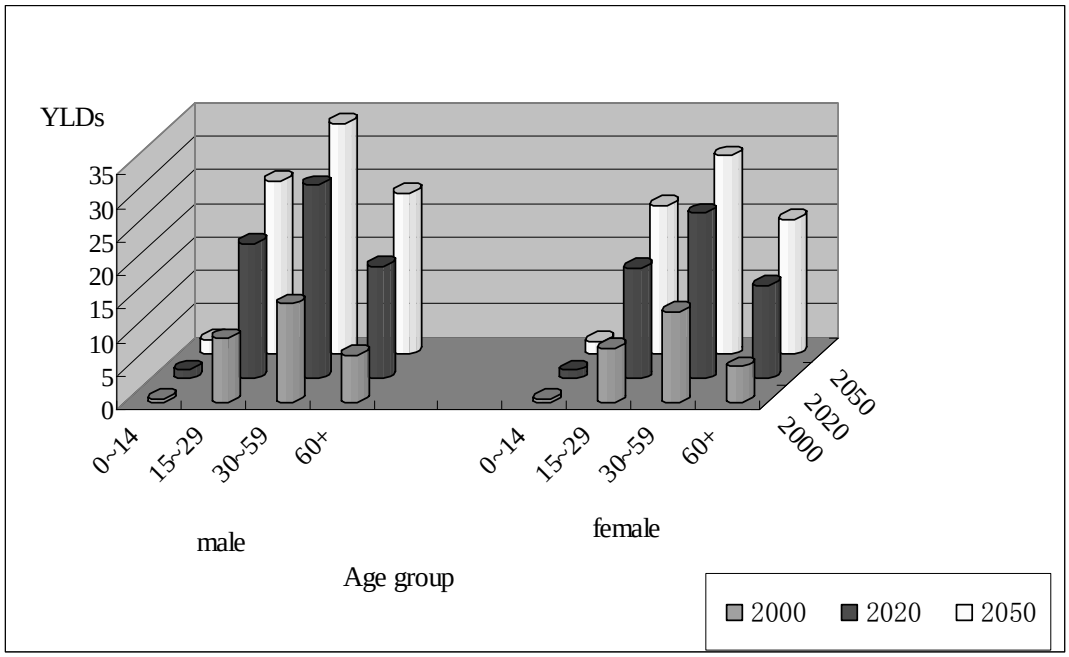
^ Projection B considers future change in both temperature and population growth

Figure 5- 5 Projected YLDs for malaria in Jinan



*The figures show the estimated highest percentage increase in YLDs

Figure 5- 6 Projected YLDs for malaria by age and sex in Jinan



5.3.2.2 Projected YLDs for malaria in Baoan, southern China

The range of estimated YLDs for malaria in Baoan in 2000 and the projected YLDs in 2020 and 2050 are presented in Table 5- 8. In 2000, the total YLDs for malaria in Baoan were 87, of which 44 were from males and 43 were from females. A clear increase in the morbidity burden from malaria has been projected under different scenarios.

Figure 5- 7 shows the projected increasing trend in the total YLDs for malaria. The figures demonstrate that, if other factors remain constant, rising temperature alone may lead to an increase in the YLDs for malaria by up to 70% by 2020 and 130% by 2050, compared to 2000. If demographic change is considered in addition to climate change, the total YLDs for malaria in Baoan would increase by up to 144% by 2020 and 188% by 2050.

Figure 5- 8 demonstrates the YLDs by age and sex, and projected YLDs considering both climatic and demographic changes, and indicates that the middle-aged population is going to bear the largest proportion of the increased burden of malaria. The YLDs indicate that adults and the elderly may experience a greater increase in the future morbidity burden of malaria, compared with other age groups.

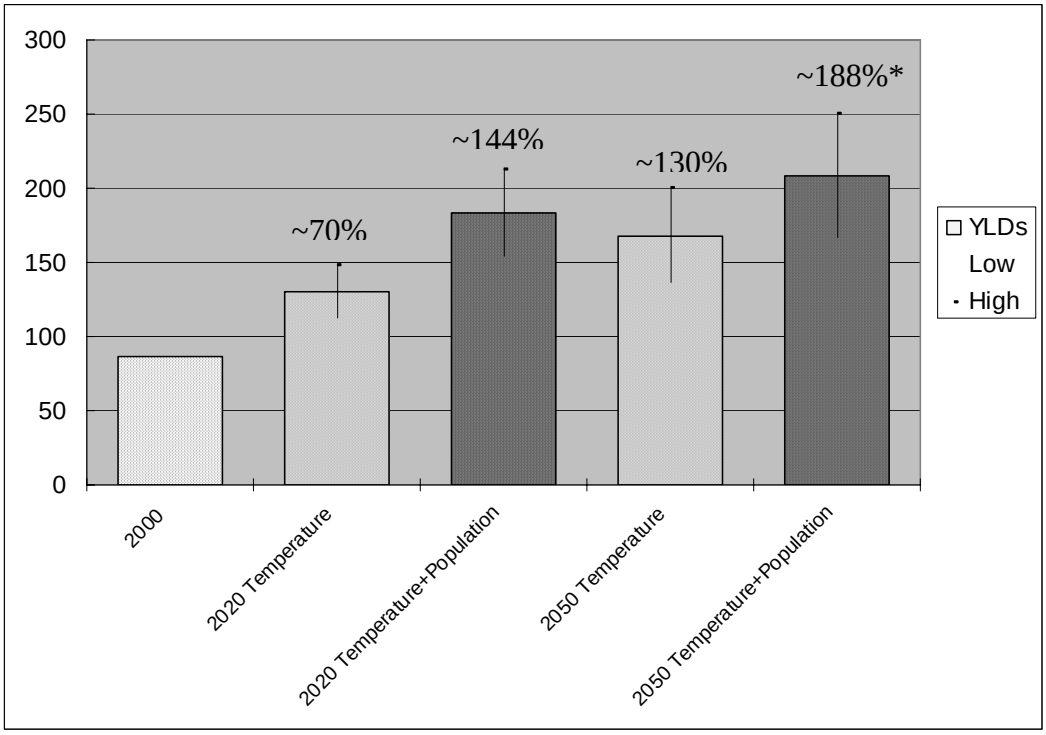
Table 5- 8 The YLDs for malaria in Baoan: 2000, 2020 and 2050

		Total	Male	Female
2000		87	44	43
2020	Projection A*	113~148	57~78	56~70
	Projection B^	154~213	78~108	76~105
2050	Projection A*	136~200	69~101	67~99
	Projection B^	166~250	84~126	82~124

* Projection A considers future change in temperature

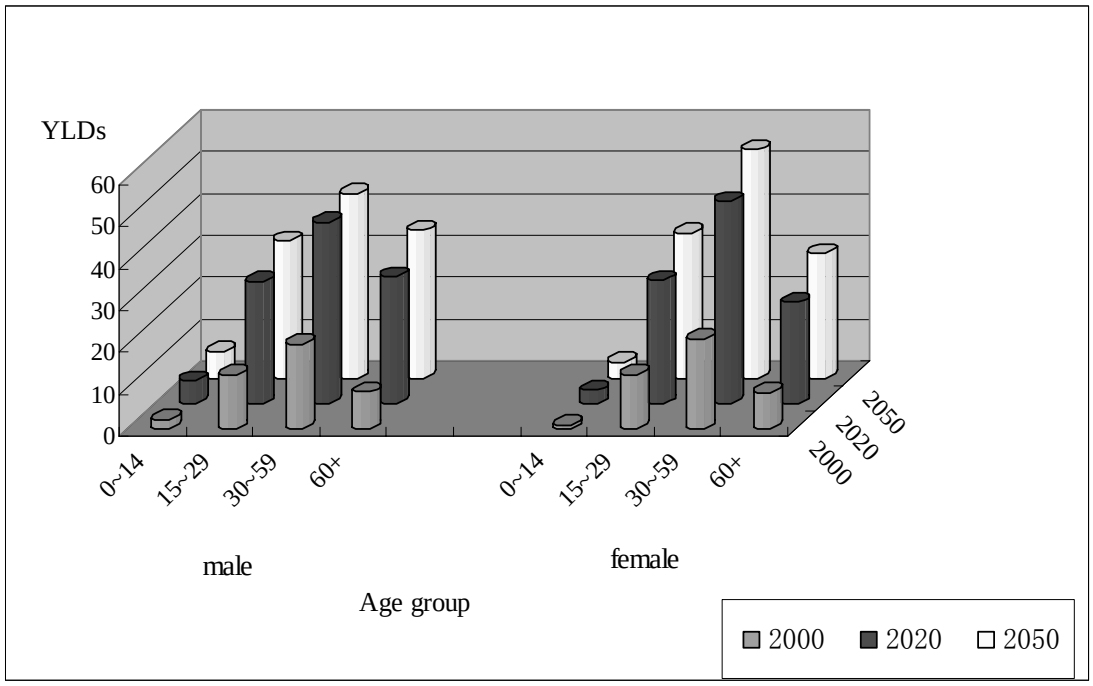
^ Projection B considers future change in both temperature and population growth

Figure 5- 7 Projected YLDs for malaria in Baoan



*The figures show the estimated highest percentage increase in YLDs

Figure 5- 8 Projected YLDs for malaria by age and sex in Baoan



5.3.3 Discussion

5.3.3.1 Future burden of RRV infection in the study regions in Australia

This is the first study to project the morbidity burden of RRV infection related to future climate change in Australia, using YLDs, in temperate and subtropical regions in Australia. Given that deaths from RRV infection are uncommon in Australia, the projected YLDs are almost equal to the total Disability Adjusted Life Years (DALYs) lost from RRV infection. Although the projected absolute numbers are still low in the future, the results indicate a significant increasing trend in the burden of RRV infection under scenarios of temperature increases, if other factors remain constant.

The future burden of RRV infection related to an increase in temperature would be similar in both the temperate and subtropical regions in Australia. It is projected by this study that the burden of RRV infection might double by 2050 in both regions, considering future changes in temperature and population structure. Although the projections in this study do not necessarily represent the best predictions of future health burden trend because of the assumptions and uncertainties in the methods, it is believed that the increasing burden of RRV infection due to global warming

represents a clear quantitative projection based on the previous GBD work of Murray and Lopez [189].

The burden of RRV infection in 2000 is estimated as the baseline for the projection, which is a limitation of this projection. The future burden of RRV infection may be underestimated because of the relatively low incidence of RRV infection in Brisbane in 2000. The notified incidence of RRV infection was less than 10/100,000 population in 2000 in Brisbane, which was only approximately 15% of the incidence in 1999 and 23% of the incidence in 2001. Therefore, it is probable that in this subtropical region the projected burden would be much higher than the estimate. On the contrary, there were relatively high notifications of RRV infection in South Australia in 1999/2000 and 2000/2001, which may cause an overestimate of future burden of this disease.

Age- and sex- specific projections of the burden due to RRV infection provide detailed information about potential vulnerable subpopulations. They suggest that there is no difference in the expected burden of RRV infection between females and males in Australia. It is also not surprising that middle-aged adults have the largest proportion of the burden of RRV infection in the future because they have the highest current notified incidence of RRV infection [45]. It is interesting to note that older people may have the highest percentage increase in the burden of RRV infection, compared to other age groups. An ageing population might significantly increase the burden of RRV disease in Australia by 2050. This result is consistent with other projections, indicating that population ageing and population growth may cause an increased burden in infectious disease in most regions of the world [190].

5.3.3.2 Future burden of malaria in the study regions in China

In China, although malaria has been successfully controlled, there has recently been an observed re-emergence in many regions. In 2003, the number of cases of malaria in China was estimated to be approximately 740,000, covering more than 900 counties in 18 provinces. This indicates a threat to millions of people living in these areas [191]. In addition, the control of malaria in a changing environment is threatened by the ongoing resistance to drugs and pesticides [192]. It is worthwhile understanding

the health burden resulting from climate change, and preparing for disease control and prevention in the future.

This is the first study conducted in various climatic regions in China projecting the future morbidity burden of malaria, considering both climate and demographic change. The results from this study suggest that if other factors, including socio-economic status, remain constant, the morbidity burden of malaria may double by 2020, and may increase by more than 170% by 2050 in both temperate and subtropical regions in China.

In China, the potential future burden of malaria due to climate and demographic changes in temperate regions would be similar to that in subtropical regions. Although a higher proportion of the burden of malaria is suffered by those living in endemic regions, mainly tropical and subtropical regions, epidemics of malaria also pose a serious threat to many millions of people in non-endemic regions, and hence prevention in temperate regions remains a priority. A possible increase in burden of malaria in temperate regions of China should be considered in disease prevention and control. Furthermore, a possible resurgence of malaria in developed countries, which currently have only imported cases of malaria, should also receive attention. For example, it has been reported that malaria may return to Great Britain by the year 2050 due to climate change [47, 193].

Population growth and ageing may have a significant impact on the burden of malaria in China. Similar to the RRV infection in Australia, the results suggest that although middle-aged males are the subpopulation mostly suffering from malaria, both old and young malaria cases would increase greatly with future changes in population structure in China. Effective measures to mitigate the future risks of malaria should focus specifically on these vulnerable subgroups, as well as the population generally.

5.3.3.3 Climate change and burden of selected vector-borne diseases in Australia and China – overview and implications

This is the first epidemiological study that attempts to project the future morbidity burden of vector-borne diseases associated with climate change at a sub-national

level in Australia and China. Despite the assumptions and uncertainties in the scenario-based projections, the results of this study suggest that an increasing trend in the future morbidity burden of vector-borne diseases may be caused by climatic and demographic change in Australia and China. This study also makes a contribution to knowledge of the role of climate change in the exacerbation of vector-borne diseases.

It is noted that an increase in the burden of vector-borne diseases may occur in temperate regions as well as in subtropical regions of Australia and China. Therefore, this possible geographic extension of vector-borne diseases should be noted by local public health practitioners and communities. In addition, it is of importance to fully understand the underlying causes of the re-emergence of malaria in China, especially the potential risks in temperate regions. This study furnishes the evidence that climate change may explain the resurgence of malaria in China.

Demographic change may have a significant effect on future burden of disease. The impact of both rising temperature and population change on vector-borne diseases would be much higher than the impact of rising temperature alone. Over the next few decades, the burden of climate-related vector-borne diseases amongst middle-aged adults and elderly people may show a greater rate of increase compared with other age groups. Health policies should be developed with a focus on these vulnerable subpopulations in particular, as well as the population generally.

The YLDs for RRV infection and malaria are low in both Australia and China, indicating the effectiveness of infectious diseases prevention and control in both countries. However, the future burden of vector-borne diseases caused by climate change may have a greater increase in China than that in Australia. It is even worse with consideration of the higher rate of population aging in China. By 2050, without effective prevention and control programs, the morbidity burden of RRV infection in Australia may increase approximately by 90%, while the morbidity burden of malaria in China may increase more than 1.5 times, compared with 2000. In addition, given the inadequate public health infrastructure and health service resources, developing countries may suffer more from climate change in the future than developed countries.

Given that RRV infection accounts for a large proportion of notified vector-borne diseases in Australia (more than 60% in Queensland and more than 80% in South Australia) [73], these results provide scientific evidence for policy makers to initiate effective preventive measures to reduce the health burden from vector-borne diseases in Australia. Other vector-borne diseases, particularly mosquito-borne diseases in Australia, such as Barmah Forest virus infection, Murray Valley encephalitis, Japanese encephalitis, and dengue fever, have not been included in this estimation, which would make the future climate-related burden even higher because of the similar effects of climate variables on these diseases [73].

The morbidity burden caused by future climate change could be much higher than estimated in this study if all climate-related vector-borne diseases in China are included. Other vector-borne diseases having similar transmission mechanisms to malaria may also be affected by climate change. For example, Japanese encephalitis (JE), a mosquito-borne disease with a clear seasonal distribution, occurs mainly in the tropical and temperate Asia and Pacific regions [144]. Therefore, this estimate is the first step in attempting to assess the future burden of vector-borne diseases associated with climate change in China. The message from this study is that in future the climate-related morbidity burden of vector-borne diseases in China may increase greatly if there is no effective public health adaptation to future climate change.

Socio-economic factors that play a role in the transmission of infectious diseases [194] have not been included in the projection due to the unavailability of data. This is a major limitation of the projection. The absence reflects the unavailability of projections of future economic status at a local level. Improved socio-economic status can significantly reduce the burden of vector-borne diseases by providing high quality health services, environmental hygiene, health education and promotion activities. However, acceleration in economic development may lead to more energy consumption and result in a higher level of greenhouse gas emissions, which is the main reason for global warming. Mitigation of climate change requires sustainable development to reduce future greenhouse gas emissions, thus generating the lowest magnitude of adverse climate scenarios. Further climate-related burden of disease studies should include other influencing factors, such as the speed of economic growth, living conditions and the state of public health services.

Other limitations on the estimate of the future morbidity burden of vector-borne diseases include the assumptions and uncertainties in the methodology for the estimation of YLDs, and uncertainties in climatic and demographic scenarios [158]. Despite the limitations in the projection, this study provides scientific evidence for the Australian and Chinese governments and local communities about the potential increase in the burden of vector-borne diseases related to global warming and demographic change.

These results present a clear signal for the necessity of policy change at an early stage. Implications for public health systems mainly include great pressure that will be put on currently overloaded health care systems, particularly for vulnerable subgroups, such as the elderly, children and those who living in rural areas. Public health interventions, such as vector monitor/control programs and self-education programs, should be started as early as possible. Multi-sector communication between public health practitioners, medical professionals, transport department and meteorological department are vital to reduce extra burden from vector-borne diseases due to future climate change.

5.4 Results and discussion - Projected burden of selected enteric infections associated with climate change

5.4.1 Salmonellosis

5.4.1.1 Projected YLDs for salmonellosis in South Australia

The estimated YLDs for salmonellosis in South Australia in 2000 and the projected ranges of YLDs in 2030 and 2050 are presented in Table 5- 9. The total YLDs for salmonellosis in 2000 in South Australia were 54. There is no difference in the morbidity burden of salmonellosis between males and females. An increasing trend in the YLDs for salmonellosis has been projected in 2030 and 2050.

Figure 5- 9 demonstrates the increasing trend in the projected YLDs for salmonellosis under different scenarios for future changes in climate and population. Taking into account the temperature scenarios alone, the YLDs might increase by up to 31% by 2030 and 56% by 2050. When considering both climate and demographic change, the YLDs for salmonellosis in South Australia may increase by up to 48% by 2030 and 89% by 2050, if other factors remain constant. Figure 5- 10 illustrates the age- and sex- specific YLDs in South Australia in 2000, 2030 and 2050 under scenarios for future climate and population change. It indicates that children are the most affected by salmonellosis.

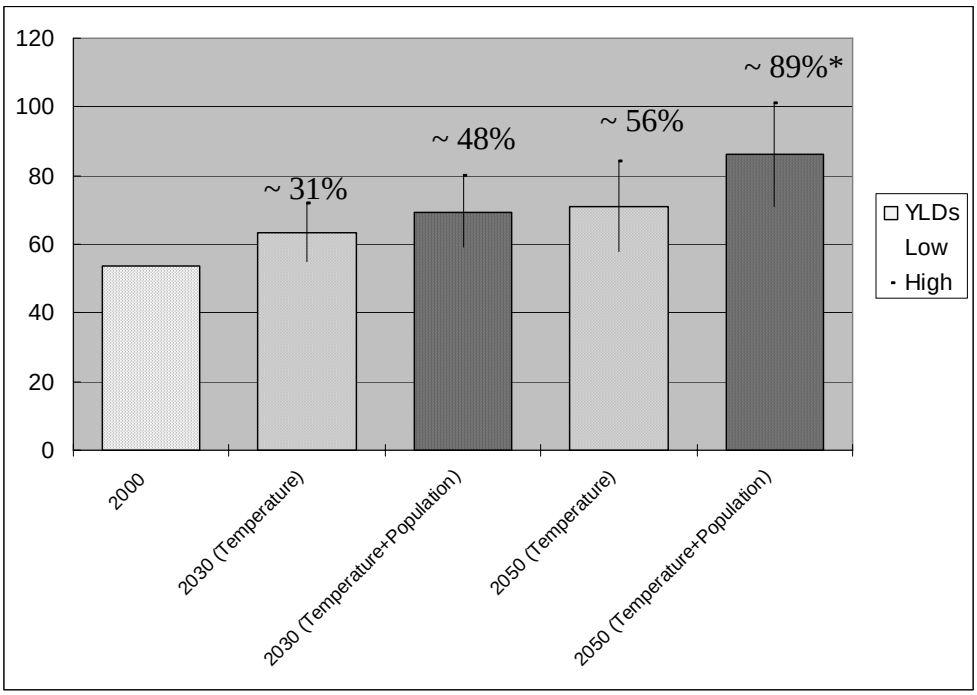
Table 5- 9 The YLDs for salmonellosis in South Australia: 2000, 2030 and 2050

		Total	Male	Female
2000		54	27	27
2030	Projection A*	56~72	28~36	28~36
	Projection B^	59~80	30~40	29~40
2050	Projection A*	58~84	29~43	29~41
	Projection B^	71~101	36~52	35~49

* Projection A considers future change in temperature

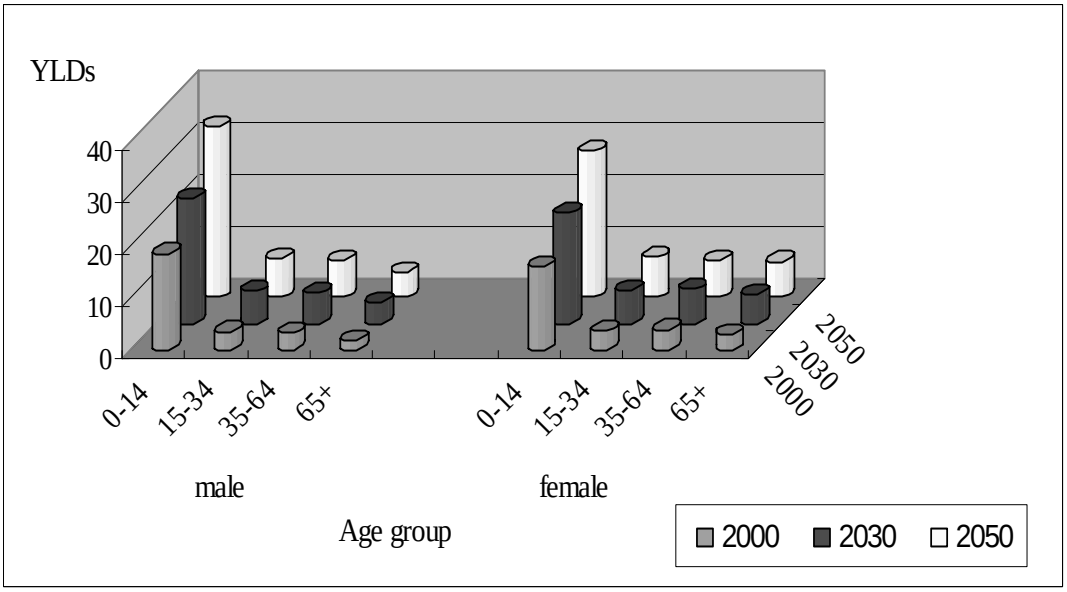
^ Projection B considers future change in both temperature and population growth

Figure 5- 9 Projected YLDs for salmonellosis in South Australia



*The figures show the estimated highest percentage increase in YLDs

Figure 5- 10 Projected YLDs for salmonellosis by age and sex in South Australia



5.4.1.2 Projected YLDs for salmonellosis in Brisbane, southern Queensland, Australia

Table 5- 10 shows the estimated YLDs for salmonellosis in Brisbane in 2000 and projected YLDs in 2030 and 2050 under different scenarios. In 2000, the estimated total YLDs for salmonellosis were 53 and the morbidity burden of salmonellosis was similar between males and females. More importantly, a consistent increasing trend in the YLDs for salmonellosis has been projected for 2030 and 2050, as shown in this table.

An increase in the total YLDs for salmonellosis is demonstrated in Figure 5- 11. It suggests that an increase in temperature may cause an increase in the total YLDs for salmonellosis of up to 57% by 2030 and 104% by 2050. When the future change in population structure is considered as well, the YLDs for salmonellosis in Brisbane may increase by up to 99% by 2030 and 143% by 2050, compared to 2000. Figure 5-12 shows that, as with South Australia, children are the most vulnerable population, accounting for the largest proportion of the burden of salmonellosis in Brisbane.

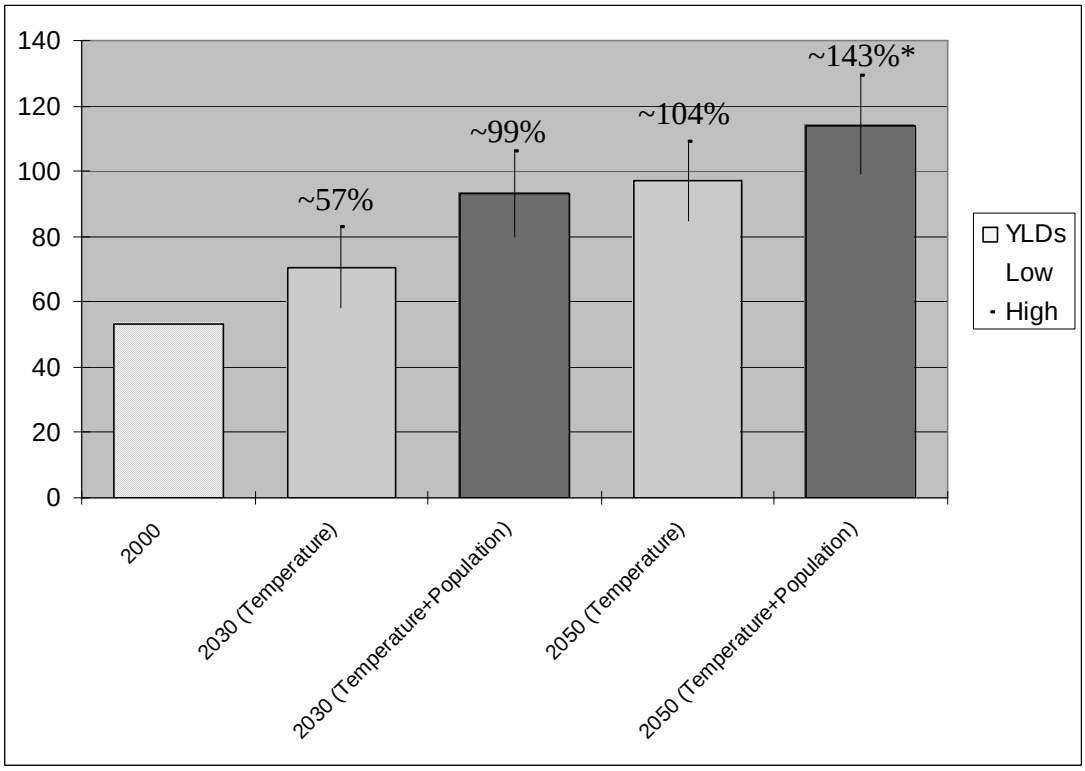
Table 5- 10 The YLDs for salmonellosis in Brisbane: 2000, 2030 and 2050

		Total	Male	Female
2000		53	28	25
2030	Projection A*	58~83	30~44	28~39
	Projection B^	80~106	42~56	38~50
2050	Projection A*	85~109	44~56	41~53
	Projection B^	99~129	51~68	48~61

* Projection A considers future change in temperature

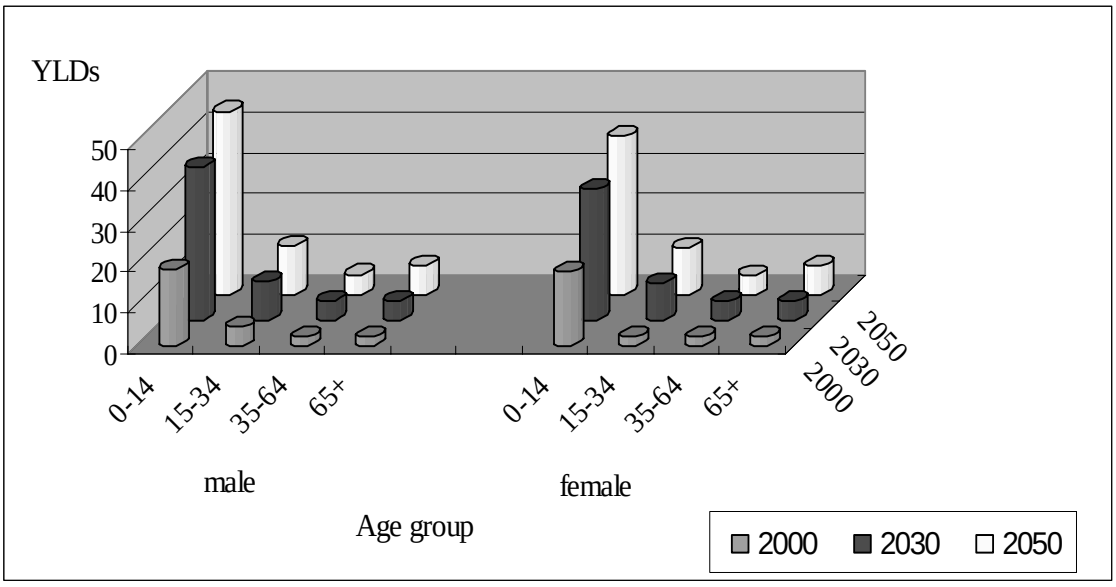
^ Projection B considers future change in both temperature and population growth

Figure 5- 11 Projected YLDs for salmonellosis in Brisbane



*The figures show the estimated highest percentage increase in YLDs

Figure 5- 12 Projected YLDs for salmonellosis by age and sex in Brisbane



5.4.2 Bacillary dysentery

5.4.2.1 Projected YLDs for bacillary dysentery in Jinan, northern China

Table 5- 11 illustrates the estimated YLDs for bacillary dysentery in 2000 and projected YLDs in 2020 and 2050 under different scenarios of climatic and population change in Jinan. It can be seen that the total YLDs for bacillary dysentery in 2000 in Jinan were more than 600. The YLDs for bacillary dysentery were slightly higher in males than in females. More importantly, a clear increasing trend in the YLDs has been projected using different scenarios.

The projected increasing trends in the total YLDs are demonstrated in Figure 5- 13. It can be seen that under the temperature scenarios alone the YLDs might increase by up to 80% by 2020 and 174% by 2050, compared to 2000. With consideration of both climate scenarios and any future change in population structure, the YLDs for bacillary dysentery in Jinan may double by 2020 and triple by 2050, compared to 2000, if other factors remain constant.

The age- and sex- specific YLDs for bacillary dysentery in Jinan are demonstrated in Figure 5- 14. They indicate that children and young adults are the most vulnerable populations, accounting for a larger proportion of the burden of bacillary dysentery than other age groups. The elderly however may have the highest rate of increase in the burden of bacillary dysentery in Jinan in the future due to the ageing of the population.

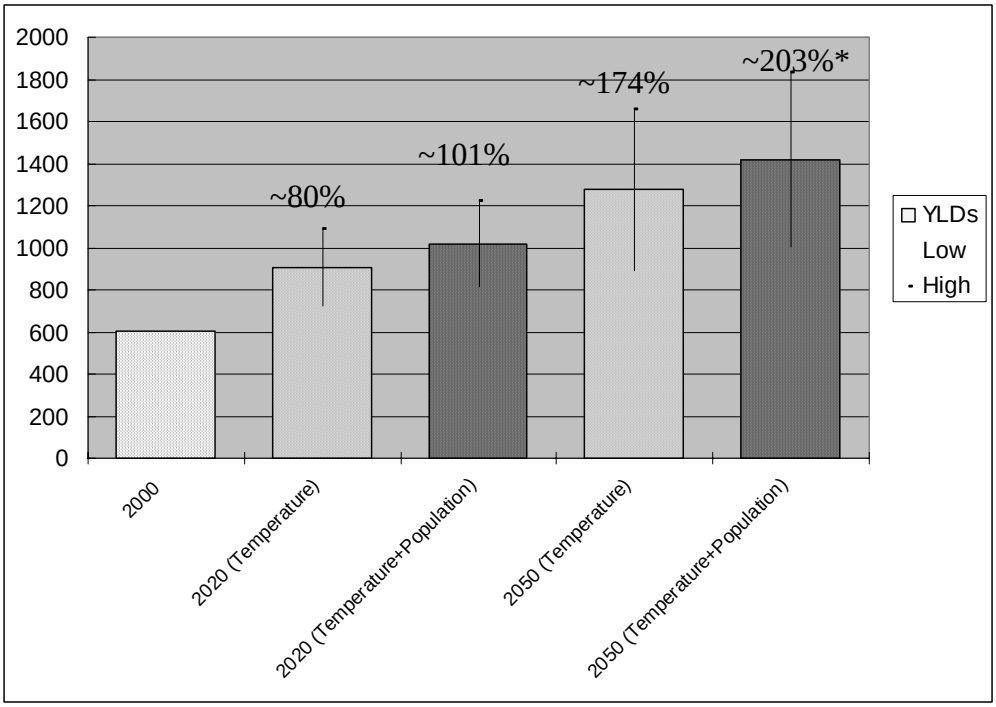
Table 5- 11 The YLDs for bacillary dysentery in Jinan: 2000, 2020 and 2050

		Total	Male	Female
2000		606	311	295
2020	Projection A*	726~1088	373~558	353~530
	Projection B^	812~1218	417~625	395~593
2050	Projection A*	891~1657	457~850	434~807
	Projection B^	1006~1833	516~941	490~892

* Projection A considers future change in temperature

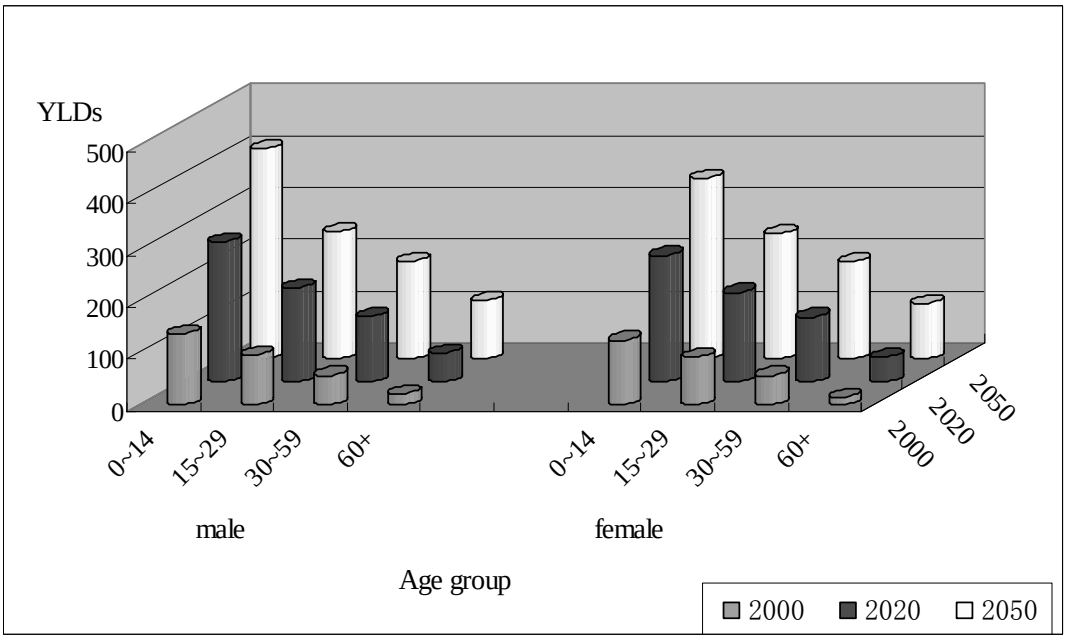
^ Projection B considers future change in both temperature and population growth

Figure 5- 13 Projected YLDs for bacillary dysentery in Jinan



* The figures show the estimated highest percentage increase in YLDs

Figure 5- 14 Projected YLDs for bacillary dysentery by age and sex in Jinan



5.4.2.2 Projected YLDs for bacillary dysentery in Baoan, southern China

The estimated YLDs for bacillary dysentery in Baoan in 2000 and the projected ranges of YLDs in 2030 and 2050 are presented in Table 5- 12. It shows that the total YLDs for bacillary dysentery were 100 in 2000, of which 55 were from males and 45 were from females. Significantly, an increase in the burden of bacillary dysentery in 2030 and 2050 has been projected by using different climatic and demographic scenarios.

Figure 5- 15 demonstrates the increase in total YLDs for bacillary dysentery in Baoan under various scenarios. It suggests that an increase in temperature may result in an up to 75% increase in the YLDs for bacillary dysentery by 2020 and a 147% increase by 2050, compared to 2000. With consideration of both climate and population change the YLDs for bacillary dysentery in Baoan may increase by up to 109% by 2020 and 226% by 2050, if other factors remain constant.

Figure 5- 16 demonstrates the estimated and projected age- and sex- specific YLDs for bacillary dysentery in Baoan. It indicates that children and young adults account for the largest proportion of the burden of bacillary dysentery among all age groups. However, an increase in the numbers of elderly people in Baoan may cause a greater increase in the burden of bacillary dysentery in this group compared with other age groups.

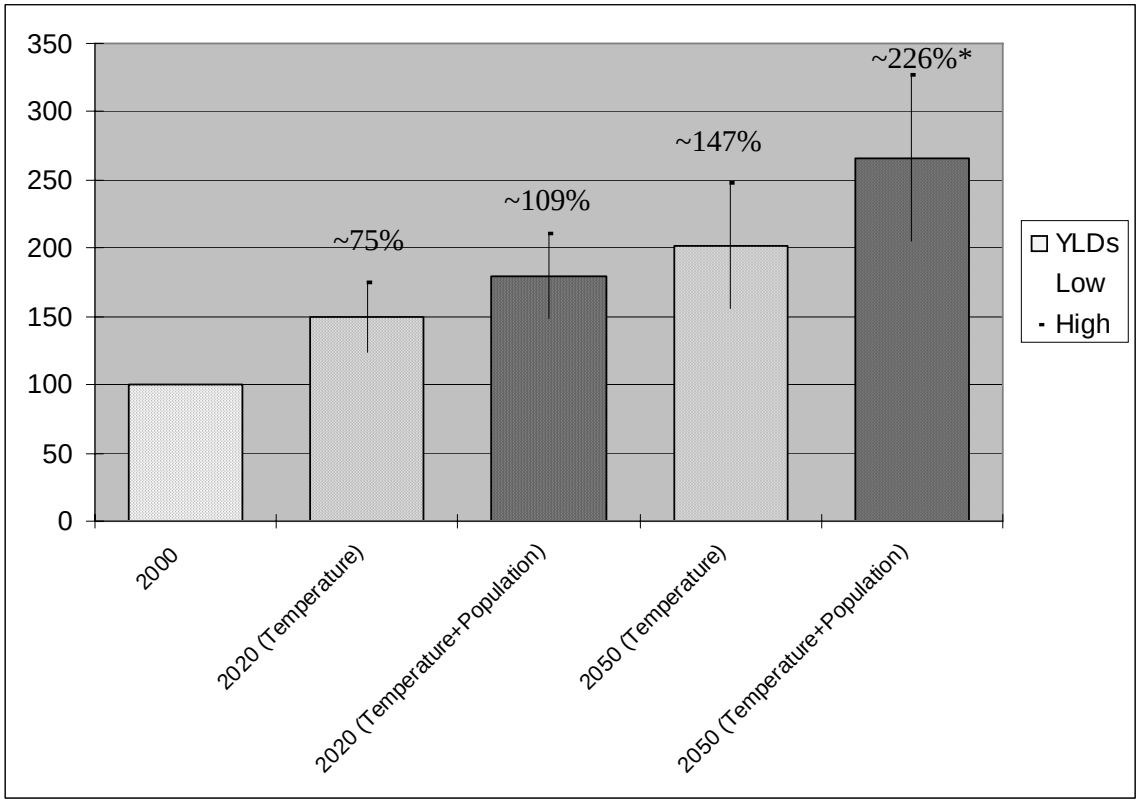
Table 5- 12 The YLDs for bacillary dysentery in Baoan: 2000, 2020 and 2050

		Total	Male	Female
2000		100	55	45
2020	Projection A*	124~175	68~96	56~79
	Projection B^	148~210	81~116	67~94
2050	Projection A*	156~248	86~136	70~112
	Projection B^	205~326	113~180	92~146

* Projection A considers future change in temperature

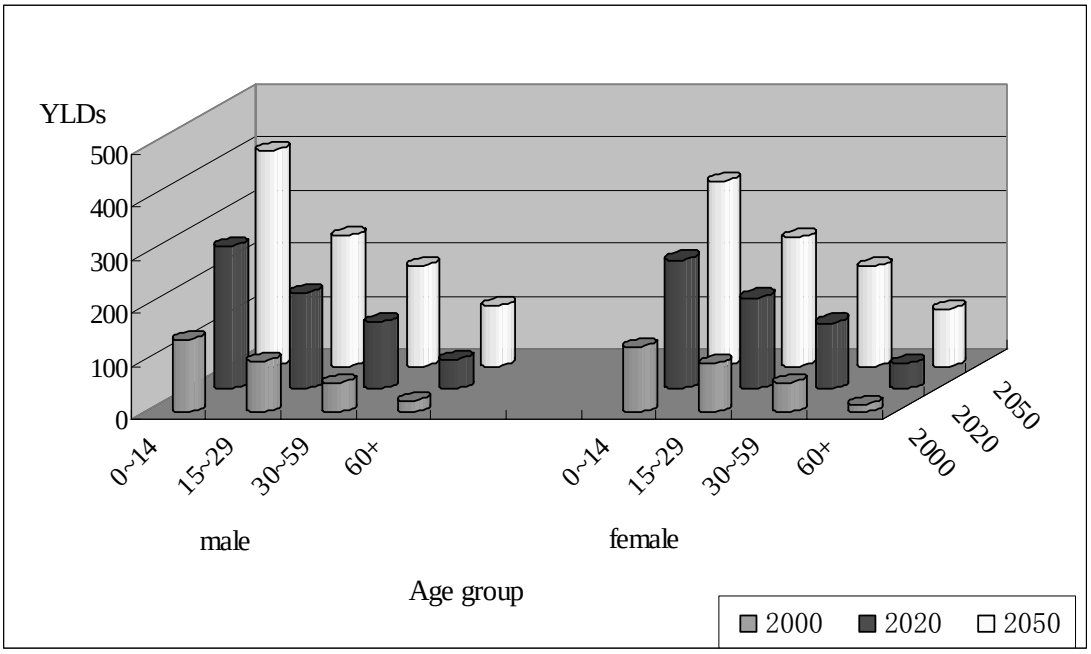
^ Projection B considers future change in both temperature and population growth

Figure 5- 15 Projected YLDs for bacillary dysentery in Baoan



*The figures show the estimated highest percentage increase in YLDs

Figure 5- 16 Projected YLDs for bacillary dysentery by age and sex in Baoan



5.4.3 Discussion

5.4.3.1 Future burden of salmonellosis in the study regions in Australia

This is the first study to estimate the future burden of salmonellosis associated with climate change in temperate and subtropical regions of Australia. This study suggests that an increasing trend in the burden of salmonellosis in Australia may occur if there are no effective measures taken into account. By 2050, the morbidity burden of salmonellosis may nearly double in the temperate region and may increase by almost 1.5 times in the subtropical region in Australia, if other factors remain constant. Given the very low mortality from salmonellosis in Australia, the projected morbidity burden could be considered to approximate the whole burden of the disease.

The burden of enteric infection in Australia is considerable. According to the latest report from the Australian government, the total national cost of food-borne illness is estimated at 1.25 billion Australia dollars each year. In Australia, it is reported that food-borne illness leads to 1.2 million visits to medical practitioners, over 300,000 prescriptions for antibiotics, and 2.1 million days of work lost each year [195]. In addition, continued challenges in *Salmonella* control have been illustrated [169]. Considerable under-reporting of enteric infection may result in an underestimation of the burden of salmonellosis. Other enteric infections in Australia should be analyzed to generate a complete picture of the future burden associated with climate change, such as *Campylobacter* infection.

The increasing trend in the morbidity burden from salmonellosis may be similar in temperate and subtropical regions in Australia. Although most studies on the climate-health relationship address the potential situation in tropical or subtropical areas, this study indicates that temperate regions, with relatively mild climate conditions, may suffer the same magnitude of health burden due to future climate change. This is of significance for national health policies for enteric infection control.

Children will be the subpopulation most affected by salmonellosis in Australia in the future. Although children living in developed countries enjoy better health and safer living conditions than those living in developing countries, they are not exempt from both the effects of unsafe and unhealthy environments and from global warming. In

Queensland, Australia, almost half (47%) of the notifications of salmonellosis are related to children under 5 years [196]. Despite the decline in diarrhoeal mortality, diarrhoea remains one of the principal causes of morbidity and mortality in children [124]. The burden of disease attributable to selected environmental factors and injury among children and young people has been investigated in Europe [197]. However, global warming was not included as an environmental risk factor in that analysis. Population growth combined with rising temperature may have an enhanced impact on the future burden of salmonellosis. The future burden of salmonellosis appears higher under scenarios of both temperature increase and population growth than under temperature scenarios only.

5.4.3.2 Future burden of bacillary dysentery in the study regions in China

This is the first study to estimate the future burden of bacillary dysentery related to climate change in temperate and subtropical regions in China. The results from this study indicate that there may be a considerable increase in the morbidity burden of bacillary dysentery in both temperate and subtropical regions in China. Compared to 2000, the morbidity burden of bacillary dysentery may double by 2020 and triple by 2050 in the study areas in China, if other factors remain constant. Therefore, this study has significant policy implications for adaptation and mitigation of future risks of global warming.

As in other developing countries, in China enteric infection is a concerned public health issue. It is estimated that the average annual episodes of diarrhoeal diseases in China is 840 million, of which 300 million occur among children under five years old. The estimated average annual incidence of food-borne disease is 0.7/person and 1.9/person for children under five [198]. The burden of such diseases may be much higher than the estimate in this study, if under-reporting was corrected for all relevant enteric infections.

The total YLDs for bacillary dysentery estimated in the temperate city, Jinan, are higher than that in the subtropical city, Baoan. Baoan is a younger city with less population than Jinan. This may reflect different population structures and a different socio-economic status between the two cities. Although it is projected that the subtropical region may have a higher rate of increase in temperature than the

temperate region, the increasing trend in the projected burden of bacillary dysentery in the temperate region is similar to that in the subtropical region.

This assessment provides evidence of a significant impact of climate change on diarrhoeal diseases among children in China. Although there is evidence of an association between climate variability and diarrhoeal diseases, the magnitude and geographical distribution of the disease burden among children related to climate change has not been assessed. Concern about the effects of environmental risks on children's health needs to be expressed at an international level [199].

5.4.3.3 Climate change and burden of selected enteric infection in Australia and China – overview and implications

The increasing trend in the morbidity burden from enteric infection has been projected for the first time in different climate regions in Australia and China. This study indicates that an increase in the burden of enteric infection may occur in the future in all study regions of Australia and China due to rising temperatures and future demographic change. If all other enteric infections had been included in this analysis, the climate-related burden of disease could be much higher, given the large burden of enteric infections in both countries.

In both Australia and China, a large proportion of health burden due to enteric infections is from children. Future population growth may have an adverse impact on the burden of enteric infection, with the effect varying for different age or sex groups. The health burden of climate-related enteric infection in the elderly may increase relative to other age groups in the next few decades. Health policies, with a focus on vulnerable subpopulations, such as the very young and the elderly, should be developed by governments at all levels.

The morbidity burden of enteric infection is much higher in China than in Australia. This may be due to the large population and poorer living conditions and environmental hygiene in China. By 2050, the YLDs of bacillary dysentery in China may double, while the YLDs of salmonellosis in Australia may increase by less than 1.5 times, compared with 2000. This indicates that developing countries may face

more serious problems caused by future climatic and demographic change than developed countries.

Limitations arise from the complexity of climate models and the reliability of disease surveillance data for enteric infection, on which the climate - health relationship is based. Climate change may combine with other environmental and socio-economic factors which play a role in the spread of enteric infection. Poverty, high population density, and poor environmental hygiene may have devastating consequences when combined with exposure to climate change. Economic development has not been included in this analysis. The vulnerability of local communities should be considered in developing policy based on robust climate science [200]. More accurate estimation and projection would be available once relevant reliable data are available.

Uncertainties are inherent in the methods and scenarios, similar to other burden of disease studies. Uncertainties could be reduced by (i) applying projections under several climate scenarios; (ii) quantifying the climate and disease relationship in a wider range of climatic and socioeconomic environments; and (iii) developing more detailed longitudinal studies of the interaction between climatic and non-climatic influences on health [188].

The challenges addressed in this research field include the widespread distribution of food, and the difficulty of tracing the origin of the infection due to the complexity of the food supply chains and antimicrobial resistance. This demonstrates the importance of robust control programs for such diseases. Despite these limitations and uncertainties, this study has presented evidence for the potential of a consistent increasing trend in the burden of enteric infection caused by future climate and demographic change, which has significant policy implications for governments and local communities. It is not only for us but also for future generations that public health strategies that incorporate preventive measures (see more details below) and responses to extra health burden associated with climate change should be developed at this stage.

Adaptations to minimize the health burden of enteric infections should include improved food processing and storage, improved access to safe water, improved sanitation and sewage disposal facilities, and increased provision of, and access to, high quality health care. It is also necessary to establish integrated trade guidelines or standards for food processing and storage to reduce the risks of food-borne disease transmission, particularly in hot seasons. At the present time, one of the most important long-term climate change adaptations is to reduce the burden of enteric infection by improved public health and environmental management [102]. Therefore, a strongly integrated public health approach, which includes microbiologists, medical clinicians, epidemiologists, veterinarians, and experts from food science disciplines, is necessary to prevent and control the risk of further increases in the burden of such diseases.

5.5 Conclusions regarding future burden of selected infectious diseases associated with climate change in study regions

An increasing trend in the health burden of vector-borne diseases and enteric infections related to climate change has been projected in all the study areas in Australia and China, if other factors remain constant. Indeed, the extra burden of disease caused by future climate change would be much higher than the estimates given in this study if all other climate-related infectious diseases are included. Although the results of the study may appear to be too far in the future for immediate action, they will be useful for consideration in the development of health policies for the next decades.

Infectious disease is not a major public health problem in both Australia and China. As an environmental risk factor, climate change makes less of a contribution to population health than other risk factors. For example, tobacco smoking is the risk factor responsible for the greatest burden of disease including chronic diseases in Australia. It was responsible for the loss of about 227,000 DALYs in 1996 [113]. Therefore, the aim of this estimate is not to set priorities among risk factors but to call for action to moderate any possible increasing burden related to climate change. However, unlike other risk factors that can be controlled or prevented, exposure to

climate change is inevitable, accelerated, global, long-term (up to several centuries) and involves complex interactions between climatic, environmental, economic, political, social and technological processes [188, 201, 202]. Therefore, necessary adaptation and mitigation strategies should be taken now.

China and other developing countries will face a more serious impact of future climate change than Australia, given the relatively poor public health system, low standard of water and food safety, low economic status, lower education level and high population density. Developing countries are more vulnerable to future climate change than developed countries, unless there is an effective public health strategy being developed at this stage to adapt to or mitigate future climate change. Collaborations and cooperation between developed countries and the least developed countries could be one of the solutions to fight against climate change.

Population growth and ageing will have an adverse impact on the health burden of the selected diseases in Australia and China. Although the interaction between social and environmental factors cannot be identified by this study, it is clearly indicated that the combined impact of global warming and demographic change on the burden of disease would be much higher than the impact of global warming alone. Young children and the elderly would be the most vulnerable subpopulations to rising temperature and demographic change. Although the population scenarios used in this estimate have their limitations, and the demographic information used should be used with care [203], future population change must be considered when estimating the burden of disease. This will assist in priority setting in international health organizations. In addition, there is a need to promote health as an essential asset of vulnerable populations.

The scarcity of health environmental data and the significant number of knowledge gaps concerning the relationship between climate and population health has resulted in many uncertainties in this study. These gaps need to be addressed in order to facilitate more precise national and international assessments on public health vulnerability to climate change. Current scientific methods cannot identify the threshold health effects of climate change, so that the burden of disease attributable to climate change is not “tolerable” [204]. The significant uncertainty about the future

effects of climate change on human population health is a reason to reduce greenhouse gas emissions, and not a reason for inaction.

It should be acknowledged that the impact of socio-economic status, including the impact from the development of the local economy and medical technology, on the transmission of infectious diseases has not been included in the projection due to the unavailability of local data. Socio-economic status plays an important role in the spread of infectious diseases. A recent European study, which considered socio-economic development, suggests that climate change would retard the decrease in health burden due to diarrhoeal diseases [205]. The interaction between climate change and socio-economic status and other environmental factors, eg air pollution, presents a considerable challenge for research into climate-related burden of disease.

Further studies to investigate the interaction among climatic, social and environmental factors on the burden of vector-borne diseases are necessary. Environmental hygiene, technology development, health service and population ageing would together affect the transmission of vector-borne diseases. Given the accelerating development of the economy, and the sharp increase in energy consumption, it is time to call for action to reduce greenhouse gas emissions by shifting from a reactive to a proactive attitude [206], to be aware of the anticipated increasing risk to population health associated with climate change. Social policies, with a wider application of sustainable development concepts, to shift the focus from economic growth to human development, are particularly needed [207].

Despite the limitations in the methodology, the projections reported in this study provide useful insights into the future burden of diseases related to climate change. These can be used by public health practitioners and governments to facilitate relevant policy making. There is a large global burden of disease, and many of the most important determinants, such as malnutrition, diarrhoeal disease due to lack of sanitation and safe water, are readily avoidable [204]. However, a considerable burden due to climate variability is inevitable if no effective public health interventions are considered at this stage. The projections can also provide useful information about possible patterns of specific infectious diseases over the next few decades. This study is of significance because currently health policy debates focus more on tackling

current problems than on avoiding future risks, unless these risks can be shown to be very large or very likely.

Improvements in early-warning systems could be achieved by incorporating climatic variables to improve resource allocation and to assist in the reduction of morbidity [159]. Other public health implications of the predicted increasing health burden associated with future climate change include education for the public, communities and industries, multi-sectoral cooperation, establishment of integrated trade standards to allow for effective responses to climate change, and the urgent need for public health strategies to prevent and adapt to future climate change.

CHAPTER VI

CONCLUSIONS

6.1 Key findings of this study

This thesis quantifies the relationship between climate variation and vector-borne diseases/ enteric infections in various climatic regions in Australia and China, and projects the future burden of target diseases related to climate (and demographic) change in these study areas. The main findings are as follows:

- Both maximum and minimum temperatures are important in the transmission of vector-borne diseases in various climatic regions in both Australia and China. River flow or high tides may also play an important role in the transmission of such diseases in different geographic regions.

  Temperature, both maximum and minimum, is the only climatic variable of significance to be included in all the regression models in all study regions. The consistent results of the positive association between temperature and RRV infection and malaria, demonstrate that either maximum or minimum temperature could be used as an indicator to predict the number of cases in various climatic regions in Australia and China.

  In Australia, a 1°C increase in either maximum or minimum temperature may cause 4%~23% extra cases of RRV infection in the temperate region, 5~8% in the subtropical region, and 6%~15% in the tropical region. This suggests that increasing temperature may result in more cases of vector-borne diseases in temperate regions than in tropical or subtropical regions in Australia.

  In China, a 1°C increase in either maximum or minimum temperature may lead to 4%~15% extra malaria cases in the temperate region, and 12%-18% in the subtropical region. This indicates that increasing temperature may lead to a greater increase in cases of malaria in the subtropical region than in the temperate region in China.

  In addition, flow of the Murray River and high tides may play an important role in the transmission of mosquito-borne disease in Australia. The results suggest

that both the flow of the Murray River in South Australia and high tides in Queensland have a significant impact on the transmission of RRV infection in Australia through their impact on different species of mosquitoes.

- Both maximum and minimum temperatures play an important role in the transmission of enteric infections in various climatic regions in both Australia and China, with a threshold temperature detected in the temperate regions but not in subtropical and tropical regions.

  Temperatures, both maximum and minimum, are the only climatic factors significantly included in the regression models, when examining the relationship between meteorological variables and enteric infections. In Australia, a 1°C increase in either maximum or minimum temperature may cause 6%~19% extra salmonellosis cases in the temperate region, 5%~10% in the subtropical region, and 4%~15% in the tropical region. In China, a 1°C increase in either maximum or minimum temperature may cause 7%~15% extra bacillary dysentery cases in the temperate region and 10%~19% in the subtropical region.

  Threshold temperatures have been detected in the temperate regions. In Australia, thresholds of 19.5°C for maximum temperature and 12.1°C for minimum temperature have been detected for the effects of temperature on salmonellosis. In China, thresholds of 17°C for maximum and 8°C for minimum temperature have been detected for the effects of temperature on bacillary dysentery. No threshold temperature has been detected in the subtropical and tropical regions in either country, which may be due to the narrow range of local temperatures.

- The effects of rainfall and relative humidity on selected infectious diseases vary in different study areas in Australia and China.

  Rainfall had a positive correlation with RRV infections in all the study areas in Australia with a lag time of approximately two months. However, significant associations between rainfall and malaria were not detected in the study areas in China. In addition, rainfall was significantly included in the time-series

regression models for salmonellosis in the tropical and subtropical areas – Townsville and Brisbane in Queensland, but not included in the temperate area – Adelaide, South Australia. Rainfall was not significantly included in the regression models in either the temperate or the subtropical areas in China.

Relative humidity was positively associated with RRV infection in Brisbane and Townsville in northern Australia, but this association was not detected in Adelaide in southern Australia. No significant association between humidity and malaria was detected in either study region in China. There was no significant association detected between humidity and salmonellosis or bacillary dysentery in either country.

- The burden of temperature-related infectious diseases may greatly increase in the future if there is no effective preventive intervention.

  With consideration of both future climatic and demographic change, by 2050, the Years of Life lost due to Disability (YLDs) for selected vector-borne diseases and enteric infections might increase by more than 100% in the study regions in Australia and China. It should be acknowledged that the climate-related burden of infectious diseases would be significantly greater than the estimate in this study if all vector-borne diseases and enteric infections were included.

6.2 Strengths of the study

Although limitations are inherent in an ecological study including this one, the strengths of the study are presented below.

- Appropriate time-series regression models, including adjusted Poisson regression and the SARIMA models, were applied to quantify the association between climate variation and infectious diseases. The nature of the time series data, including multicollinearity, autocorrelation, lag effects, seasonal variation and long-term trend, has been controlled appropriately in the regression analyses.

- This study examined various meteorological variables, including maximum and minimum temperatures, rainfall, relative humidity and air pressure, as well as the flow of the Murray River in South Australia and high tides in Queensland, as potential risk factors for infectious diseases. Mean temperature was not used because averaging maximum and minimum temperatures may not reflect real variations in temperature.

- The estimate of the morbidity burden of selected infectious diseases associated with climate change at a local level provides more relevant information for governments and all levels and benefit further studies in this area. Such burden of disease studies can be conducted in other developing countries.

- Weekly-based analyses, depending on availability and nature of time series data, could strengthen the power of the results. Monthly data may conceal variation in weather and disease occurrence within the period, while daily data are often not applicable because there may be no cases (many zeros) for most days over a study period. Moreover, with consideration of the transmission of target infectious diseases, which may involve pathogen growth in vectors, spread via food or water and contact opportunities, weekly data are the most suitable to be used to examine the association between climate variation and infectious diseases.

- The availability of high quality surveillance data in Australia, which includes the onset date of diseases and the place of acquisition of infections, makes the assessment more accurate. There are always lag times between the onset date and notified date of diseases due to delays in reporting. A disease notification system including the onset date of diseases increases the accuracy of results in quantifying the effect of climate variation on infectious diseases. Similarly, residential address is often not the place of acquisition of infection. The investigation and recording of the place of acquisition is of great benefit for this study because of the possible different relationship between climate variation and infectious diseases in various climatic regions.

6.3 Significance of this study

This thesis has made an important contribution to current knowledge by improving the understanding of the relationship between climate variation and infectious disease. This study has detected geographical differences in the association between climate variation and selected vector-borne diseases and enteric infections in Australia and China. Moreover, this is the first study, at a sub-national level, to project the future burden of selected infectious diseases related to climate change, in terms of the Years Lost due to Disability (YLDs). The effect of the Murray River flow on vector-borne disease in South Australia has been investigated for the first time.

The finding of a quantitative relationship between temperature and salmonellosis and bacillary dysentery in both Australia and China confirms the impact of temperature on enteric infections. This is also the first report of a threshold for the effect of temperature on enteric infections in temperate regions in Australia and China.

This study shows the importance of conducting research on the effect of climate change on population health in China. It reports one of the few studies conducted in China to examine the effects of climate variation on population health. This thesis provides scientific evidence that climate variation may be one of the reasons for the resurgence of malaria in China and it is the first study to quantify the relationship between climate variation and bacillary dysentery, the most common enteric infection in China.

Increasing trends in the morbidity burden of vector-borne diseases and enteric infections have been projected for the first time, using climate and population change scenarios in different climatic regions in Australia and China. Despite the assumption and uncertainties in the projective study, this thesis has found that extra burden would be caused by future climate change in both countries should other factors remain constant. This finding should alert current policy makers to the need to develop relevant policies to mitigate the future morbidity burden related to climate change.

Countries other than Australia and China can take advantages of the findings of this study in the battle to prevent future risks of climate change, particularly for undeveloped countries with large populations and a variety of climatic regions. In such countries, current thinking regarding the effect of climate change and resulting adaptation and mitigation are not sufficiently advanced to reduce the exposure to future climate change and the loss of health lives. All governments should be made aware of the possible impact of climate change on their people, and generate effective public health measures at an early stage.

This study responds to the latest agenda [208] for research on environmental change and population health, which addresses the focus on empirical studies of current health effects and scenario analyses of future health effects. In addition, this thesis has provided valuable information for public health practitioners, local communities and governments to prevent and reduce future risks of climate change on population health.

6.4 Challenges faced in this study

- Data availability and reliability

  It should be acknowledged that reliable data are essential for ecological studies such as this. In addition to health surveillance data, other datasets, including density of vector populations, socio-economic status and host behaviors, are also important in estimating the effects of climate variability on population health. Moreover, systematic long-term rather than cross-sectional epidemiological studies are needed for an accurate prediction of disease risks.

  In addition, under-reporting is inevitable for infectious diseases, particularly enteric infections. In most countries, there are no records of the original location of acquisition of infection, no records of onset dates, and no detailed individual information. These shortages of datasets weaken the results.

Collecting data of reliable quality is a great challenge, especially in developing countries. For example, results based on surveillance data during the late 1960s and 1970s in China have to be interpreted with great caution. Data sharing is another issue in developing countries because not all surveillance data can be accessed by the public or researchers. One of the reasons for relatively few such studies in developing countries may be the lack of reliable data over a long-term period.

- Simplified causal relationship between climate variation and infectious diseases

  The transmission of infectious diseases is complex, with many factors such as socio-economic status, environmental hygiene, vaccines, drug-resistance, human behaviors and vectors playing a part. Meteorological variables may influence the transmission of infectious diseases via various pathways, including affecting vector populations, water and food safety, and host behaviors. It is not fully understood what role these factors may play in the causal relationship, and the nature of possible synergistic counteractive effects. It is assumed in this study that changes in the number of cases would occur with changes in meteorological variables only if other factors remain constant.

- Uncertainties and assumptions in methodology

  There are several levels of uncertainty inherent in the assessment of climate-related health risks. Statistical models vary to the extent to which they allow for non-climatic confounders, such as socio-economic development and public health interventions. The estimation of the exposure to climate change may not be accurate due to the lack of complete knowledge about how the climate system will respond to continuing change in the composition of gases in the atmosphere [209]. Assumptions have to be made for the projection of future burden related to climate change because it cannot be known in advance how technology, society, and human behavior will change over the coming decades.

- Interpretation of the results

  Given the above challenges in this research field, the interpretation of findings and results from such studies should be made with care. Based on an incomplete understanding of the relationship between climate and population health, the results can only be presented in terms of probabilities, or given confident intervals at a certain statistical level. More importantly, researchers should be cautious in generalizing the results, as there may not be similar climatic and socio-economic conditions in other locations.

6.5 Implications and recommendations

Climate variation and climate change is an emerging threat to global public health. Extra burdens may be brought to the current public health system. These burdens include additional cases of diseases, spatial change in diseases, re-emergence of infectious diseases and the introduction of new diseases. By addressing the challenges in this field of study, the recommendations and implications for a better adaptation and mitigation to future climate change are as follows.

6.5.1 Further research directions for climate change and infectious diseases

It is still a big challenge for researchers to fully understand the impact on population health of climate variation and future climate change, with many uncertainties in existing knowledge. The main task should be identifying key variables and thresholds of predictable impacts on climate-related diseases in order to provide rapid and effective public health responses. Integrated assessment should be performed in various climatic regions incorporating various factors to study the impact of climatic variables (and other factors) on different infectious diseases. In addition, in order to mitigate the extent of future climate change, innovative research on finding new clean energy sources and reducing green house gas emissions should receive great support from governments. Furthermore, assessment on adaptive strategies and preventive measurements has not been studied yet. Further studies examining the relationship between climate and infectious diseases could be conducted as follows:

- Other climate-related infectious diseases, such as Dengue Fever, Barmah Forest virus infection, Japanese encephalitis and *Campylobacter* infection, should be included in further studies to confirm the association between climate variation and infectious diseases. Furthermore, investigation of the association between climatic variables and serotypes of the infectious diseases, such as *Salmonella typhimurium* and *Salmonella enteritidis,* will clarify the relationship between climate variation and infectious diseases, given the different transmission pathways for various serotypes.

- More climatic regions should be included, especially in developing countries with large populations exposed to climate change, because the effects of climate on infectious diseases vary depending on different local climatic situations.

- The impact of climate change on a population subgroup should be studied. Given that the impact of climate variation on population health varies across different population subgroups, future studies should be conducted focusing on vulnerable subpopulations, e.g. children, elderly or indigenous populations.

- Projections of the mortality and morbidity burden of disease attributable to climate change would be of great value in current policy making. More projective studies should be conducted, based on scenarios of future climate, including changes in temperature, rainfall, humidity and sea level, as well as changes in demography and socio-economic status.

- Advanced statistical models which include additional influencing factors, such as vector populations and socio-economic status, would certainly enhance the power of the statistical analysis, thus rendering the results more reliable. Reports show that existing social inequalities in health status will be exacerbated by long-term climate change [210]. However, only a very limited number of studies have examined the relationship between social factors, climate change and health [211].

- Assessment of adaptation and mitigation measures to climate variation and climate change has yet to be included in studies. Cost-effectiveness research on public health interventions should be developed. Innovative research on finding new clean energy sources and reducing green house gas emissions should be fully supported.

6.5.2 Education programs

Education of the public, government officers, clinicians, researchers and industries can increase the awareness of the impact of climate change. Appropriate information on how to adapt to and mitigate the effects of climate change should be widely circulated. All education programs should be evidence-based rather than interest-centred.

Public health practitioners should take an active role in these education programs. It should be acknowledged that public health practitioners themselves must be trained about the link between climate variation and population health [212]. Health education programs aimed at public health practitioners should be undertaken to produce information about the adverse impacts of climate change, the potential extra health burden that climate change may cause in the future, and preventive measures that can be implemented to reduce any future risks of climate change.

The public should be aware of how to prevent and reduce health risks associated with climate change. For example, they should be notified about appropriate food storage temperatures and cooking food thoroughly to avoid enteric infection, particularly when the environmental temperature is high. In terms of preventing vector-borne diseases, information on self protection measures, such as timely preventive medicines before travelling and the wearing of long-sleeve clothes, should be widely distributed. For instance, many people from Adelaide go swimming and fishing in the Murray River region in summer, and relevant health education programs via the media and public seminars/booklets should be conducted before the epidemic season. Additionally, education about some simple ways to reduce green house gas emissions in household living could be effective. In particular, education of school children is a strategy that focuses on vulnerable subgroups and addresses future generations.

Government officers, including those from local councils, should be informed and regularly updated about the latest research findings on climate change and its impacts. In addition, it is the government's responsibility to guarantee that accurate and relevant information is accessible to the public. Funding should be allocated to varying educational programs, such as official information websites, newspapers, movies and free publications.

Clinicians and other health professionals should also be equipped with up-to-date knowledge about the impacts of climate variation and climate change. In addition, clinicians play a role in educating their patients and the community because of the close relationship between them (see 6.5.5).

Industries play an important role in preventing and reducing the risk of climate change. Employers of food handlers or of workers in the livestock industries should train staff to understand the significance of keeping a high standard of hygiene in food preparation, animal husbandry, transportation, storage and sale, especially at a high temperature. Contamination at every step of food processing may be caused by environmental factors, such as temperature and humidity. Industries should be educated about how to reduce future green house gas emissions by selecting green facilities and manufacturing techniques. The importance of keeping a high standard of environmental hygiene, awareness of the risk of climate variation on food safety and the potential risks on the transmission of enteric infection should be widely distributed.

Education programs should be conducted at different levels, including governments, research institutions, communities and individuals, in order to achieve the most efficient distribution of relevant knowledge.

6.5.3 Public health practice

Public health practitioners should monitor and provide rapid responses accordingly to prevent and reduce predicted risks associated with climate change. Systematic surveillance and forecasting are of importance to reduce climate-related health burdens. Improvement of health surveillance systems will also enhance the quality of

such studies. Enhanced surveillance data have multiple benefits, as the data are crucial for the statistical analysis and evaluation. Disease surveillance data can be improved by active surveillance which adds information on the source of infections, onset dates and detailed individual information.

Besides disease surveillance, comprehensive surveillance systems should also improve their analysis and distribution functions and guarantee early accurate information sharing with relevant authorities, including government, community and clinicians. Additionally, setting up a universal disease surveillance system at a national level would be a great benefit for research and public health practice, based on which, results from different study areas could be compared.

It is recommended that the surveillance or investigation of the density of local vector populations, socio-economic status, and human activities is conducted regularly, systematically and consistently by local health authorities and government. Relevant research could be undertaken involving these additional factors that influence the transmission of infectious diseases.

Integrating local meteorological variables and river flow/high tides into disease surveillance systems could improve the accuracy of early warning systems for infectious diseases. The findings of this study, including threshold temperatures, lag times and different quantitative relationships between climate variation and selected infectious diseases, imply that public health measures should consider local climatic conditions, which may lead to effective warning systems and faster response to disease epidemics.

Advocacy for adapting to and mitigating climate change should be a longstanding public health activity. Advocate activities by public health practitioners in development of policies or strategies for reducing climate change and its impact may include but not limited to lobbying decision makers for initial preventive measures in reducing climate change impact, addressing adverse impact of climate change on population health to a wide audience and encouraging cooperation actions from all relevant sectors. Rather than just providing information, persuasion should be another key task for public health practitioners. Once committed to the objective of

tackling climate change, public health practitioners should build up maximum support by strategic planning of the ways they will argue the case, including special attention to counteracting any strength of their opponents' arguments in the on-going debate on climate change. Such counteraction should be supported by high quality evidence-based research.

6.5.4 Current public health systems

Potential extra health burden due to future climate change may have a great impact on currently overloaded public health systems in both developed and developing countries. Current public health strategies lack consideration of the changing environment with a potential adverse effect on public health. Public health mechanisms have not, traditionally, been closely linked with other climate-related agencies, such as meteorological institutions, to allow early warning of potential changes in climate-related disease incidence. This should be remedied as early as possible.

The concept of a "holistic approach" in public health should be widely adopted. Protecting populations against climate change will involve responses of different kinds, acting at different levels. They may range from biological interventions to behaviour change, modification of physical environments, and altering social and economic settings.

6.5.5 Community participation

Local communities can play an important role in tackling climate change. The battle against for climate change cannot be successful without community understanding and input. Involvement by the community is essential in developing strategies because it enables: the views and expectation of the community to be presented and understood; improving communications links to, from and within the community; decision making following review of all available information; projects that are based on local needs are more acceptable to the local community. Community involvement helps to deliver programmes which more accurately target local needs. Therefore, the local community should be involved in the partnerships of climate change at an early stage.

Communities can also facilitate the implementation of relevant policies and the adaptation to climate change in the following ways: (i) increasing the awareness of community residents and local schools of the risks of climate change and the preventive measures to reduce the impact of climate variation/climate change on infectious diseases; (ii) ensuring circulation of appropriate information to respond to the potential risks of climate variation/climate change on infectious diseases; (iii) building greenhouse-friendly communities by good community design, local traffic control, and appropriate surveillance related to climate variation/climate change; (iv) supporting people living in rural and remote regions to better adapt to future climate change.

Local industries and institutions have responsibilities to reduce the risks arising from climate change. They will help to manage climate-related risks by incorporating long-term decisions in the reduction of greenhouse gas emissions and developing performance standards for working processes, particularly for water and food industries, and training/educating employees on issues related to climate change.

6.5.6 Inter-sectoral action and international collaboration

To adapt to and mitigate the effect of climate change is not something governments or any one sector can do alone. Effective prevention and intervention strategies will be possible only if the efforts of relevant sections, including governments, communities, industries, research institutes, clinical professionals and individuals, are coordinated and integrated.

In 1989Australia started a collaboration network among many organizations that contribute to protection against communicable diseases, the Communicable Disease Network Australia (CDNA). The network is responsible for national communicable diseases surveillance strategies. “The success of the Network is a tribute to the foresight and vision of the many government and non-government groups and individuals involved.” [213]

The responsibility for a better adaptation to problems arising from future climate change should be taken by all sections of society. A shared health, environment, and development agenda could address the element of the burden of disease that is

environment-related. Inter-sectoral collaboration which includes governments, local communities, food industries, and professional institutions such as universities, is the most practical and effective way to a fast, effective response to future climate change.

Recognising the compelling need for national and international cooperation to reduce the severity of climate change and its health effects is required. Strategies of an international dimension should also be translated into regional and local actions. To face this global exposure to climate change, evidence-based strategic plans should be considered by policy makers and implemented at an international level. Developed countries should provide necessary help to poor countries. A good example is that Australia will contribute $7.5 million to the Least-Developed Countries Fund of the United Nations Framework Convention on Climate Change to limit the impact of climate change on some of the poorest and most vulnerable countries. In these areas, the most vulnerable to climate change have the least capacity to cope with its impacts. This Partnerships initiative will also support collaborative programs coordinated by other international organizations, such as the World Bank, the Asian Development Bank [214].

Although existing international organizations, such as the Intergovernmental Panel on Climate Change (IPCC) and the United Nations Framework Convention on Climate Change (UNFCCC) have taken the lead in conducting assessments of the impact of climate change [215], there is no consensus about appropriate strategies for dealing with the consequences of climate change. An international public health policy to adapt to climate change is crucial to global health security.

6.5.7 Implications for policy and economy

The results of this study indicate local consequences of climate variation and future climate change. Its implication for policy makers and governments at all levels is significant. Scientific uncertainties are no excuse for inaction, especially recognizing that the impacts of climate change may be increasing in the future. Governments should take effective public health measures at an early stage to reduce any possible increase in the infectious disease burden related to climate change. It is time to call for action to introduce public health policies which are based on scientific evidence and knowledge of local conditions. Sustainable development policies with

consideration of reducing green house gases and environmental degradations need immediate action for future generations.

Although the Australian government has not ratified the Kyoto protocol, national concerns about global climate change have resulted in initial measures to adapt to or mitigate climate change. The Australian government announced that total funding for international climate change initiatives in 2007-08 is expected to reach approximately $100 million [214]. However, debate on climate change is still heated, reflecting no consensus among politicians.

Given China's global impact on climate change, this country is obviously the most important partner of the international working party. "Changing the model of growth" was emphasized strongly at the last session of the National People's Congress in March. It was also the theme of the China High Level Development Forum 2007 [216]. Excessive energy and resource consumption, environment pollution/degradation and social disparity and vulnerability have been recognized as the main reasons for the policy change. The question is how China can shift its growth pattern to achieve sustainable development, in which mitigating climate change is embedded.

It is noted that the most effective way to retard climate change is to reduce the level of greenhouse gas emissions [140]. It is also believed that timely and strong policy action to further reduce greenhouse gas emissions would diminish the extent and severity of estimated future health effects [64]. Environmental labeling for consumers is highly recommended. It is also necessary to call for the rapid implementation of policies that provide tangible economic incentives for choosing environmentally sustainable products and services.

Accordingly, greenhouse gas strategic plans should be developed by governments, industries and communities. Actions for reducing greenhouse gas emissions, for innovative technologies, and for climate change, should be articulated and given higher priorities. Accordingly, more resources should be allocated to research on the relationship between climate and population health, the impact of climate change on

ecology, and the development of new safe, clean energy to reduce greenhouse gas emissions.

The knowledge gained through this study will enable researchers and health policy makers at all levels of government to have a better understanding of the potential impact of climate change on population health. Taking the findings of this thesis into consideration, it is clear that there is a long way to go to achieve a full understanding of the impact of climate variation and change on population health. The latest report from the Intergovernmental Panel on Climate Change (IPCC) marks a turning point in climate change research. The debate is no longer about whether we believe climate is changing, but about what we should do about it [217]. It is urgent for local, national and international levels of government to develop and implement sustainable policies to prevent or reduce the climate-related burden of disease, not only for current populations but also for future generations.

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APPENDICEX

A. Equations for time-series adjusted Poisson regression models

1. Poisson distribution [140]

The Poisson distribution is a discrete probability distribution. It focuses on certain random variables N that count, among other things, a number of discrete occurrences that take place during a time-interval of given length. The probability that there are exactly k occurrences (k being a non-negative integer, k = 0, 1, 2, ...) is

$$f(k;\lambda) = \frac{e^{-\lambda}\lambda^k}{k!},$$

where

- e is the base of the natural logarithm (e = 2.71828...)
- k! is the factorial of k
- λ is a positive real number, equal to the expected number of occurrences that occur during the given interval.

As a function of k, this is the probability mass function. The Poisson distribution can be derived as a limiting case of the binomial distribution.

2. Standard multiple Poisson regression [140, 217]

Poisson regression is similar to regular multiple regression except that the dependent (Y) variable is a count that follows the Poisson distribution. This procedure allows for both numeric and categorical independent variables. There is no assumption that the dependents and independents are related linearly or homoscedastically.
In general, the multiple Poisson regression model can be written as the following

$\log_e(Y) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots$

and so $Y = (e^{\beta 0})\,(e^{\beta 1 X1})\,(e^{\beta 2 X2})\ldots$

In other words, the typical Poisson regression model expresses the log outcome rate as a linear function of a set of predictors.

3. Time-series adjusted multiple Poisson regression [140, 143]

In order to control the potential seasonality, long-term trend, autocorrelation of dependent and independent variables, extra variables are included in the regression model. For example, if temperature and rainfall are significantly correlated with the number of cases and then included in the regression model as independent variables, the equation could be written as the following:

$$\ln(Y_t) = \alpha + \beta_1 \ln(Y_{t-1}) + \beta_2 \ln(Y_{t-2}) + \ldots + \beta_p \ln(Y_{t-p}) + \beta_{p+1}\text{temperature}_t + \beta_{p+2}\text{temperaruep}_{t-1} + \ldots + \beta_{p+q}\text{temperaturep}_{t-q} + \beta_{p+q+1}\text{rainfall}_t + \beta_{p+q+2}\text{rainfall}_{t-1} + \ldots + \beta_{p+q+r}\text{rainfall}_{t-r} + \beta_{p+q+r+1}\sin(2\pi t/T) + \beta_{p+q+r+2}\text{Year},$$

where

- t is the time point, t-1, t-2… are the previous 1, 2… time points
- *p, q, r* are the orders of autocorrelation and determined by correlation analysis
- α is unknown nuisance parameters
- β_1, β_2, β_3… are unknown parameters of interest
- T is seasonal period; T equals 12 for monthly data and 52 for weekly data.

B. Equations for SARIMA models

1. ARIMA [69, 141, 219]

The model is generally referred to as an ARIMA(*p*,*d*,*q*) model where *p*, *d*, and *q* are the order of the autoregressive, integrated, and moving average parts of the model respectively.

Given a time series of data X_t where *t* is an integer index and the X_t are real numbers, then an ARMA(*p*,*q*) model is given by

$$\left(1-\sum_{i=1}^{p}\phi_i L^i\right)X_t=\left(1+\sum_{i=1}^{q}\theta_i L^i\right)\varepsilon_t$$

where *L* is the lag operator, the φ_i are the parameters of the autoregressive part of the model, the θ_i are the parameters of the moving average part and the ε_t are error terms. The error terms ε_t are generally assumed to be independent, identically distributed variables sampled from a normal distribution with zero mean.
An ARIMA(*p*,*d*,*q*) process is obtained by integrating an ARMA(*p*,*q*) process. That is,

$$\left(1-\sum_{i=1}^{p}\phi_i L^i\right)(1-L)^d X_t=\left(1+\sum_{i=1}^{q}\theta_i L^i\right)\varepsilon_t$$

where *d* is a positive integer that controls the level of differencing (or, if *d* = 0, this model is equivalent to an ARMA model). Conversely, applying term-by-term differencing *d* times to an ARIMA(*p*,*d*,*q*) process gives an ARMA(*p*,*q*) process.
It should be noted that not all choices of parameters produce well-behaved models. In particular, if the model is required to be stationary then conditions on these parameters must be met.

2. SARIMA [69, 141, 219]

A seasonal ARIMA model is classified as an ARIMA(p,d,q)x(P,D,Q) model, where P=number of seasonal autoregressive (SAR) terms, D=number of seasonal differences, Q=number of seasonal moving average (SMA) terms. The general model can be written as

$$\Phi_P(B^s)\ \phi(B)\ ,s^D,^d x_t = \alpha + \Theta_Q(B^s)\ \theta(B)\omega_t$$

where $\phi(B)$ and $\theta(B)$ of orders p and q represent ordinary autoregressive and moving average components and $\Phi_P(B^s)$ and $\Theta_Q(B^s)$ represent seasonal autoregressive and moving average components of orders P and Q. $,s^D$ and $,^d x_t$ are seasonal difference components.

C. Abstracts of accepted manuscripts

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El Niño Southern Oscillation (ENSO) and dysentery in Shandong province, China

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Abstract

To investigate the impact of the El Niño Southern Oscillation (ENSO) on dysentery transmission, the relationship between monthly dysentery cases in Shandong Province of China and the monthly Southern Oscillation Index (SOI), a broad index of ENSO, was examined over the period 1991–2003. Spearman correlations and generalized linear models were calculated to detect the association between the SOI and dysentery cases. Data from 1991 to 2001 were used to estimate the parameters, while data from 2002 to 2003 were used to test the forecasting ability of the model. After controlling for seasonality, autocorrelation, and a time-lagged effect, the results indicate that there was a significant negative association between the number of dysentery cases and the SOI, with a lagged effect of 2 months. A one-standard-deviation decrease in the SOI might cause up to 207 more dysentery cases per month in Shandong Province. This is the first report of the impact of the Southern Oscillation on dysentery risk in China, indicating that the SOI may be a useful early indicator of potential dysentery risk in Shandong Province.
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Keywords: Climate; Southern Oscillation Index; Dysentery; Time-series

1. Introduction

Many studies have examined the relationship between climate variability and population health (Kovats and Haines, 2005; Patz et al., 2005). However, little is known about the effects of climate variation on food-borne disease transmission. In particular, impact of the El Niño Southern Oscillation (ENSO) events, resulting from changes in global atmospheric circulation that affect local climate, usually causing more warm and dry days (Australian Bureau Of Meteorology, 2005), on food-borne diseases such as dysentery has not been examined. The impact of ENSO events on other aspects of human health has been well addressed (Kovats et al., 2003).

Located in eastern China (Fig. 1), with 90 million population, Shandong province has had 30,000 cases of dysentery notified annually during the past decade. This paper quantifies the relationship between dysentery and the Southern Oscillation Index (SOI), an index of the ENSO. The purpose of the study was to find a potential indicator for future food-borne disease risks in eastern China.

2. Materials and methods

2.1. Data sources

Dysentery is a notifiable disease in China. All notified cases are based on clinical diagnosis in hospitals. Monthly data on the number of dysentery cases for the period 1991–2003 were provided by a passive surveillance system at the Shandong Provincial Centre for Disease Control and Prevention, which deals with communicable disease notifications in the province. Monthly SOI values over the same period were retrieved from the Australian Bureau of Meteorology.

2.2. Data analyses

Spearman's correlation was used to quantify the correlation at different lagged times. General linear models (GLM) adjusted for autocorrelation and seasonality were used for regression analysis. Data from 1991 to 2001 were used to estimate the parameters, and data from 2002 and 2003 were used to test the forecasting ability of the regression model.

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Climate variations and bacillary dysentery in northern and southern cities of China

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KEYWORDS
Bacillary dysentery;
Climate;
Temperate;
Subtropical;
SARIMA

Summary *Objectives:* This paper was aimed at examining the relationship between meteorological variables and bacillary dysentery in different climatic and geographic areas in China.
Methods: Jinan in northern China, with a temperate climate, and Baoan in southern China, with a subtropical climate were chosen as study areas. Spearman correlations and seasonal Autoregressive Integrated Moving Average (SARIMA) models were used to quantify the association between meteorological variables and dysentery. The Hockey Stick model was used to explore the threshold of the effect of temperatures.
Results: Maximum temperature, minimum temperature, rainfall, relative humidity and air pressure were significantly correlated with the incidence of dysentery in the both cities, with lag effects varying from zero to two months. In the SARIMA models, maximum and minimum temperatures were significantly associated with dysentery transmission. The thresholds for the effects of maximum and minimum temperatures were 17 °C and 8 °C, respectively, in the northern city. No thresholds were detected in the southern city.
Conclusions: Climate variations have different impacts on the transmission of bacillary dysentery in temperate and subtropical cities in China. Public health action should be taken at this stage to reduce future risks of climate change with consideration of local climatic conditions.
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Introduction

Bacillary dysentery, caused by *Shigella* bacteria, is a bacterial infection of intestines that results in severe diarrhoea. Patients who are infected with *Shigella* often develop bloody diarrhoea, fever, and stomach cramps with an incubation of one or two days.[1] The infection is spread from person to person via oral-feces, food or drinking water. Epidemics are frequent in overcrowded populations with poor sanitation and most cases occur in summer and autumn. While most cases of bacillary dysentery are mild and do not require drastic treatment, excessive dehydration can be fatal in a severe attack if treatment is unsuccessful.

Bacillary dysentery is still a public health problem in China. While morbidity and mortality due to bacillary dysentery has decreased considerably in China in the

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ORIGINAL PAPER

Climate variations and salmonellosis transmission in Adelaide, South Australia: a comparison between regression models

Ying Zhang · Peng Bi · Janet Hiller

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Abstract This is the first study to identify appropriate regression models for the association between climate variation and salmonellosis transmission. A comparison between different regression models was conducted using surveillance data in Adelaide, South Australia. By using notified salmonellosis cases and climatic variables from the Adelaide metropolitan area over the period 1990–2003, four regression methods were examined: standard Poisson regression, autoregressive adjusted Poisson regression, multiple linear regression, and a seasonal autoregressive integrated moving average (SARIMA) model. Notified salmonellosis cases in 2004 were used to test the forecasting ability of the four models. Parameter estimation, goodness-of-fit and forecasting ability of the four regression models were compared. Temperatures occurring 2 weeks prior to cases were positively associated with cases of salmonellosis. Rainfall was also inversely related to the number of cases. The comparison of the goodness-of-fit and forecasting ability suggest that the SARIMA model is better than the other three regression models. Temperature and rainfall may be used as climatic predictors of salmonellosis cases in regions with climatic characteristics similar to those of Adelaide. The SARIMA model could, thus, be adopted to quantify the relationship between climate variations and salmonellosis transmission.

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Keywords Climate · Multiple linear regression · Poisson · Salmonellosis · SARIMA · Time-series

Introduction

Salmonellosis is one of the most common and widely distributed food-borne diseases, with millions of cases being reported worldwide every year (WHO 2005). An estimated 1.4 million cases occur annually in the United States (CDC 2004) and *Salmonella* causes more deaths than any other food-borne pathogen in England and Wales (Adak et al. 2002). In Australia, *Salmonella* is one of the most common agents responsible for food-borne disease outbreaks, with 7,917 cases notified to OzFoodNet, the Australian national foodborne diseases surveillance system, in 2002 (OzFoodNet 2002). This was a 10% increase compared with the previous 4-year period. An up-to-date estimation indicated that *Salmonella* may be the cause of 92,000 cases of gastroenteritis annually in Australia (Hall et al. 2005).

More salmonellosis cases occur in the warmer season, which could be due partly to higher temperatures and other climatic variables. Few studies have investigated the relationship between climate factors and enteric infections, using historic surveillance disease datasets. Positive association between temperature and salmonellosis and other enteric infections has been reported in limited studies (Kovats et al. 2004; D'Souza et al. 2004; Louis et al. 2005; Tam et al. 2006). In terms of the relationship between other climatic variables, e.g. rainfall, humidity, and El Nino, with enteric infections, published results are not consistent, with some studies claiming a positive correlation while others have not detected any associations (Curriero et al. 2001; Checkley et al. 2000; D'Souza et al. 2004; Martinez-Urtaza et al. 2004).

VECTOR-BORNE DISEASES IN AUSTRALIA

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Vector-borne diseases in Australia

Vector-borne diseases notified to the National Notifiable Diseases Surveillance System (NNDSS) include mosquito-borne diseases caused by alphaviruses (Barmah Forest virus and Ross River virus) and flaviviruses (Dengue Fever/Dengue Shock Syndrome, Murray Valley encephalitis, Kunjin and Japanese encephalitis), and malaria[1]. In the last decade, more than 61,000 cases of vector-borne diseases have been notified to the NNDSS, which accounts for 6.3% of the total notifications[2]. The commonest vector-borne diseases in Australia are Ross River virus infection and Barmah Forest virus infection, which represent more than 80% of all notified vector-borne diseases. The proportion of notified vector-borne diseases has decreased in the past ten years, from 16% of total notifications in 1996 to 4% in 2005. However a significant factor in this trend has been the introduction of a number of non vector-borne notifiable diseases over the last ten years. Geographically, more than 85% of notified cases of vector-borne diseases came from Queensland, New South Wales and Western Australia. Ross River virus infection is the most notified vector-borne disease in almost all States and Territories except ACT. Rates of notified vector-borne diseases have fluctuated over the last ten years; with considerable year to year variation.

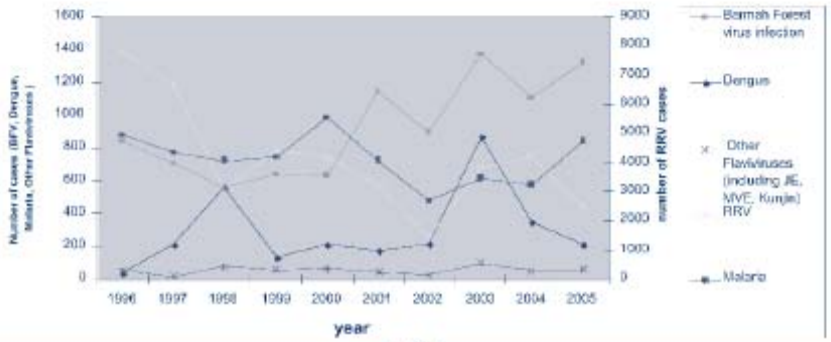
Ross River virus infection (RRV) and Barmah Forest virus infection (BFV)

RRV is the most common mosquito-borne disease in Australia. There have been more than 41,000 cases notified to NNDSS during the last decade with the most serious situation occurring in 1996 (Figure 1). The vertebrate reservoir hosts of RRV could include marsupials, placental mammals and birds, for example kangaroos, horses and rats.[3] There are over 40 species of mosquito vectors, with *Aedes vigilax, Aedes camptorhynchus* (saltmarsh along coastline) and *Culex annulirostris* (inland) being the most important.[3] In terms of seasonal distribution, peak incidence of the disease is through the summer and autumn months, when the mosquito vectors are most abundant. Studies suggest that climate variability is related to the transmission of RRV.[4,5] BFV has been notified to NNDSS since 1995. It is noticed that the number of BFV notifications in 2005 increased 1.5 times compared with that in 1996 (Figure 1). In NSW, the notified number of BFV cases increased more than 2 times compared with ten years ago, and an outbreak was observed in SA in 2005 and 2006. The increase in notified cases of BFV may also reflect increased awareness among the general community and GPs of the disease as well as changes in testing procedures. Barmah Forest virus and Ross River virus demonstrate many similarities. They have similar disease symptoms and seasonal distribution. Most affected people by BFV and RRV are middle aged and there seems to be no gender difference.

Dengue and other notified Flavivirus infections

Dengue is the most common arboviral infection in the world, with four distinct virus serotypes.[6] *Aedes aegypti*, the major vector, has adapted well to urban environmental conditions such as poor housing, overcrowding and inadequate sanitation.[7] Globally, it is suggested that climate change could increase the

Figure 1. Notified Vector-borne Diseases to NNDSS 1996-2003



Public Health Bulletin

Climate change and water-borne diseases

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Introduction

According to the most recently released report from the Intergovernmental Panel on Climate Change (IPCC) in 2007, the global average surface temperature has increased approximately 0.74 ºC during the last century.[1] For the 21st century, based on the best estimate for a 'high scenario', it is estimated that there will be a 4.0 ºC increase in temperature with a likely range of 2.4 to 6.4 ºC and the sea level may rise in the range of 26cm to 59cm. It is very likely that there will be an increase in frequency of warm spells, heat waves and events of heavy rainfall. Human beings will suffer from more hot days, more extreme rainfall, and more floods and droughts, which may have effects, direct and indirect, on population health including water-borne diseases.

Water-borne disease is a global public health problem. In the United States about 9 million cases occur every year.[2] Food-related diseases account for about 10% of morbidity and mortality in the UK, with costs of about £6 billion annually; and among these, many are water-borne infections.[3] The cost of enteric infection, including both food- and water-borne infections, has been estimated at over A$2.6 billion each year in Australian communities.[4] According to the World Health Organization, infectious diseases transmitted by contaminated water and food in developing countries are a constant and frequently fatal threat to population health.[5] For example, diarrhoeal diseases are estimated to cause an annual 2.7 billion cases and 1.9 million deaths, mostly in infants and young children.[5]

The control of water-borne diseases is still a big challenge and it is critical to understand the underlying causes, including the role of climate variability, in their transmission.[6] Although water-borne disease is multi-causal, the growth and spread of the responsible micro-organisms are influenced by climate variations.[2,7] Temperature and relative humidity directly influence the rate of replication of the pathogens and the survival of the agents in the environment. Rainfall, especially heavy rainfall events, may affect the frequency and level of contamination of drinking water. Moreover, climate change may influence water resources and sanitation so that water supply is effectively reduced. Such water scarcity may necessitate using poorer quality sources of fresh water such as water from rivers, which are often contaminated. All these factors may result in an increased incidence of water- and food-borne diseases.[2]

Relationship between climate variation/change and water-borne diseases

It is very difficult to identify where and how a change in climatic conditions might alter the hazards posed by water-borne diseases.[8] However, the relationship between climate variation and water- and food-borne diseases has been documented by limited studies conducted in Europe, Australia, the USA and Asia.[2,9,10-14] and the association between climate variation and bacillary dysentery (shigellosis) in China has also been reported recently.[15] Most of these studies suggested that climate change with increased temperature will bring about more cases of water- and food-borne diseases. One study indicated that each 1 ºC increase in temperature is related to a 5% increase in the risk of severe diarrhoea.[11] Two studies suggested that other climatic variables such as rainfall also played an important role in enteric infection transmission,[16,17] although previous studies reported inconsistent results.[10,11]

The impacts of climatic variables on water-borne diseases vary across different climatic regions, including the thresholds of weather variables, lag times of effects and seasonal patterns in a number of cases. Highly urbanised populations and well-managed water treatment systems in metropolitan areas may conceal the association between rainfall and water-borne diseases. More studies in different climatic areas are needed to further understand the relationship.

In Australia only a few studies have investigated the relationship between climate variations and water- and food-borne diseases. OzFoodNet, the Australian national food-borne diseases surveillance system, recorded 14,716 cases of campylobacteriosis and 7,917 cases of salmonellosis, the most notified enteric infections, in 2002.[18] A study based in Queensland showed a positive association between salmonellosis and temperature.[12] In another it was reported that a 1 ºC increase in temperature might cause an approximately 10% increase in the number of salmonellosis cases in Australia.[19] *S. Mississippi*, a major contributor to *Salmonella* infections in Tasmania, has been reported to be associated with human contact with native animals and untreated drinking water, mostly that collected in rainwater tanks.[20] Climate change might have affected the growth and survival of *S. Mississippi* by changing the behaviour of both host animals and human beings and increasing their exposure to contaminated drinking water.

The associations between campylobacteriosis and both temperature and rainfall have been studied at an international level, including in Melbourne and

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Climate Change and the Transmission of Vector-borne Diseases: A Review

Ying Zhang, Peng Bi and Janet E Hiller

Abstract

This paper reviews studies examining the relationship between climate variability and the transmission of vector and rodent-borne diseases including malaria, dengue fever, Ross River virus infection and Haemorrhagic Fever with Renal Syndrome. The review has evaluated their study designs, statistical analysis methods, usage of meteorological variables, and results of those studies. We found that the limitations of analytical methods exist in most of the articles. Besides meteorological variables, few of them have included other factors that can affect the transmission of vector-borne disease, eg socio-economic status. Additionally, the quantitative relationship between climate and vector-borne diseases are inconsistent. Further research should be conducted among different populations with various climatic/ecological by using appropriate statistical models.

Article in press. Journal of Environmental Health. Accepted 2007.

Climate Change and Disability Adjusted Life Years

Ying Zhang, Peng Bi and Janet E Hiller

Abstract

A review on the studies of Disability Adjusted Life Years (DALYs) lost attributable to climate change has been conducted, including the methodological issues and the research results. According to our review, little is known about DALYs lost due to climate change, except for the results, based on limited information, presented in the Global Burden of Disease study in 2002. Additional difficulties are encountered in measuring DALYs attributable to climate change than with the burden attributable to other causes. Further studies linking DALYs and climate change should be conducted in various populations and in different ecological regions, including developing countries.

Public Health Reports. Accepted July 2007.

Climate Variations and the Transmission of Bacillary Dysentery in Jinan, Northern China: A Time-series Analysis

Ying Zhang, Peng Bi and Janet Hiller

Objectives. This study aims to quantify the relationship between climate variations and bacillary dysentery in Jinan, a city in northern China with temperate climate, in order to have a better understanding of the effect of climate variations on enteric infections.

Methods. The weather variables and number of the cases of bacillary dysentery over the period 1987-2000 has been studied on a monthly basis. Spearman correlation between each weather variable and dysentery cases was conducted. Seasonal Autoregressive Integrated Moving Average (SARIMA) models were used to perform the regression analyses.

Results. Maximum temperature (1-month lag), minimum temperatures (1-month lag), rainfall (1-month lag), relative humidity (without lag) and air pressure (1-month lag) were all significantly correlated with the number of dysentery cases in Jinan. After controlling for the seasonality, lag time and long-term trend, the SARIMA model suggested that a 1ºC rise in maximum temperature might relate to more than 10% (95%CI:10.19%~12.69%)increase in the cases of bacillary dysentery in this city.

Conclusions. Climate variations have already affected the transmission of bacillary dysentery in China. Temperatures could be used as a predictor of the number of dysentery cases in a temperate city in northern China. Public health interventions should be undertaken at this stage to adapt and mitigate the possible consequences of climate change in the future.

Keywords Bacillary dysentery, weather, time-series, socio-economic