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Links Between Climate, Water And Waterborne Illness, And Projected Impacts Of Climate Change

Final Technical Report to HPRP

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Executive Summary

Research goals were to investigate the incidence of waterborne illness in Canada, describe the complex systemic inter-relationships between disease incidence, weather parameters, and water quality and quantity, and address possible consequences of climate change on the incidence of waterborne diseases.

Specific objectives of the research were to:

1. Review the existing state of national and international knowledge on the association between weather events, water quantity and quality, and waterborne illness, and build a combined geo-referenced database of existing Canadian weather data, water quality and quantity data, and waterborne illness data
2. Describe the incidence and distribution of waterborne illness in Canada and weather events occurring concomitantly with illness, and test associations between weather events and waterborne disease incidence and outbreaks.
3. Model and quantify associations between weather variables, water quality and quantity, and incidence of waterborne illness, using temporal-spatial analyses in several regions of Canada.
4. Project the impact of global climate change on the risk of waterborne illness by coupling the information gained in Objective #3 to several accepted climate change model scenarios.
5. Disseminate findings to policy audience; engage decision-makers from environment and health in an ongoing discussion of the impacts of climate change on waterborne disease hazards.

There were four main empirical conclusions of this work:

1. **Waterborne diseases are a burden to Canadians now.** Many Canadians, particularly the young and elderly, are affected by gastrointestinal disease annually, at considerable cost to society. Some of this burden of disease is waterborne, but it is not yet possible to determine how much. Outbreaks of waterborne disease are not a rare occurrence in Canada. In addition, thousands of Canadians are hospitalized each year with gastrointestinal illness. There is a need for improved integration of disease surveillance systems in order to improve our ability to assess the occurrence of endemic and epidemic gastrointestinal illness in Canada. Improvements are urgently needed in epidemiological data and in microbiological techniques to facilitate the attribution of disease to a waterborne or other source, and to enable the development of targeted control measures.
2. **Waterborne disease risk is related to ambient temperature and rainfall.** There is now substantial evidence that various types of weather affect gastrointestinal disease risk in many parts of Canada. Extreme precipitation increases the risk of epidemic waterborne disease twofold. Precipitation also contributes to the risk of endemic gastrointestinal illness, implying that some portion (as yet inestimable) of endemic gastrointestinal illness must be waterborne. Epidemic waterborne illness is linked to heat accumulation over a 6-week period – perhaps representing thawing conditions during cold months, or heat waves in summer. Warm (but not hot) weather conditions over a 6-week period (suggesting spring or autumn conditions) were found to be the most significant contributors to hospitalizations due to gastrointestinal illness in Alberta and Ontario.
3. **Climate change will alter the distribution and risk of gastrointestinal risk in parts of Canada.** Downscaling techniques allow for the consideration of climate change

projections in epidemiological models of disease risk. Such downscaled data should be widely available to allow for widespread applications in research in health and other sectors. Better regional climate change models will increase future abilities to include climate change projections into disease models. Simple examination of total precipitation, maximum and minimum temperature data is not sufficient to understand the impact of climate change on future patterns of weather. Other measures, such as 5-day precipitation, seasonal averages, and degree-days may be required to ascertain climate change impact on waterborne disease risk. Preliminary results from case studies in southern Alberta found an increased risk of hospitalizations with a diagnosis of acute gastroenteritis (particularly in spring) with climate change by the end of the 21st century. Other preliminary research on extreme weather thresholds historically and under climate change conditions suggests that future weather conditions (particularly heavy rainfall and warmer maximum temperatures) may increase the risk of waterborne disease outbreaks. Research on the impacts of climate change on waterborne disease risk is ongoing.

4. **Some Canadian populations have developed adaptive responses to extreme weather events.** The South Tobacco Creek, MB project identified a number of important aspects to adaptation to extreme weather. The organization included mainly young adults with strong social networks, who owned small mixed farms that were in close proximity, and had connections to political and government bodies (decision makers). The organization has shown the ability to be socially adaptive even as it promotes ecological resilience in watershed management. The group's network of small dams has markedly decreased water turbidity in the creek after heavy rainfall. Turbidity in the source water decreases the efficiency of drinking water treatment, a problem for communities downstream from South Tobacco Creek. Successful adaptation relies upon strong leadership locally and within government, strong social networks, successful interventions, a regulatory and legislative environment that supports community action and leadership, long-term funding, and long term monitoring of current ecological conditions into the future.

The project produced new databases of meteorological, water quantity and quality, and meteorological data. It also generated a large database of downscaled climate change data from two Global Climate Models (HadCM3 and CGCM2) for a representative sample of Canadian locations. A comprehensive literature review, updated at the end of the project, is also included. Several new projects have been funded and will build on the work of this project.

Researchers and interested stakeholders, from policy and practice in environment and public health, met at the end of the project, to discuss avenues for policy action on the results of the research. General themes emerging from these discussions included: recognition that our understanding of the complex interactions among climate, environmental change, and health outcomes is uncertain; the need for clearer and more effective communication between scientists, the general public, and policy-makers in several government departments; and the need to act now on in the considerable knowledge we already have, particularly on source water protection. Indeed, to wait for certainty when we already know, with a high degree of probability, that not protecting source waters will have strong negative impacts on the health of Canadians is to behave irresponsibly. Further, the group suggested the implementation of the O'Connor recommendations must continue in order to enhance Canada's resilience to risks posed by a changing climate. Water supply and treatment system upgrades must be

designed with climate change projections in mind, such that they continue to be effective. A strong, coordinated and integrated disease surveillance system will be key to detecting and responding to the health impacts of climate change. The coordination and implementation of proactive policies must be coordinated across government sections such as Environment Canada, Health Canada, Public Health Agency of Canada, and Agriculture Canada, and with provincial and local involvement. Finally, scientists should engage in programs of public communication and discourse so that these issues are planted firmly in the public agenda, and decisions made are informed by the best, most recent science available.

1. Introduction

Two important issues relevant to the health of Canadians are addressed in this project: the risk of waterborne illness and the health impacts of global climate change.

1.1. Waterborne illness

Access to clean, safe water is a recognized as a fundamental human right by the World Health Organization. Nobel prize winning biochemist, Albert Szent-Gyorgyi (Hungary) advised, "There is no life without water." Contaminated water accounts for 2 million worldwide deaths annually (CDC Fact Sheet, 2003).

Canada holds 7% of the world's renewable freshwater supply (Environment Canada, 2004). The Government of Canada acknowledges the importance of a safe water supply, and publishes guidelines on drinking water quality. Waterborne illness results when pathogens enter the water supply without detection and are then consumed, either directly through drinking water or indirectly from contaminated food, by unsuspecting humans. A significant proportion of enteric illness is attributed to waterborne pathogens, although its magnitude is not known because of the lack of epidemiological and microbiological data.

For drinking water to be a source of illness, water must first become sufficiently contaminated, escape treatment, or treatment must fail. Often, multiple safety barriers must fail before people are exposed to infectious hazards. Human sewage, leaking septic systems, manure runoff from agricultural lands, and wild animal wastes may all contaminate surface water later used for drinking water. Groundwater may become contaminated by surface contamination of wells, subsurface inflows, improperly situated septic fields, or leaking dumps (chemical contamination). Drinking water may also become contaminated during or after the treatment process. A persistent threat to public health, antiquated combined sewer systems (CSS) carry both storm water and raw sewage to the sewage treatment plant. When water flow is too great (heavy rainfall, snowmelt, etc.), sewers overflow directly into a surface body of water (river, lake or ocean). Thus pathogens, industrial wastes, and city street contaminants run untreated into a river or lake, which may be a drinking water source or used for recreation or fishing.

Although the Canadian burden from waterborne illness is unknown, there is evidence that it accounts for a significant proportion of enteric illness. Payment et al. (1991) estimated that 35% of enteric diseases in Montreal were due to preventable waterborne illness. Most of the 4015 cases of giardiasis and 599 cases of cryptosporidiosis reported in Canada in 2003 (Public Health Agency of Canada, 2004) were presumed waterborne. Furthermore, the incidence of waterborne illness is most certainly under-reported since illness is usually self-limiting in healthy adults, and medical attention is not sought (Frost et al., 1998). Majowicz et al (2004) estimated under-reporting of acute gastrointestinal illness (from all causes) in a Canadian community to be 313 cases to one. Severe disease can sometimes occur, often in the very young, the elderly, and in people with immune systems compromised by other illness or chemotherapy. Large outbreaks with severe consequences caused by *E. coli* O157:H7 and *Cryptosporidium* have alarmed Canadians and brought demands for political action. Canadian First Nations communities may be at particularly increased risk of

waterborne illness due to poor availability of safe drinking water in remote areas (Rosenberg et al., 1997).

Waterborne pathogens are spread through contaminated drinking water or exposure to contaminated water while swimming or participating in other activities, or secondarily through food contaminated with bad water (Rose et al., 2001). All of these transmission patterns may be affected by climate variability and thus potentially by climate change.

Canada's waterborne illness burden is presumed to be due to infectious gastroenteritis. Other infections, such as Hepatitis A virus, Leptospirosis, and Legionellosis, account for a small proportion of cases. At this time in Canada and elsewhere, inadequate epidemiological evidence hampers identification of the source of exposure to infectious gastroenteritis. Investigations of outbreaks of illness, with several people becoming ill from exposure to a common source, currently contribute to the best available epidemiological data. For estimates of non-outbreak (endemic) levels of waterborne illness in the community, epidemiologists rely on indicator organisms that are predominantly waterborne, such as *Giardia*, *Cryptosporidium*, and portions of *Campylobacter, E. coli* and *Salmonella* to estimate the burden of waterborne illness. Hospitalization rates for acute gastroenteritis are also used to assess the burden of infectious gastroenteritis, but the agent responsible for the disease and its source are rarely included in the hospital discharge database.

1.2. Links between climate and waterborne illness

Weather is a favourite topic of conversation, yet many are unable to make a distinction between weather and climate. Weather refers to short-term, usually day-to-day meteorological activities in a place; climate is typically represented by an average (30 year cycles, usually) of meteorological conditions for a given place, as recorded by daily observations. The effects of weather can be obvious – an extreme rainfall event may result in swollen streams and rivers, for example – but climate changes are generally subtler, taking us decades to track, understand and interpret.

Easier to comprehend is the link between weather events (short-term), climate (long-term) and waterborne pathogens leading to illness in humans. Following on the previous example of an extreme rainfall event swelling streams and rivers beyond their natural capacity, it is logical to conclude that the excess water has to go somewhere. Over-flowing into a city's sewer system or seeping through contaminated soil and into a groundwater source are both reasonable explanations for where excess water may settle. Just as feasible is to draw the conclusion that some of this excess water may carry in it pathogens detrimental to human health, if not found and treated before consumption.

The impact of extreme weather events on waterborne illness may be widespread and is often a factor in triggering waterborne disease outbreaks. Curriero et al. (2001) found that more than half the waterborne disease outbreaks in the United States during the last half-century followed a period of extreme rainfall, with 68% of outbreaks following storms of a severity that ranked in the top 20% for that region. Excess rainfall resulted in surface contamination of groundwater and contributed to the Walkerton outbreak of *E. coli* O157:H7 (Auld et al., 2001) and has contributed to other outbreaks in North America (Patz et al., 2001; MacKenzie et al., 1994; Rose et al., 2001).

Since weather is a determinant of waterborne disease outbreaks, it is likely to be a contributing factor to endemic cases of disease. Understanding the impact weather has on waterborne illness past, present and future is fundamental to our ability to predict and prepare for expected public health challenges, including those brought about by climate change.

1.3. Implications of climate change for waterborne disease hazard

Global climate change scenarios suggest that "the globally averaged surface temperature is projected to increase by 1.4 to 5.8 degrees Celsius over the period 1990 to 2100" due to the accumulation of greenhouse gases in the atmosphere (IPCC, 2001). Most of Canada can expect longer summers, milder winters, and increased summer drought (http://www.climatechange.gc.ca/). Projections of more extreme weather, such as cloudbursts (causing flooding and landslides) and heat waves (causing drought and forest fires), would be consistent with climate change (Francis and Hengeveld, 1998). Recent research (Kharin and Zwiers, 2005) foresees an increase in the probability of extreme precipitation events by a factor of two as we near the end of the 21st century. In Canada, it is conceivable that excess precipitation could increase our risk of waterborne illness through flooding (increased run-off, decreased effectiveness of treatment), high temperatures (pathogen replication) and drought (through concentration of pathogens in smaller volumes of water, decreased hygiene measures due to water shortages). Heavy rainfall or snowmelt may flush manure, human sewage, wildlife and pet droppings into surface drinking water reservoirs or ground water, and can lead to widespread contamination of drinking water sources. Canadians may also see more frequent disease in their pets from serious waterborne zoonoses such as leptospirosis, with clear potential for transmission to humans (Prescott et al., 1999).

There is a need to develop a better understanding of the potential impacts of climate change on epidemic and endemic waterborne disease, and the factors that influence risk of waterborne disease in Canada. This project has undertaken research to help begin to fill this need.

2. Goals and Objectives

The goals of this research were to investigate the incidence of waterborne illness in Canada, describe the complex systemic inter-relationships between disease incidence, weather parameters, and water quality and quantity, and to project the potential impact of global climate change on those relationships.

The research addresses the possible consequences of climate change on the incidence of (waterborne) infectious diseases and on vulnerable populations that are important for public health policy and identifies where and how the expected environmental changes resulting from climate change will affect population health in terms of waterborne disease incidence, outbreaks, and hospitalizations. This project also provides the evidence to implement adaptation and impact policy, with empiric evidence of weather- and water-related risk factors for waterborne illness, and projected changes under conditions of global climate change. Specific objectives were to:

1. Review the existing state of national and international knowledge on the association between weather events, water quantity and quality, and waterborne illness, and build

a combined geo-referenced database of existing Canadian weather data, water quality and quantity data, and waterborne illness data.
2. Describe the incidence and distribution of waterborne illness in Canada and weather events occurring concomitantly with illness, and test the associations between weather events and waterborne disease incidence and outbreaks.
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3. Methods

The project was ordered into three phases. In Phase 1, a literature review was conducted, case studies designed, and databases assembled. A review of historical waterborne disease outbreak data was also completed. In Phase 2, statistical models of the associations between various meteorological measures, measures of illness, and water quantity and quality variables were developed, using several case studies. In addition, a case study was conducted in Manitoba of community adaptation to extreme weather. Finally in Phase 3, the most recent climate change model outputs were downscaled and these data used to assess the impact of climate change on waterborne disease risk. The work of this project is ongoing, through the research of several graduate students, and new projects that build on this project's work on waterborne illness and climate change. In particular, the modeling of climate change data is preliminary, with final results anticipated within a year. Detailed methodologies for the analyses are presented in this section.

3.1. Effect of high impact weather on waterborne outbreaks: a case-crossover study design

A case-crossover design (Maclure, 1991) was used to evaluate the association between high impact weather events (i.e. short term weather events that contribute high volumes of water and cause substantial overland flow) and waterborne disease outbreaks. This design is intended for the study of a transient effect of an irregular exposure on the occurrence of a rare acute outcome and has frequently been used to study the effects of air pollution exposure on health outcomes (Bateson and Schwartz, 2004; Levy et al., 2001; Neas et al., 1999; Yang et al., 2004). The exposures of the 'case' just prior to the event are compared with the distribution of exposures for the 'case' from a different time period using matched case-control analytic techniques (Lumley and Levy, 2000). Comparisons are made within subject and thus time-invariant confounders are inherently controlled (Navidi and Weinhardl, 2002).

For our study, each outbreak of waterborne disease was considered a 'case'. Control periods in the same locations were matched by day of onset of the outbreak using a time-stratified matched case-crossover. To reduce bias, the study period was divided *a priori* into distinct

strata. The year of the outbreak included the exposure period for the case, and the remaining years provide control exposure periods (matched by month-day) (Figure 1) (Levy et al., 2001). The 27-year time period (1975-2001) was stratified into six mutually exclusive strata, five strata of five years each and one for the period 2000 to 2001 (Figure 2). This design provided four controls for each case to maximize the power of our sample size of 92 outbreaks.

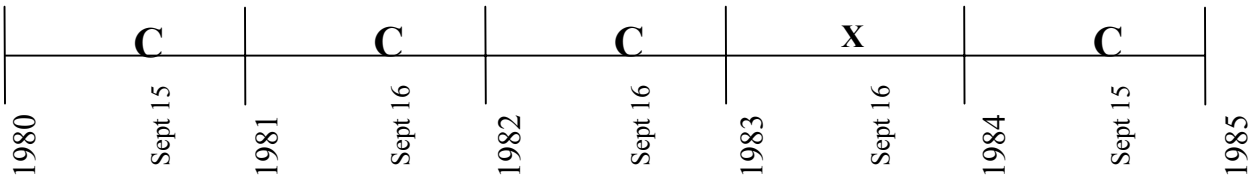


Figure 1. An example of selection of four controls from within a selected stratum where 'X' indicates an outbreak on September 16, 1983 and 'C' indicates a control in each of the other four years of the stratum, taking leap year into account.

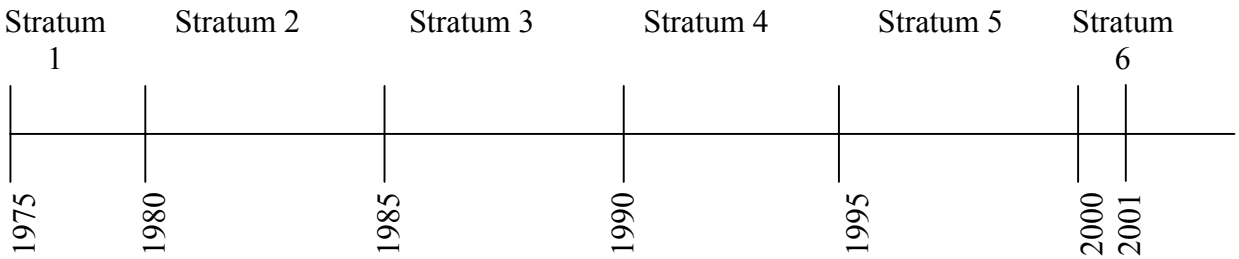


Figure 2. The 27-year time period divided *a priori* into six mutually exclusive strata.

A six-week time frame prior to the day of onset was selected as the hazard time period for both case and controls. This period is thought to be enough time for water to leave the source, become contaminated, to be consumed by susceptible people, infection to occur and manifestation of symptoms for waterborne pathogens. Previous studies have found a lag of up to four weeks between turbidity and hospitalizations for acute gastrointestinal illness (Aramini et al., 2001), and a lag as great as two months between heavy rainfall and waterborne disease outbreaks (Curriero et al., 2001).

Data manipulation and analysis were conducted using Statistical Analysis Software (SAS) 8.0 (SAS Institute Inc., Cary, NC, USA) and S-Plus (Insightful, Seattle, WA, USA). Cox proportional hazard modeling was used to perform the conditional logistic regression analysis and statistical tests were two-tailed.

Model building proceeded in a forward stepwise manner to determine important risk factors (using an inclusion criteria of p-value <0.05) and incorporated both likelihood ratio and Wald procedures. All models incorporated year effects to deal with potential year-to-year variability. Two-way interaction terms were considered based on biological plausibility.

These included interactions of ecozone with degree-days, AR, AR percentile, SF and SF percentile; the main effects of ecozone are not estimable owing to the matching of cases and controls by ecozone. A log transform was used to reduce the right-skewness of the maximum five-day rolling average stream flow. Linearity assumptions were assessed by fitting higher order models and by partial residual analysis.

3.2. Outbreak and climate thresholds: threshold modelling

Twenty-three outbreaks were selected from a list of 288 that occurred across Canada from 1974 to 2001 (Schuster et al., In Press). Outbreaks were chosen because the associated epidemiological reports specifically referred to weather conditions being a causative factor in the outbreak.

Meteorological data from the closest active weather station were obtained from Environment Canada. Wherever possible, the station chosen was located at an airport, to ensure the best data record. Analyses were undertaken using maximum and minimum air temperature, rainfall and precipitation data. Percentile calculations were based on the available record for a particular station. The data period examined did not exceed six months prior to each outbreak. The first eight weeks were examined in detail and the remaining period was used to ascertain ground and snow pack conditions, where necessary.

Initial variables included daily rainfall totals, daily precipitation totals (rain and snow combined), 5-day rainfall and precipitation sums (running totals), and 1-week temperature sums (Tmax and Tmin). Maximum and minimum values for all variables were calculated on a weekly and bi-weekly basis, beginning with the week prior to an outbreak and ending in the eighth week prior to an outbreak. These were then converted to percentile values and results examined for consistent extreme occurrences (i.e. in the top or bottom quartiles).

Hydrological data were extracted from the closest station that was least influenced by built up areas. Data were only available for 16 outbreaks. Maximum daily discharge values were identified for the first and second week prior, as well as the first two weeks combined.

Once established, climate thresholds were applied to downscaled climate change scenario data of daily maximum and minimum temperatures and daily precipitation amounts where data was available. Only 9 outbreaks, from the original 23, were selected for this analysis due to climate downscaled data availability. Future climate data were generated using two spatial and temporal downscaling methods: **SDSM**, a Statistical Down Scaling Model (Wilby et al, 2002); and **LARS-WG**, a stochastic weather generator (Semenov & Barrow, 1997; Semenov & Brooks, 1999). These downscaling tools were chosen due to their worldwide use, free availability, publication in refereed journals, and because they are well-documented, and user-friendly. A comparison is made using three future time slices centered around 2020s, 2050s and 2080s, by employing scenarios from **CGCM2** A2 scenarios and **HadCM3** A2 scenarios (see section 4.4.1).

3.3. Mapping endemic gastrointestinal disease: spatial analysis

3.3.1. Bayesian mapping – Atlantic Provinces

Disease mapping is becoming a necessary tool in health research because it provides a visual summary of complex geographical information to highlight areas that are at high risk of disease. The most important function of a map is to illustrate patterns in disease distribution (Elliott et al., 2000). A simple statistical approach to mapping is Poisson inference, which gives a picture of the geographical distribution of the incidence of non-rare diseases in the population. When rare diseases are considered this method is not appropriate and therefore Bayesian models should be considered.

Acute gastro-intestinal disease (GID) is a relatively rare disease. The incidence of reportable illness due to enteric pathogens in the Atlantic Provinces ranged from approximately 15 to 65 cases per 10,000 per person-year. Several geographical areas had no case counts. As well, some geographical areas had low population counts. For these reasons, a Bayesian method was employed to smooth and stabilise disease rates for each province in the study area (Atlantic Provinces).

The Bayesian method was developed to account for the extra-Poisson variation in the data (Elliott et al., 2000). This method shrinks unreliable standardized rates towards the overall mean rate to produce smoothed maps. This allows us to work with noisy data where it is difficult to identify the true picture of disease rates because of small counts.

Bayesian methods, which remove the random component from maps, combine information provided in each area by the observed variable of interest (using the Poisson likelihood) and information about relative risks in each area and their variability across the map (using the prior disease rates). The prior models can either be independent, spatially structured or both for area-specific relative risk parameters (Elliott et al., 2000). Prior models rely on already known patterns, distribution and knowledge of the relative risks of disease, θ. The prior distribution is parameterized by hyper-parameters φ, which control the degree of variability in the relative risks across areas (Elliott et al., 2000). Further details on Bayesian methods are included in Appendix A.

3.3.2. Kriging

Kriging is a data interpolation method used for dealing with data that are continuous (also known as geostatistical data) in nature and are spatially referenced. Kriging will be used for many of the land use, demographic and meteorological variables in later analysis of gastroenteritis risk in Atlantic Canada. The method examines the second order (local) spatial effects or spatial dependence. Details of this method are provided in Appendix B.

3.3.3. Cluster detection of gastroenteritis hospitalizations in Atlantic Canada

Disease mapping and clustering are important when describing data in spatial epidemiology and allow for the description of spatial variation in disease risk. Spatial variation in risk is due to unknown factors and they can be real level factors or individual level factors. Disease mapping provide a visual summary of data, generate hypotheses, describe the data, highlight areas of apparent high risk and aid in policy formation and resource allocation. Although

some caution is required with maps, as they can be misleading, since data quality problems can bias map interpretation, large areas can dominate visually and rates based in areas with small populations can be unstable.

Clustering refers to the pattern of the location of disease cases, relative to non-cases. Patterns may occur because cases are more clustered in one area than non-cases and this can be due to an infectious agent or genetic susceptibility or to measured or unmeasured risk factors (Elliott et al., 2000). We were concerned mainly with unmeasured risk factors, since we often take into account known risk factors. If a disease exhibits spatial clustering, then areas of high risk will lead to an excess of cases, defined as "clusters". Clusters depend on boundaries chosen both spatially and temporally. Cluster detection in the process of finding or classifying the observed spatial distribution of disease can be used to look for etiologic clues or disease surveillance. Several different methods are available for cluster detection but specifically the SaTScan statistics (Appendix C).

In our analysis, visual inspection of maps of disease incidence for both watersheds and CSD were examined for spatial patterns in the incidence of GID. Maps for each year of data were examined to see if patterns could be identified from year to year. The SaTScan statistic (Kulldorf, 1997) was used to formally investigate spatial clustering of disease for watersheds and CSD level data for each province. The SaTScan statistic examined the spatial distribution of a factor, in this case disease incidence, for potential disease clusters. The statistic identified areas that can be classified as either the primary cluster or one more secondary cluster. The centroid of each watershed or CSD was used to represent the spatial location of the geographical area since the SaTScan statistic requires point location to calculate the statistic. The SaTScan statistic was also used to identify clusters that occur in both space and time.

3.4. Interpolation methods for risk maps of gastrointestinal hospitalization risk for Alberta and Ontario

3.4.1. Thin-plate splines

Thin-plate spline (TPS) modelling is a multi-dimensional interpolation procedure. The method assumes unique and non-co-linear (Donato and Belongie, 2002) observed data, and continuity at each date point. Additionally, all partial derivatives up to order *m* must be continuous (C^m continuity) (Hartkamp et al., 1999). As such, the TPS method is appropriate for use of interpolation of continuous climate data. This applies specifically to temperature variables. Precipitation data does not exhibit continuity and thus requires other interpolation methods. Mathematical equations and interpretation for the TPS can be found in Appendix D.

TPS Interpolation of Alberta and Ontario Temperature Data

Data to be interpolated, extracted using the python code (Appendix E), consisted of unobserved minimum and maximum daily temperatures specific to space-time events extracted from a hospitalization discharge database from southern Alberta and Ontario, 1992 through 1998. Events identified locations and dates for cases or controls of waterborne

disease. This data consisted of latitude, longitude, date of case or control, and elevation, as determined by the Canadian Digital Elevation Model (CDEM). Coordinates of space-time events were based on a central postal code point. Figure 3 shows the highlighted study regions for Alberta and Ontario. Figure 4 shows the magnification of the Alberta study region including the location of stations used for interpolation, validation and case-control events.

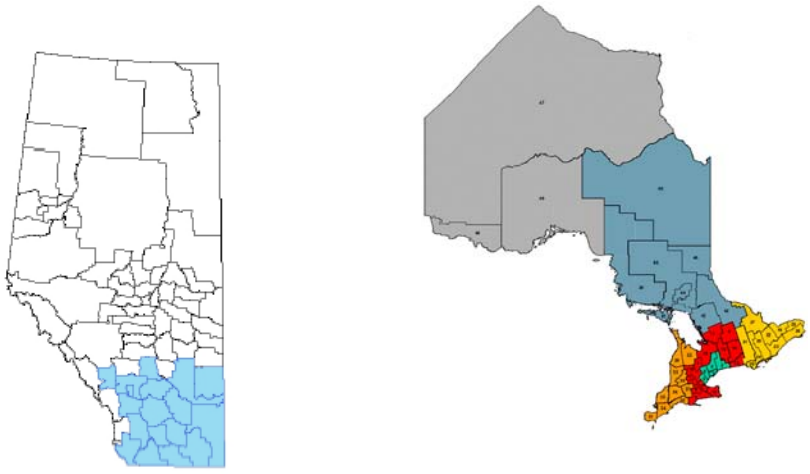


Figure 3. Maps of Alberta (left) and Ontario (right). Highlighted areas are the study regions of interest due to data availability.

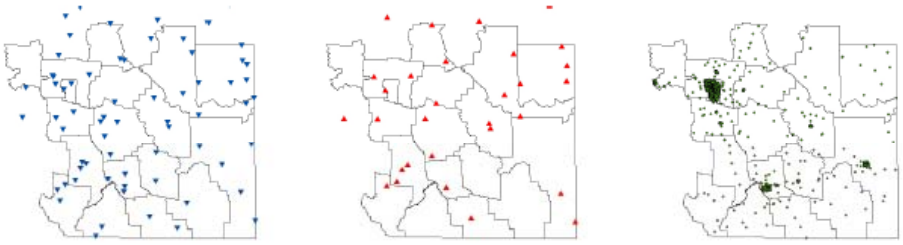


Figure 4. Magnification of the Alberta study region by (a) location of stations used for interpolation, (b) location of stations used for validation, and (c) case and control hospitalization events.

To alleviate potential computational issues, the interpolation proceeded as follows. For each day of the study, a temporal window was created. This allowed the current TPS model to be produced with current observed daily information, as well as that within a time span of five days. This generated 11 days worth of predictions (5 days prior to, the day of and 5 days following the event). To prevent temporal edge effects, only the middle 7 predictions were recorded. The window was then moved to the next day, and the process repeated. Once each day was interpolated, up to seven values for each space-time prediction was created. These were averaged to produce a final set of interpolates for each space-time event.

The set of interpolated data was explored to check for consistency. A few problems were noted. Specifically, 134 space-time events (from a possible selection of over 4.8 million) had

interpolated minimum temperatures that exceeded the maximum temperature. In these events, the 42-day average minimum and maximum temperatures were replaced.

Further inspection of interpolates revealed issues related to spatial edge effects. That is, predicted values exceeding ±100°C. In these cases, the offending value was replaced by the average minimum or maximum temperature for that particular day, as required. To further eliminate extremely unusual readings (for example, temperatures in the ±50°C range), each interpolate was compared to the observed date specific distribution of maximum or minimum temperature. Cases were deemed unusual if the predicted temperature exceeded more than three standard deviations from the observed daily mean. In such events, temperature was replaced with a randomly selected value derived from a normal distribution representative of the observed daily values.

To ensure that the interpolation technique was adequate, interpolates were compared to a list of known climate values. This was done for each of the daily TPS surfaces modeled and the initial investigation of interpolated data suggested a good fit.

Looking solely at the Root Mean Square Errors (RMSE) of Prediction for each of the minimum and maximum daily temperatures, we found that the average weekly temperatures fit well with *RMSE* (*Maximum*) = 4.228°C and *RMSE* (*Minimum*) = 4.403°C. The smaller the average weekly temperature, the better the fit.

Investigation of the average weekly temperatures further suggested that the model predicted very well. Comparing the average weekly-predicted temperature with the average weekly-observed temperature, we obtained *RMSE* (*Maximum*) = 2.94°C and *RMSE* (*Minimum*) = 3.04°C.

Therefore, the simulation showed that inclusion of elevation and temporal covariates in the TPS model is better than just using the latitude and longitude in terms of predictability. It also showed that inclusion of lag variables into the thin-plate method could produce even stronger results, however obvious limitations prevent this from occurring.

3.4.2. Inverse distance weighting

Inverse distance weighting (IDW) is an interpolation method that uses data observed at locations neighbouring an unobserved point. Data is averaged based on the observed values at the neighbours and weighted according to the distance from the unobserved location. Weighting can be based on inverse distance, inverse squared distance, or any other factor. Details of the IDW can be found in Appendix F.

IDW Interpolation of Alberta and Ontario Precipitation Data

The IDW method of interpolation was used to determine unobserved precipitation values given a weighted average of nearest neighbours. Specifically, a 5-point nearest neighbour method was used for the interpolation of precipitation data for Ontario and southern Alberta within the time span of the study.

Locations for interpolation were determined by the location of case or control events as extracted from the Canadian Institute for Health Information (CIHI) hospitalization database from 1992-1998.

The first step in the interpolation process involved determining a list of stations that were geographically closest to the case or control in the database and the five closest stations were selected. From this list, a weight was determined for each neighbour proportionate to its distance from the case or control, specifically the inverse squared distance. Stations closer to the case or control were weighted higher than those farther away and overall the weights should sum to one.

To complete the interpolation process, the precipitation value at each weighted station was extracted from the Environment Canada climate database for each temporal location of the cases or controls. The precipitation data was weighted as determined by the distance from the unobserved location using observed data. In this way, each space-time event was assigned an unobserved precipitation value.

To test the adequacy of prediction, histograms of each climate variable were presented for both observed and interpolated values. The predicted values adequately followed observed distributions for each of the variables considered, except for snow depth, which showed very different distributions. This suggests that the interpolation procedure used was either not adequate enough, or inappropriate for the type of variable considered.

3.5. Climate change scenarios

3.5.1. Global Climate Models (GCMs)

Climate change scenarios may be defined as plausible descriptions of future states of the world's climate. They are produced by Global Climate Models (GCMs) that endeavour to represent the physical processes of and feedbacks among the earth's atmosphere, oceans, cryosphere and land surfaces. In essence, these massive computerized models simulate the complex climate system using mathematical equations that describe the radiation budget, its translation into heat and motion, and the different stages of the hydrological cycle. GCMs take into consideration also possible future emissions of greenhouse gases and aerosols into the atmosphere, which in turn, depend on socioeconomic factors such as population growth, energy use and economic development. The Intergovernmental Panel on Climate Change (IPCC) developed many possible emission scenarios (known as SRES scenarios) that have been classified into four major types (A1, A2, B1, B2) depending on whether or not the scenario has a 'global' or 'regional' development focus, and whether or not it is driven by 'environmental' or 'economic' considerations (IPCC, 2000).

Most GCMs have a horizontal resolution of between 250 and 600 km. This resolution is very coarse, particularly when studying waterborne disease outbreaks that most often occur at a local geographical scale. Figure 5 illustrates, as an example, the wide range of scenario outcomes for mean air temperature and precipitation for the Ottawa region when several GCMs and different SRES experiments are considered.

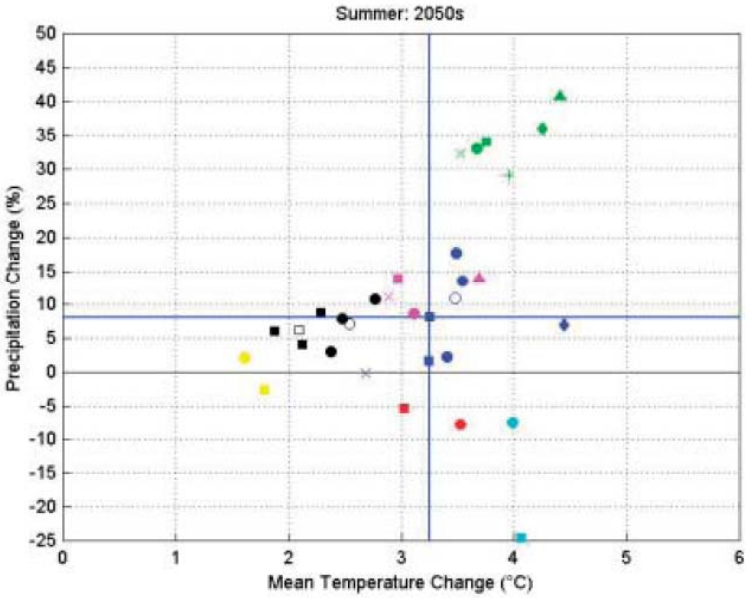


Figure 5. Scatter plot of changes in mean temperature and precipitation for the Ottawa region for the 2050s summer season, as projected by several GCMs and experiments undertaken with the SRES emissions scenarios. The blue horizontal and vertical lines represent the median changes based on this suite of climate change scenarios. Each colour represents a different GCM and each symbol represents a different SRES experiment with the corresponding GCM. (Source: Barrow et al., 2004)

The limitations of GCMs are highlighted in the IPCC Third Assessment Report (IPCC, 2001).

> "In climate research and modeling, we should recognize that we are dealing with a coupled non-linear chaotic system, and therefore that the long-term prediction of future climate states is not possible. The most we can expect to achieve is the prediction of the probability distribution of the system's future possible states by the generation of ensembles of model solutions."

Furthermore, climate modelers caution users of grid-point scenario data generated by GCMs (CCCma, 2005).

> "The user should be aware that grid-box values are not directly comparable to station data. Climate models attempt to represent the full climate system from first principles on large scales. Physical "parameterizations" are used to approximate the effects of unresolved small-scale processes because it is not economically feasible to include detailed representations of these processes in present-day models. Caution is therefore needed when comparing climate model output with observations or analyses on spatial scales shorter than several grid lengths (approximately 1000 to 1500 km in mid-latitudes), or when using model output to study the impacts of climate variability and change. The user is further cautioned that estimates of climate variability and change obtained from climate model results are subject to sampling variability. This uncertainty arises from the natural variability that is part of the observed climate system and is generally well simulated by the climate models."

In spite of GCM limitations and the added uncertainties associated with the different demographic projections, GCM outputs may be considered useful illustrations of what may happen on a large scale. They can provide users with a perspective of what is probable, as well as some indications of the 'range' of what is plausible (Hengeveld, 2004). In this respect, we employed the output of two IPCC-recognized GCMs, namely the Canadian CGCM2 and the UK HadCM3 to derive several large-scale meteorological variables and indices of potential applications in studying waterborne disease outbreaks. For example, in Figure 6 the CGCM2 projected the number of days with heavy precipitation (> 50mm) would generally increase in the 2050s, compared to the baseline climate (1961-1990) over much of Canada, particularly on the west coast and in eastern Ontario and southern Quebec. The UK model (Figure 7) suggested a somewhat different distribution of these precipitation events, showing an increase on the west coast and from Manitoba eastward. In Figures 8 and 9, the two models project a consistent increase in July degree-days >0ºC over all of Canada's land areas, but with some differences in the magnitude of the increase. The examples in Figures 6 to 9 employ SRES scenario A2, which refers to a very heterogeneous world with continuously increasing population. Economic development is primarily regionally oriented and per capita economic growth and technological change more fragmented (IPCC, 2000).

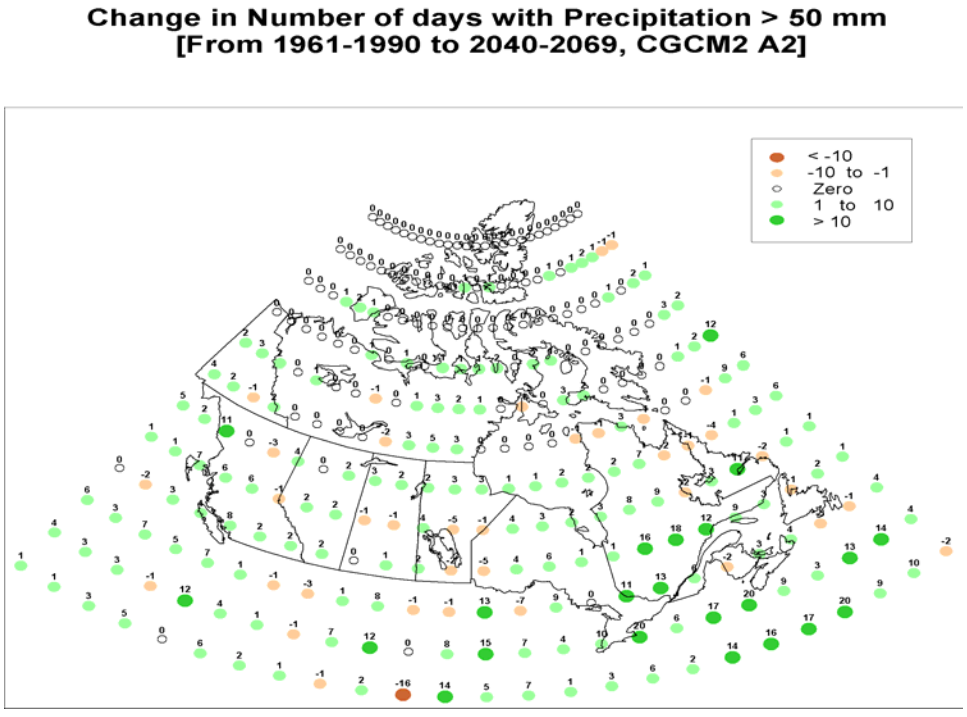


Figure 6. Change in Number of Days with Precipitation > 50mm (from the 1961-1990 to 2040-2069 A2)

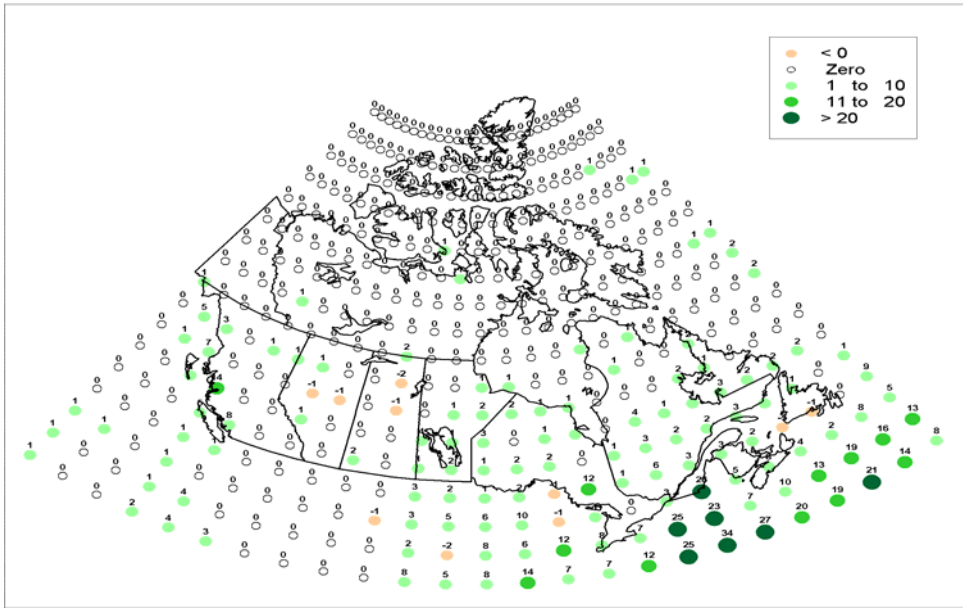


Figure 7. Change in Number of Days with Precipitation > 50mm (from the 1961-1990 to 2040-2069 HadCM3 A2)

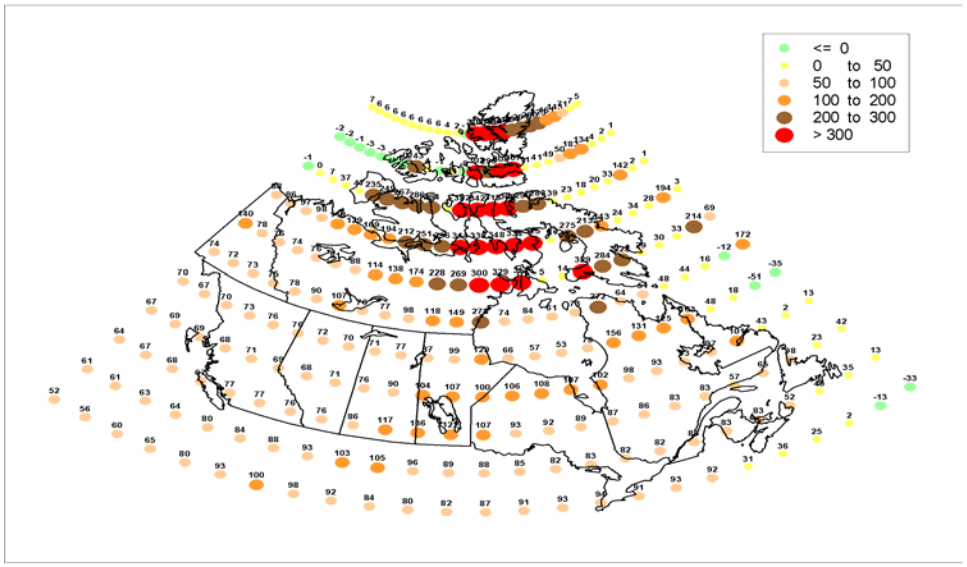


Figure 8. Change in Degree-days > 0ºC (1961-1990 to 2040-2069) of the July Maximum Temperatures (CGCM2 A2)

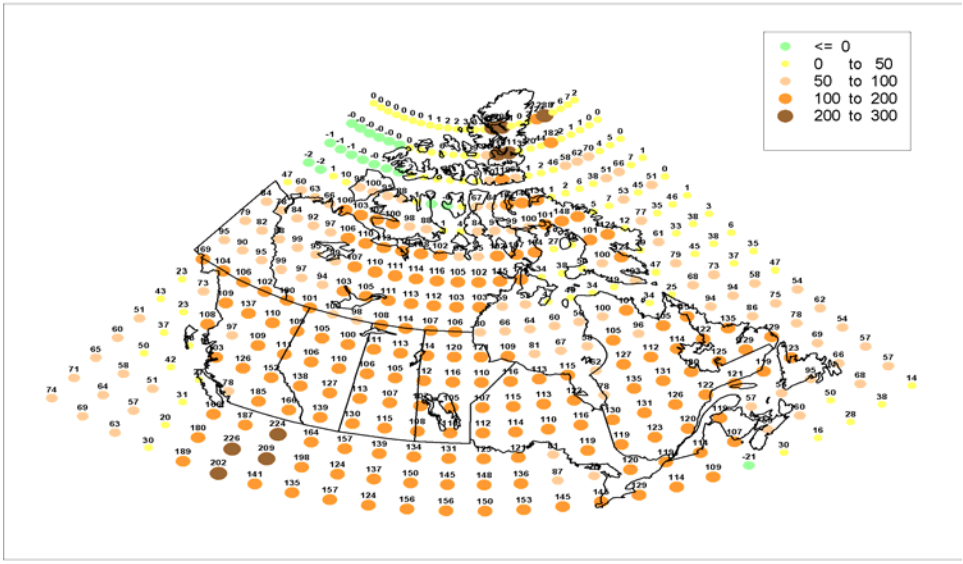


Figure 9. Change in Degree-days > 0ºC (1961-1990 to 2040-2069) of the July Maximum Temperatures (HadCM3 A2)

3.5.2. Regional Climate Models (RCMs)

Regional Climate Models (RCMs) are high-resolution models (40-50 km) that contain a better representation of some climate processes as well as the underlying topography. They can simulate climate features and physical processes in much greater detail for a limited area of the globe while drawing large-scale information from the coarse-resolution GCMs. Considerable progress has been made in recent years in developing the Canadian RCM, and its results will soon become available to the impacts and adaptation assessment community. It should be noted, however, that because of the higher RCM resolution, the cost and extensive computer time required to run climate change experiments with these models would limit the suite of results available for scenario construction. Moreover, there may be only a single experiment available for a particular region, which could severely limit exploring a range of plausible futures in an impact assessment.

3.5.3. Statistical downscaling

Statistical downscaling operates on the premise that 'site-specific' meteorological variables are driven by the large-scale meteorological conditions in conjunction with the 'local' physiographic features such as topography, land-water distribution, surface cover, etc. A statistical model can therefore be obtained which relates a site-specific meteorological history with the large-scale features of the baseline climate (1961-1990) as obtained from GCMs. The statistical model can then be used in combination with GCM outputs to derive future scenarios at the local scale. An inherent limitation in statistical downscaling is the

assumption that the statistical relationships developed for the present climate will remain valid under future climate conditions (Barrow et al., 2004).

We employed grid-point scenarios expressed as monthly mean changes from the baseline climate (1961-1990) to three future 30-year climatic periods centered on 2020s, 2050s and 2080s. These projections are accessible through the websites of the Canadian Climate Impacts Scenarios[1] and the Climate Change Scenarios Network[2]. Simple spatial interpolation translated GCM grid-point scenarios into site-specific monthly mean changes. These projected changes were then used to perturb the parameters of a stochastic weather generator, LARS-WG, in order to simulate future 'daily' weather data. LARS-WG has been extensively used as a consistent and computationally inexpensive downscaling method (Semenov and Barrow, 1997; Semenov and Brooks, 1999). The weather generator analyzes observed weather at a site and, using the parameters derived, is able to produce a series of synthetic weather data of any arbitrary length, statistically similar to the observed weather data. We generated three sets of 30 years of daily maximum and minimum temperatures and 24-hr precipitation amounts, centered on 2020s, 2050s and 2080s, which allow us to examine the climate (30-year climatic normals) of the three future periods. It should be emphasized however that this downscaling tool does not generate daily data for a specific year in the future, but rather for any user-defined arbitrary period representing 2020s, 2050s or 2080s. The historical weather observations used in calibrating LARS-WG were obtained from the climate archives of the Meteorological Service of Canada, Environment Canada[3].

It is therefore suggested that the combined use of GCM output and LARS downscaling tool provides a suitable approach for the construction of climate change scenarios for studying waterborne disease outbreaks.

3.6. Adaptation

The research uses two main theoretical concepts: vulnerability (V) and resilience (R).

V = f {exposure; adaptive capacity}
R = f {ability to absorb change; self-organization; adaptive capacity}

Vulnerability is defined as a function of both exposure to a climate stimulus - in our case an extreme precipitation event - and the adaptive capacity to manage or reduce the impact of that event. Vulnerability is a location-specific measure that is not static, rather it changes over time, sometimes increasing, sometimes decreasing depending on the interaction of its two constituent parts.

Resilience is defined as a combination of i) the magnitude of shocks that an eco-social system can absorb and remain within a given state, ii) the degree to which the eco-social system is capable of self-organization, and iii) the degree to which the eco-social system can learn, experiment and innovate or build adaptive capacity. Thus, similar to definitions of vulnerability which encompass both biophysical and (socially-constructed) social

[1] http://www.cics.uvic.ca/scenarios/
2 http://www.ccsn.ca/index-e.html
[3] http://climate.weatheroffice.ec.gc.ca/

vulnerability, resilience is understood in this research to incorporate both biophysical changes on the landscape and the social institutions required to manifest those changes. The idea of resilience is captured in Holling's "Adaptive Cycle," which emphases its cyclical nature over time through the four phases of exploitation, conservation, release and reorganization.

Vulnerability and resilience are often portrayed as opposites in the literature on human security, natural disasters, and climate change adaptation. This research suggests that the two concepts are not mere opposites, but rather that vulnerability (V) can be reduced and adaptive capacity increased through a process of building resilience (R). Part of the key to understanding the relationship between the two is to study the critical period of transition from vulnerability to resilience.

It is important to understand that the two terms V & R are not opposites, one is not the 'flip side' of the other - just because vulnerability is low does not guarantee that resilience will be high. Vulnerability is defined as a function of both exposure to a climatic extreme and the adaptive capacity to deal with the impacts of that exposure. Resilience is defined as the combined ability to absorb change, the ability to self-organize and adaptive capacity - or the ability to experiment, innovate and learn.

The 'exposure' aspect of vulnerability is made up of two components - a) actual exposure to an extreme event and b) biophysical vulnerability of the landscape - the greater the biophysical vulnerability of the landscape, the great the possible impact of exposure to an extreme. The 'absorb change' aspect of resilience has the potential to mitigate the impact of exposure to an extreme - that is by increasing a landscape's ability to absorb change and reducing biophysical vulnerability. The other aspect of vulnerability, 'adaptive capacity' is also an element of resilience; resilience also has an added component, 'self-organization', which is a sense is a particular aspect of adaptive capacity - or the ability to internally organize to affect change.

The study of community-based adaptation to climate change requires a qualitative research approach to meet the challenge of attempting to understand both the detailed process behind adaptation and the human motivations of the same. The primary research method was the open-ended, semi-structured interview. Thirty interviews were conducted with two different groups of participants, ranging in length from one to three hours:

1. **Members of the Deerwood Soil and Water Management Association**.

Twenty farmer interviews were conducted (50% of the Deerwood members farming in the watershed), including interviews with the Deerwood field technician, the current and past president, 11 of 12 Deerwood Executive Committee members and 6 other Deerwood members (who have all been past Deerwood Executive Committee members and have been significantly active in Deerwood project activities over the past twenty years).

2. **Members of the South Tobacco Creek Project Steering Committee**

Interviews were conducted with 10 Steering Committee members representing Prairie Farm Rehabilitation Association (PFRA), Environment Canada (EC), Department of Fisheries and Oceans Canada (DFO), Manitoba Agriculture, Manitoba Water Stewardship, and the University of Manitoba.

Several standard techniques were employed to select interview subjects. Instead of using random sampling techniques to select a subset of interview subjects from the Deerwood membership list, a 'snowball sampling' technique was used. In this technique, the research interviews start with key informants and each informant is asked to name other potential research subjects based on their knowledge and experience. These subjects are then contacted for interviews and they in turn are asked to suggest other research subjects. Additional interview subjects are sought as long as current subjects continue to suggest new names. This sampling technique was chosen because the goal of the research was to form a comprehensive picture of the formation and evolution of the DSWMA group over its twenty-year history. Thus, it was deemed important to identify and speak with Deerwood members who have been very active in the group at various points in time.

This sampling technique has the possibility of introducing bias into the research because the researcher is directed to speak to people whom the interview subjects believe to be important or key contributors. It is possible to miss a subject who may have played an important but subtle, or unacknowledged, role. The research team attempted to minimize this bias by interviewing a significant number of local Deerwood members (20 members or 50% of the Deerwood membership farming land in the STC).

In addition to the in-depth interviews, several other research methods were used to gather a comprehensive picture of the twenty years of activities in the South Tobacco Creek watershed, including direct participant observation at three local community meetings and secondary document reviews. These documents included government documents, past graduate theses, and research reports from the DSWMA.

4. Major Findings and Policy Implications

4.1. Outbreaks of waterborne illness in Canada

Data on waterborne outbreaks occurring between 1974 and 2001 were analysed, to identify trends, review the current status of monitoring and reporting, and gain a better understanding of the impact of drinking water quality on public health and disease burden. Findings will appear in the *Canadian Journal of Public Health* 2005 (summer), under Schuster et al. (In Press).

Data from outbreak investigations, published and unpublished, were categorized by type of drinking water provider and categorized as *definitely*, *probably* or *possibly* waterborne, based on available epidemiological record. Drinking water systems were categorized as public (municipal), semi-public (privately owned systems providing drinking water to the public), or private (privately owned systems providing water to a family or small group of families).

Data included 288 outbreaks of disease linked to a drinking water source (Table 1). Almost half of the outbreaks were reported in semi-public systems, followed by 99 (34 %) in public systems and 51 (18 %) in private systems. Over one third of all outbreaks were categorized as *definitely* waterborne, based on adequate epidemiological evidence in available documentation. Another 61 outbreaks (21 %) were categorized as *probably* waterborne,

while 128 of the outbreaks (44 %) could only be categorized as *possibly* waterborne, based on available information. Of outbreaks categorized as *definitely* waterborne, most were in public systems. Outbreaks in semi-public, and to a greater extent in private systems, were less likely to be categorized as *definitely* waterborne.

Table 1. Outbreaks categorized by type of drinking water system and by strength of evidence of a waterborne source.

	Public	Semi-public	Private	Total
Definitely waterborne	59 (60 %*)	28 (20 %)	12 (24%)	99
Probably waterborne	17 (17 %)	25 (18 %)	19 (37 %)	61
Possibly waterborne	23 (23 %)	85 (62 %)	20 (39 %)	128
Total	99 (100%)	138 (100%)	51 (100%)	288

*The percentages in parentheses refer to the bottom total – that is, for each type of drinking water system, the proportion of outbreaks that were definitely, probably or possibly waterborne.

Annual totals for all outbreaks were highest during the period 1989 to 1996 (Figure 10). Of the 288 outbreaks, 194 (67 %) were reported during this period. The increase seen in 1991 is presumed a result of the in-depth reporting by the Institut national de santé publique du Québec (INSPQ), which began in 1991 (INSPQ, 2000).

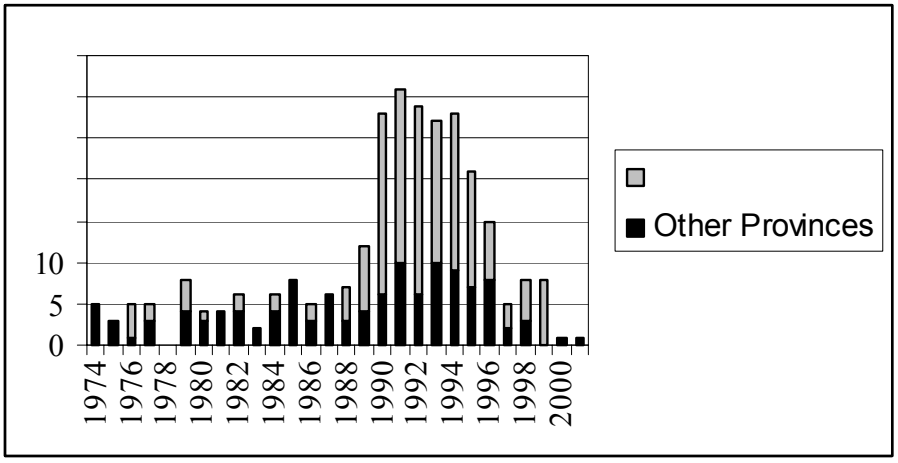


Figure 10. Number of outbreaks by year; also demonstrating the effect of enhanced surveillance by INSPQ in Québec

Pathogens: The pathogen responsible for a given outbreak was unknown in 134 (47 %) of the data. In remaining outbreaks, the most commonly reported cause was *Giardia lamblia*, found in 51 (33%) outbreaks. *Campylobacter* was the next most cited cause 24 (16%) outbreaks, while *Cryptosporidium*, Hepatitis A, Noroviruses and *Salmonella* each accounted for 10 or more outbreaks (Figure 11 and 12). The majority of outbreaks in semi-public and private systems did not document any pathogenic source. Outbreaks in public water systems often included documentation of laboratory confirmed pathogens.

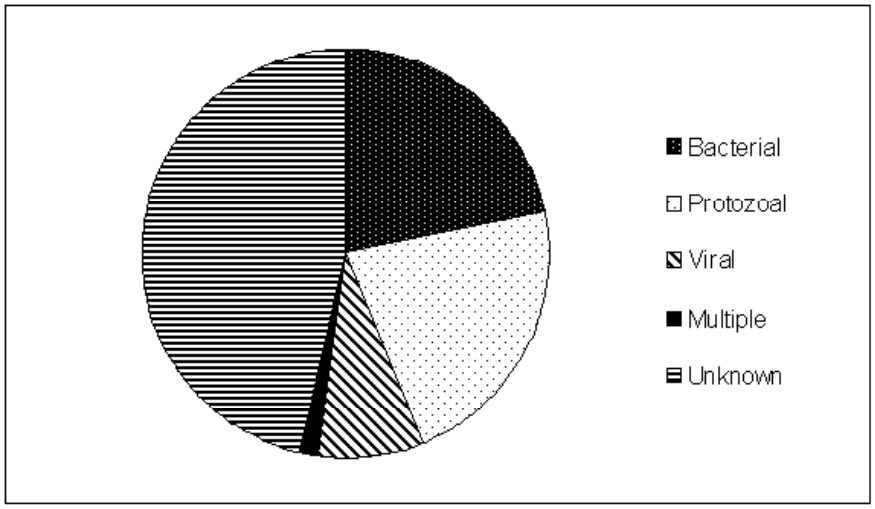


Figure 11. Types of pathogens identified in outbreaks 1974 - 2001

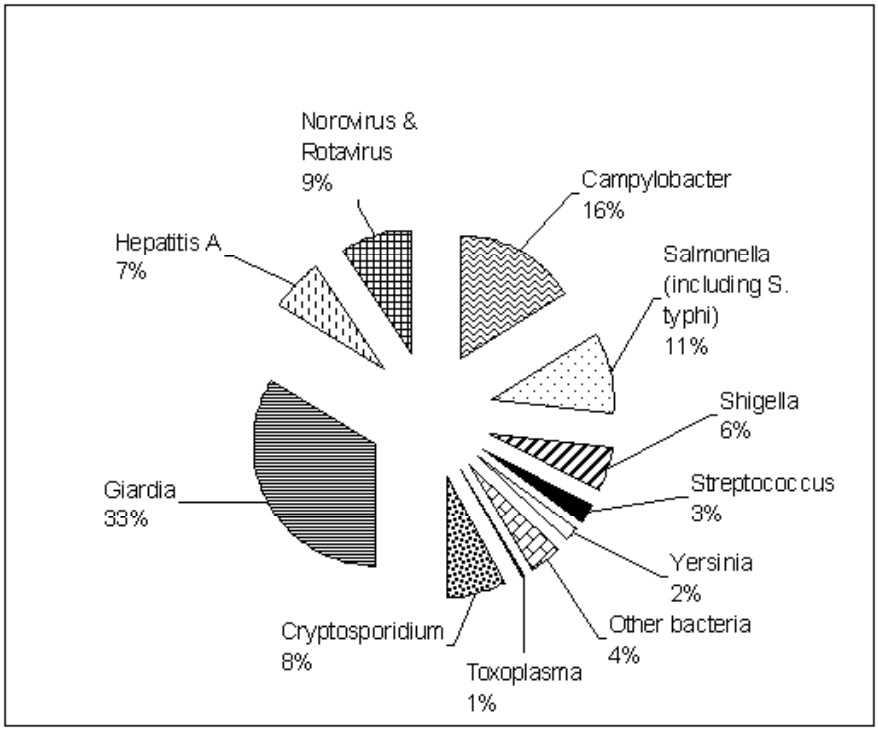


Figure 12. In outbreaks where a single pathogen was identified (n = 150), distribution of pathogens with number of outbreaks attributed to each pathogen shown (other bacteria include: *Aeromonas hydrophilia, Bacillus cereus, Enterobacter hafniae, pathogenic E. coli, Pseudomonas spp. Staphylococcus aureus*)

Causative Factors: For the majority of outbreaks, accompanying documentation contained information on circumstances or barrier failures that were considered by the investigators to have contributed to the outbreak. For this analysis, these data were grouped into 10 categories (Table 2).

Table 2. Factors Contributing to Waterborne Disease Outbreaks by type of drinking water supplier (Public, semi-public or private systems), as provided in epidemiological records[i])

	Water Supply			
	Public	Semi-public	Private	Total
Weather Events:				
Heavy Rainfall	6	0	3	9
Drought	1	1	0	2
Flood	1	0	1	2
Spring runoff	8	1	1	10
Snow melt	1	0	0	1
Animals:				
Wildlife	31	2	1	34
Livestock	6	2	0	8
Frozen wastes	2	0	0	2
Agriculture	4	0	1	5
People:				
Septic Tanks	1	13	7	21
Sewage	8	4	1	13
Cess Pool	0	0	1	1
Non-specific Contamination[ii]	6	45	14	65
Water treatment issues	34	11	2	47
Technical				
Human Source	1	0	0	1
Human Error	4	2	0	6
Recommendations ignored	4	0	0	4
Sanitation	1	3	1	5
Communication	0	1	0	1
No community resistance to pathogen	1	0	0	1
Legislation/Enhanced Treatment Techniques[iii]	34	10	5	49
GWUDI[iv]	3	5	1	9
Water Recycling	0	0	1	1

[i] Some outbreaks were associated with multiple causative factors
[ii] Faecal coliforms were identified as being present, but the exact source was unknown
[iii] If legislation had been in place or enhanced treatment technologies used (e.g. filtration), the outbreak would not have occurred
[iv] Groundwater under direct influence of surface water

In some cases, several factors were documented as having contributed to the outbreak. Of the 288 outbreaks documented here, 223 of them documented a single contributing factor or circumstance. In 9 outbreaks, more than three contributing factors were documented.

Issues with water treatment process and the need for more stringent or enhanced treatment techniques were reasons most frequently cited in outbreak reports as contributing to the occurrence of an outbreak.

Seasonality: In all three water system categories, the majority of outbreaks occurred in spring and summer seasons (79 and 93 outbreaks respectively). Failures or inadequacies in water treatment did not display a seasonal pattern in any of the water system categories.

Meteorological conditions or specific weather events were most often implicated in spring. Several outbreaks occurring in public systems in summer were also attributed, at least in part, to weather events.

Severe weather, close proximity to animal populations, treatment system malfunctions, poor maintenance and inadequate treatment practices were associated with reported disease outbreaks resulting from drinking water supplies. However, issues related to accuracy, co-ordination, compatibility and detail of data exist. A systematic and coordinated national surveillance system for comparison purposes, trend identification and policy development is needed so that future waterborne disease outbreaks can be avoided.

4.2. Endemic gastrointestinal disease in Canada

Pathogens that contribute to endemic gastroenteritis may be transmitted by several routes including food, person-person and through drinking water. The number of people sporadically infected through exposure to contaminated water is still unknown and it is difficult to link source water to illness. Pathogens that are known to be predominantly waterborne are *Giardia*, *Cryptosporidium*, and some proportion of *Campylobacter, E. coli* and *Salmonella*. These pathogens are reportable in Canada and are entered into the National Notifiable Disease Registry (NNDR). *Cryptosporidium* has only been reported in Canada since the year 2000.

Data from NNDR are described for all of Canada, by age, by gender and by province. In Canada from 1988 to 2001 there has been a decrease in the incidence rate of *Salmonella* from 43.36 to 18.37 cases per 100,000 and *Giardia* from 33.87 to 16.29 cases per 100,000. There was a slight increase in incidence rate for *E. coli* in 2000 rising to 8.81 cases per 100,000, due to the outbreak of disease in Walkerton, Ontario. The rate of *Campylobacter* appears to be declining, but is subject to considerable variability (Figure 13).

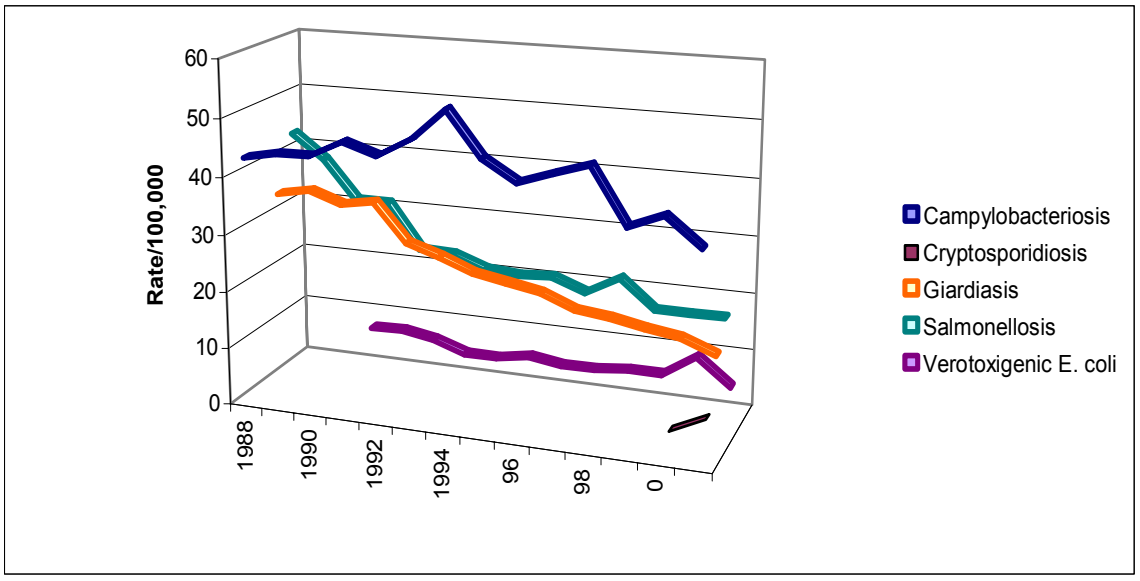


Figure 13. Incidence of disease of the population per 100,000 of *Giardia*, *Salmonella*, *E. coli*, *Cryptosporidium* and *Campylobacter* for all of Canada from 1988-2001 (all ages and all genders)

Figure 14 shows the age-specific incidence for each pathogen in 2000. Incidence was highest in children 0 to 4 years of age for *Cryptosporidium* (10 per 100,000), *Giardia* (38 per 100,000), *Campylobacter* (69 per 100,000), and Verotoxigenic *E. coli* (23 per 100,000). *Campylobacter* in the adult population (age16 to 60) was considerable, at a rate of 44 per 100,000. The incidence rate of *Campylobacter* was also high in children aged 5 to 14 (35 per 100,000), and in the elderly (30 per 100,000).

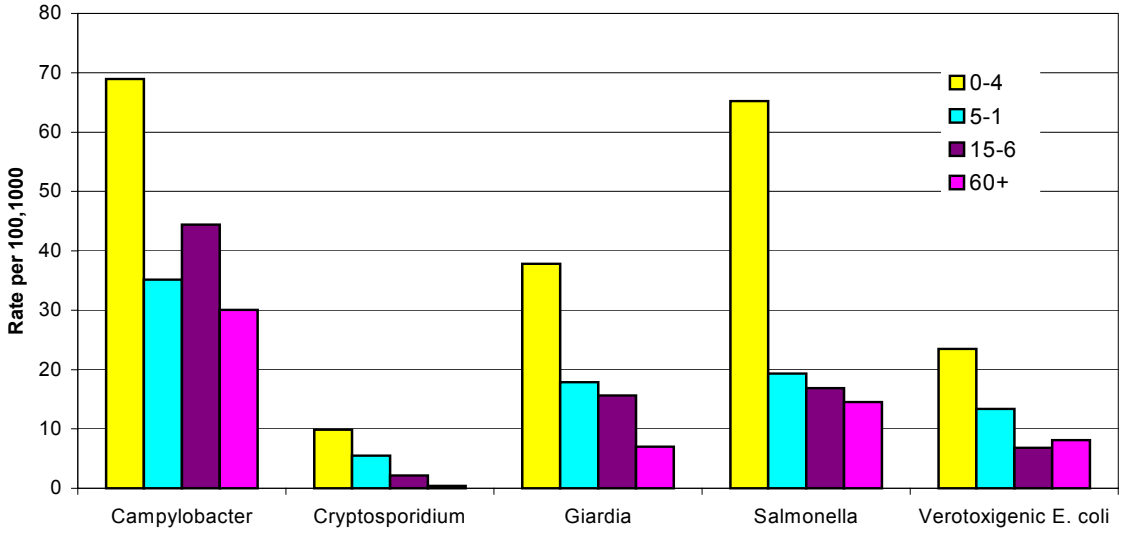
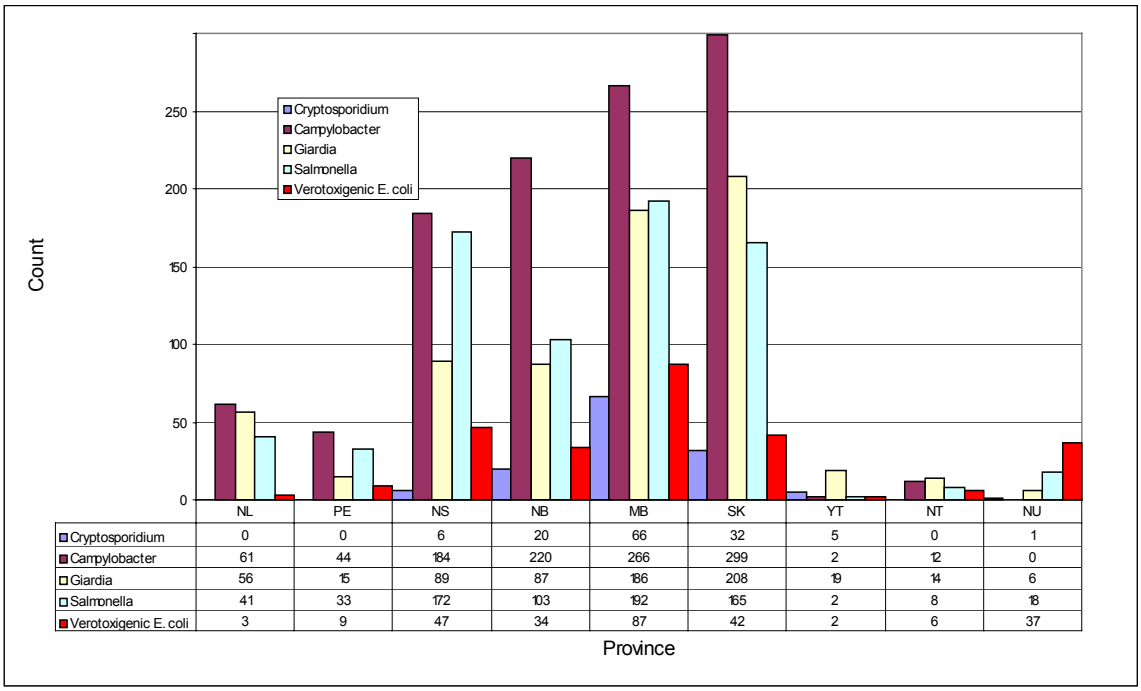


Figure 14. Incidence of *Giardia*, *Salmonella*, *E. coli*, *Cryptosporidium* and *Campylobacter* by age group for Canada, 2000.

Provincial distributions for each pathogen are represented in Figure 15a and 15b. The highest numbers of cases occur in the most populous provinces, Ontario, Quebec, Alberta and British Columbia. These data are subject to provincial differences in laboratory submission rates, testing, reporting and targeted surveillance, and making inter-provincial comparisons problematic. However, some differences are of interest. *Campylobacter* is the most frequently reported pathogen in all provinces, except for the Territories, where *Giardia* or *Salmonella* are more often found. Differences in laboratory testing may account for this.

The Canadian Institute for Health Information (CIHI) receives national hospital discharge abstracts data from 85% of hospitals across the country. The data show that, between 1993-1997, the mean age of cases hospitalized with acute gastrointestinal illness was 39.8 years (0 to 108 years), with the largest number of hospitalizations occurring in adults 20 to 49 years of age, followed by the elderly and children under 5 (Table 5, Appendix G). In most cases where infectious gastroenteritis was suspected, no pathogen was isolated. For those cases with confirmed etiology, viral agents were most frequently found in children and young adults, whereas bacterial etiologies were more frequent in adults and the elderly. There was a decline in hospitalization rates for gastrointestinal illness from 278 per 100,000 in 1993 to 246 per 100,000 in 1997.



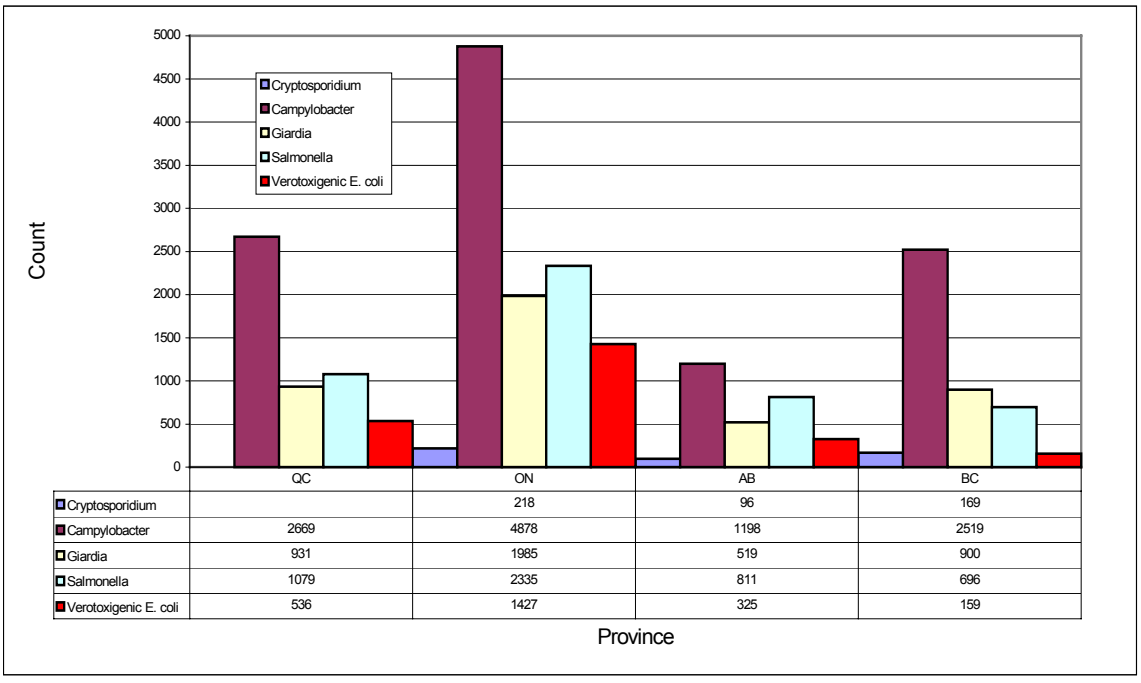


Figure 15 a. and b. Count of *Giardia*, *Salmonella*, *E. coli*, *Cryptosporidium* and *Campylobacter* by province for 2000.

4.2.1. Atlantic Canada Study

Temporal Analysis

The monthly incidence of acute GID for each Atlantic province is summarized in Figure 16, encompassing the entire study period. Three provinces (Nova Scotia, Newfoundland-Labrador and Prince Edward Island) have similar incidence that cycles roughly 3 cases per 10,000 per person-month. New Brunswick demonstrated a higher incidence of acute GID, cycling approximately 17 cases 10,000 per person-month. There does not appear to be any secular trend in the data. Visual inspection of the incidence over time indicates a seasonal component is present, with peaks occurring in late spring to early summer (March to June) in all provinces. Prince Edward Island exhibited a secondary peak in late autumn to early winter (November to January).

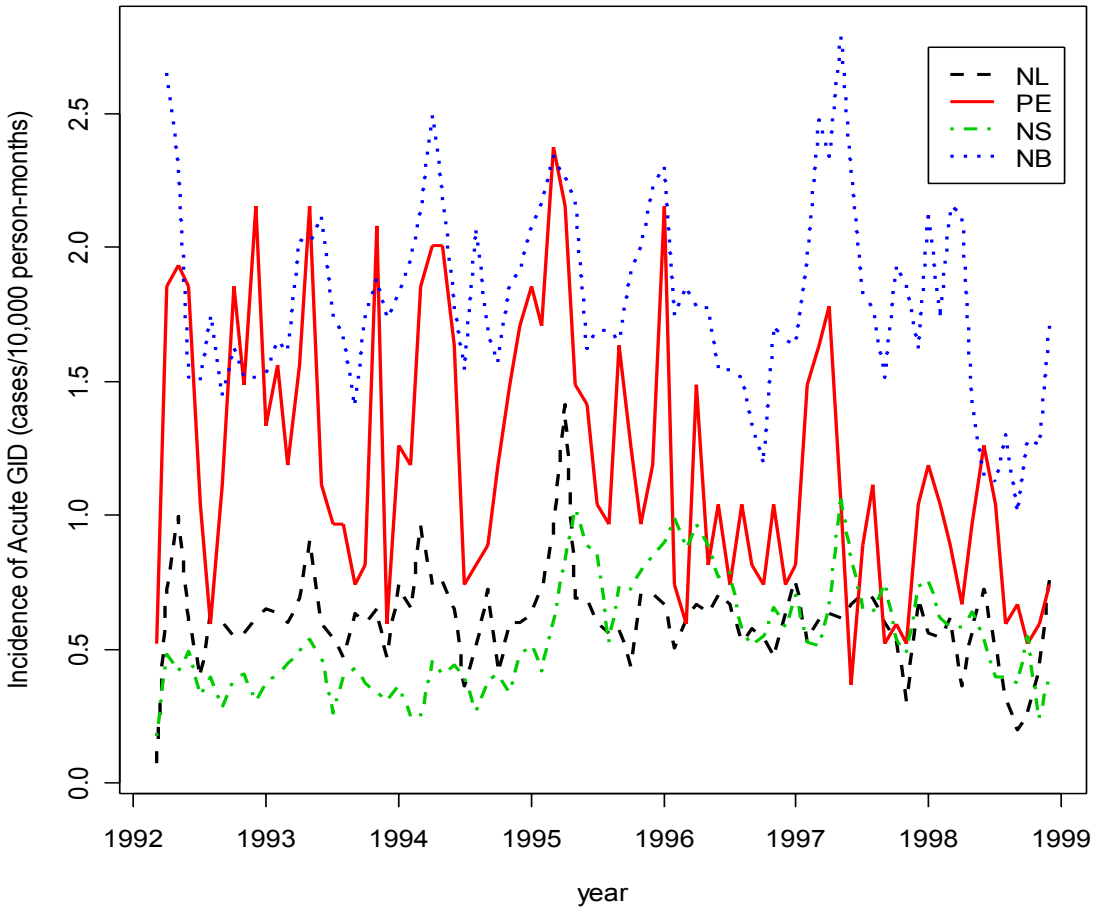


Figure 16. Monthly incidence of acute GID for the Atlantic provinces for the time period January 1, 1992 to December 31, 1998. Month 0 represents January 1, 1992.

There was a significant difference in the incidence of acute GID (cases per 10,000 per person-month) between males and females (p-value < 0.001) for all of the Atlantic provinces,

with males having lower incidence rate than females. The 0 - 4-year age group exhibited the highest incidence of acute GID, followed by the 60 years and older group. Incidence rates of acute GID is high in early life, then lowers between the ages of 20 - 49, when the incidence begins to climb for people aged 50 and older. This trend was seen in all Atlantic Provinces.

Autocorrelation plots were used to explore seasonal and other trends in data. For each province, there is a significant one-month and two month lag in the data, indicating the incidence rate for the current month is strongly correlated with the incidence rate of the previous two months. Figure 41 (Appendix H) illustrates a seasonal pattern for gastrointestinal illness hospitalization in Newfoundland-Labrador and New Brunswick. The pattern is less apparent for Prince Edward Island. Nova Scotia displayed evidence of a long-term trend, peaking in 1995, where a significant increase in gastrointestinal illness-related hospitalizations was seen (Figure 16, previous page).

Kulldorf's SaTScan statistic was used to test for temporal clusters in the data. The primary cluster identified for each province captured the months in spring and early summer and in some cases, winter months (PE and NS) (see Table 6, Appendix H). The mid-point of temporal intervals for three provinces (NL, NS and NB) was in either March or April. Prince Edward Island's primary cluster mid-point occurred in February.

Spatial Analysis

Spatial scan statistic (SaTScan) was used to detect local clustering of disease. Clusters represent an increased incidence of disease compared to areas in the rest of the province. Table 7 (Appendix H) shows clusters for each province, their associated *p*-values and relative risk associated with each cluster. Empirical Bayes smoothing of disease rates was performed to stabilize rates in areas with low population counts.

Inspection of New Brunswick's consolidated census subdivision (CSD) disease rates reveals possible disease clusters in southwest and southeast corners of the province, with a few central and northwest CSDs (Figure 17). When examining data aggregated to the watershed level (also yearly incidence of acute GID), possible clusters appear in the northwest and western watershed and possibly in the northeast/northern watershed (Figure 18).

The SaTScan statistic reveals several significant primary and secondary spatial clusters for New Brunswick CSDs (Figure 19). The primary CSD spatial cluster contained 27 CSDs and was located in the northeast corner. Secondary spatial clusters were revealed in the central area of the province, southeast and southwest corners (Figure 19). The primary cluster and one secondary spatial cluster were significant, according to the SaTScan statistic (Figure 19). Cluster analysis on the watershed level revealed two clusters, a primary cluster (18 watersheds in the north) and a secondary cluster containing a single watershed in the southwest of the province (Figure 19).

Results of the spatial scan statistic for Nova Scotia are shown in Figure 20. One significant primary cluster and five significant secondary clusters were identified. The primary cluster contained two CSDs and was located in the northeast area of the province on Cape Breton Island (Figure 20). Secondary clusters were located in the south and western areas of the province, with the exception of one cluster located in the north, close to the New Brunswick

border (Figure 20). The SaTScan statistic revealed one primary cluster and four significant secondary clusters on the watershed level. The primary spatial cluster included four watersheds, located in the same area as the primary CSD spatial cluster; with secondary clusters located in watersheds in the north, west and south areas of the province (Figure 20).

Prince Edward Island's SaTScan revealed one primary cluster containing one CSD and one secondary significant cluster with nine CSDs present (Figure 21).

The SaTScan statistic revealed a significant primary and seven secondary spatial clusters for Newfoundland and Labrador CSDs (Figure 22). All identified clusters were found on the island of Newfoundland only (Figure 22). The primary CSD spatial clusters contained seven CSDs and were located on the west coast of Newfoundland. The secondary spatial clusters were in the east and southeast areas of the province (Figure 22). On the watershed level, the SaTScan statistic revealed two significant clusters, a primary cluster on the eastern coast consisting of three watersheds and a secondary cluster on the west coast of Newfoundland containing three watersheds (Figure 22).

Further research will address the significance and meaning of the hospitalization clusters. In addition, analyses of the role and impact of various agricultural and meteorological variables are planned, to better understand the determinants of enteric disease in Atlantic Canada.

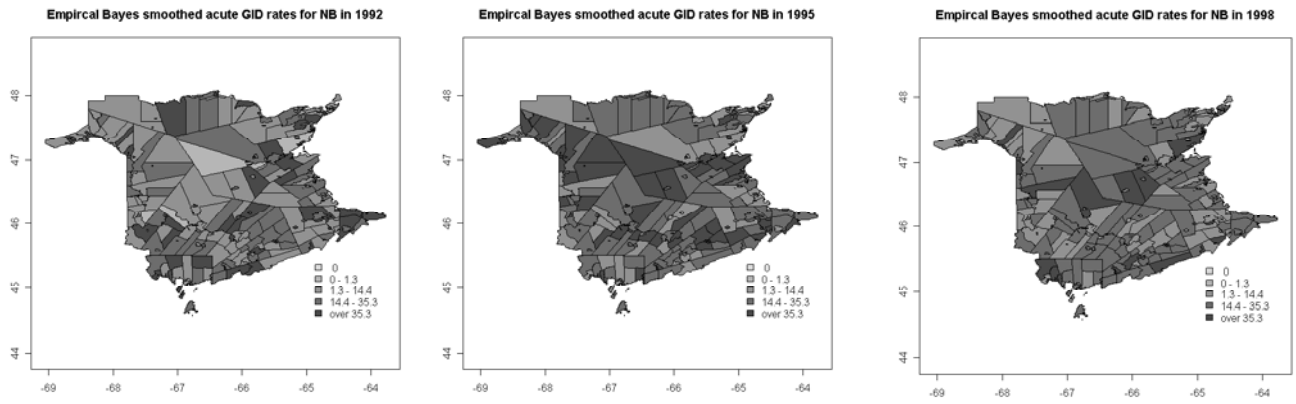


Figure 17: Empirical Bayes smoothed incidence of acute GID rates for New Brunswick consolidated census subdivisions (cases per/100,000 per person-year) for 1992, 1995 and 1998.

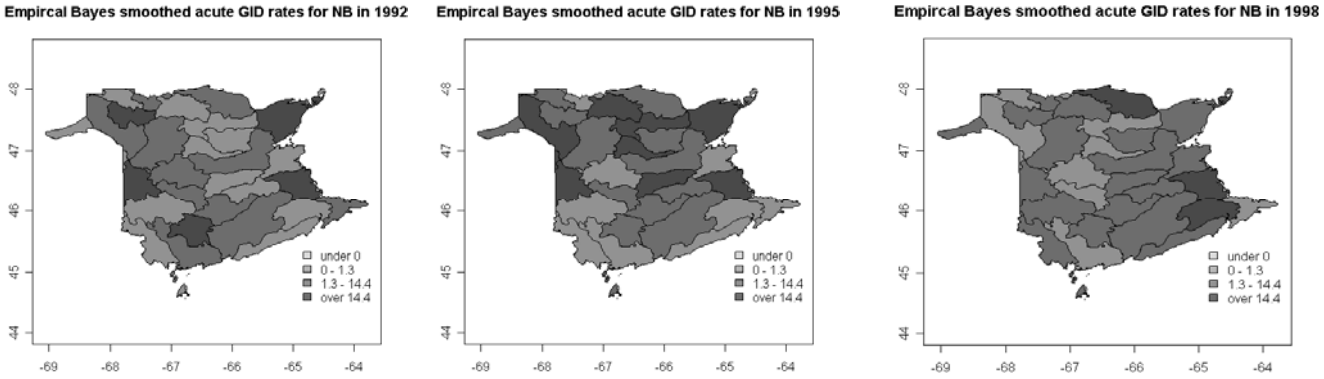


Figure 18: Empirical Bayes smoothed incidence of acute GID rates for New Brunswick watersheds (cases per/100,000 per person-year) for 1992, 1995 and 1998.

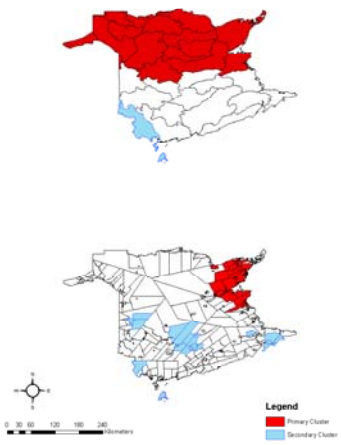


Figure 19: Primary and secondary spatial clusters for acute gastro-intestinal illness in New Brunswick watersheds (top) and consolidated census subdivisions (bottom) from 1992 to 1998.

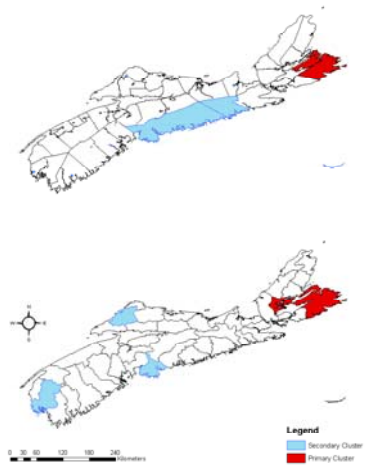


Figure 20: Primary and secondary spatial clusters for acute gastro-intestinal illness in Prince Edward Island watersheds (top) and consolidated census subdivisions (bottom) from 1992 to 1998.

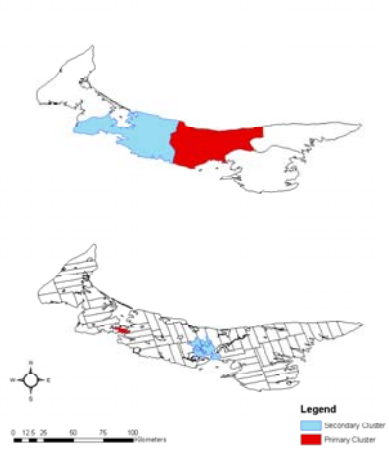


Figure 21: Primary and secondary spatial clusters for acute gastro-intestinal illness in Nova Scotia watersheds (bottom) and consolidated census subdivisions (top) from 1992 to 1998.

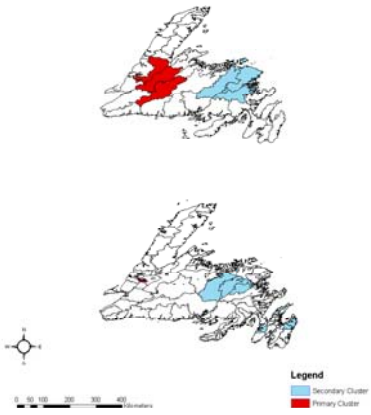


Figure 22: Primary and secondary spatial clusters for acute gastro-intestinal illness in Newfoundland Island watersheds (top) and consolidated census subdivisions (bottom) from 1992 to 1998.

4.3. The Association between weather and waterborne disease

Research Objective #3: Model and quantify the associations between weather variables, water quality and quantity, and incidence of waterborne illness using temporal-spatial analyses in several regions of Canada.

4.3.1. The effect of high impact weather events on waterborne disease outbreaks in Canada

Links between precipitation, air temperature and stream flow, and the occurrence of waterborne disease outbreaks for all outbreaks in Canada from 1974 to 2001 were investigated. Data for 288 drinking water related waterborne disease outbreaks occurring in 1974 to 2001 (compiled by Schuster et al. (In Press). The definition of a waterborne disease outbreak used was two or more cases of disease, occurring at the same place and time, linked to a drinking water supply. Outbreaks that were ambiguous in space or time were excluded. The strength of recorded evidence linking the outbreak to a drinking water source was used to further classify outbreaks as *possibly*, *probably* or *definitely* waterborne. Only outbreaks classified as *probably* or *definitely* waterborne were included in our analysis.

Rainfall was incorporated into the model as three variables: accumulated rainfall (AR) in mm, smoothed using a five-day moving average; the maximum percentile of accumulated rainfall amount (AR percentile); and the number of days between maximum percentile and the case or control onset date (AR days) (Table 8, Appendix I). Air temperature was also modeled using three variables: degree-days, derived by the total degree-days above 0ºC; the maximum air temperature (max. temp.) in ºC, smoothed using a five-day moving average; and the number of days between maximum temperature and the case and the control onset date (max. temp. days) (Table 8). Stream flow was modeled using six variables: peak stream flow in m^3/s (SF peak); percentile of peak stream flow (SF peak percentile); the number of days between peak stream flow and onset date of the case or the control (SF peak percentile days); maximum stream flow (SF) in m^3/s, smoothed using a five-day moving average; maximum percentile of maximum stream flow (SF percentile); and the number of days between the maximum stream flow and the onset date of the case or the control (SF days) (Table 8).

In Canada, peak stream flow due to snowmelt and spring thaw can occur between December and May, depending on geographic location and weather. Only waterborne disease outbreaks occurring between January and May (75 outbreaks) were included for this part of the analysis. A six-week hazard time frame was employed to encompass any peak in stream flow that occurred between December and May prior to the onset date of these 75 outbreaks. When more than one peak (i.e. distinct independent increase in stream flow) was present during this six-week hazard period, the peak closest in time to the onset date was chosen. Significant variables in the final model were degree-days (p-value <0.01) and accumulated rainfall (AR) percentile as a dichotomous variable categorized into above and below the 93^{rd} percentile (p-value = 0.01).

Controlling for all other factors in the final model (Appendix I), we found that extreme rainfall events – 5-day rainfall accumulations in the top 7% for that location – increased the odds of waterborne disease outbreak by a factor of 2.283 (95% confidence interval = 1.216, 4.285). The model also showed that heat accumulation (as modeled by degree days above zero) increased the

odds of waterborne disease outbreak by 1.007 per degree-day (95% confidence interval = 1.002, 1.012). Practically speaking, this translates into a large increase in waterborne outbreak hazard for a small increase in daily temperature. For example, given a minimum daily air temperature greater than 0ºC over the 42-day period, a 5ºC increase in maximum daily air temperature would result in over a four-fold increase ($1.007^{(5*42)} = 4.33$) in waterborne disease outbreak risk, all else being equal (95% confidence interval = 1.52, 12.24).

This study is the first of its kind in Canada to examine the association between high impact weather events and waterborne disease outbreaks. It is also the first application of case-crossover methodology to an investigation of weather and infectious disease phenomena. It highlights the potential contribution of warmer temperatures and extreme rain to waterborne disease outbreaks.

In future studies, knowledge of the microbiological causes, source water characteristics (i.e. ground water or surface water), and characteristics of water treatment for a waterborne disease outbreak, would contribute to more specific identification of the time to event relationship. Alternate derivations of variables could provide further insight into the association of high impact weather events and waterborne disease outbreaks in Canada. Future studies should explore the interaction between rainfall events and temperature, in sequence or together, and would benefit from improvements to the epidemiological documentation of outbreak events.

4.3.2. Outbreaks and climate thresholds

In this section, an analysis of meteorological and hydrological data from an 8-week time period preceding 23 selected outbreaks from the list presented in Section 4.1 was used to investigate the possibility of precipitation and temperature threshold levels beyond which outbreaks may be more likely. Where they occur, such thresholds can be applied to current and future climate conditions as a forecasting tool for increased risk of waterborne disease illness, particularly in more susceptible drinking water systems or individuals. However, additional quantitative modeling and validation of such thresholds would be required before they could apply.

Research undertaken in the U.S. (Curriero et al., 2001) has demonstrated a link between high precipitation events and waterborne disease outbreaks and Thomas et al (Unpublished) have reported finding a significant and positive association in Canada between the likelihood of a waterborne disease outbreak and both preceding accumulated temperature (degree-days) and amount of rainfall.

We conducted a forensic analysis of weather events preceding confirmed waterborne disease outbreaks across Canada to explore and describe thresholds in temperature and precipitation that might contribute to enhanced potential water contamination and therefore increased risk of waterborne disease. Most microbial contaminants in water are deposited on, or just beneath, the ground as a result of domestic and wild animals, agricultural practices, human activity, urban pollution and aeolian processes. Transfer of biological contaminants from soil to a drinking water source must occur in a timely manner, ensuring viability and infectivity of pathogens. This occurs principally through overland flow, which results when the ground is saturated from previous heavy rainfall or snowmelt; the ground is frozen; the ground is dry from a period of little or no rainfall; or rainfall intensity is greater than soil infiltration rate. Biologically meaningful meteorological thresholds for drinking water contamination must include ground conditions, precipitation events, and temperature that contribute to overland flow events.

Thresholds are linked to conditions resulting in overland flow events and can be combined with susceptibility (history of waterborne disease outbreaks; inadequate water treatment practices; treatment failures, maintenance and malfunctions) in order to assess vulnerability more comprehensively. Given this type of information, water users can increase monitoring, alter treatment practices, issue alerts or, in extremely high-risk areas, stop water intake temporarily, in order to protect the population.

Of the 23 confirmed outbreaks of waterborne disease included in this analysis, 11 were linked to rainfall events, 12 to snow melt or spring runoff events, 2 to floods, 2 to droughts and 1 to poor weather, as indicated in the epidemiological record of the outbreak investigation. It should be noted that as a result, this analysis depends entirely on the quality and accuracy of the epidemiological record.

Eleven outbreaks occurred in spring,8 in summer,3 in winter and 1 in autumn. Table 9 (Appendix J) summarises the number of outbreaks exceeding percentile thresholds for variables with the most consistency between outbreaks. These are assumed, therefore, to be the most significant variables preceding an outbreak. Critical periods for extreme weather events appear to be the second week prior to an outbreak event and the sixth to eighth weeks prior to an outbreak (see Table 9 for more details).

Maximum 1-day rainfall is more important than total amounts in the 2-week period prior to an outbreak. Total amounts of rainfall during this period are, at best, the average expected for time of year, falling below the 85th percentile in 20 of the outbreaks and below the 50th percentile in 14 outbreaks. The average maximum 5-day cumulative rainfall was more important than total daily rainfall summed over the two weeks, with 7 outbreaks above the 90th percentile and 12 above the 85th percentile. In 3 of the outbreaks, precipitation (i.e. snowfall - because if it had been rainfall, it would also show up in the rainfall percentiles) was more significant in the 2 weeks prior than rainfall. In 2 of these outbreaks, precipitation was greater than the 90th percentile, even though rainfall was below the 85th percentile.

Discharge data were available for 16 outbreaks. Within the 2 weeks prior to an outbreak, maximum daily discharge exceeded the 90th percentile for 7 outbreaks and the 85th percentile for 9 outbreaks. One record of drought indicated average flow in the 3rd to 8th week period prior to the outbreak as being in the 1st percentile, calculated over the length of the record (i.e. some of the lowest flows experienced during the period of record). The 1-day maximum rainfall in the week prior to this outbreak was in the 93rd percentile. Average flow in the 3rd to 8th weeks prior to outbreaks was greater that the 90th percentile for five outbreaks.

In summary, it is apparent from an initial investigation that maximum single-day rainfall and maximum daily maximum and minimum air temperature over the 2-week period immediately prior to an outbreak were important indicators for an outbreak, as variables for the majority of cases exceeded the 85th percentile of historical record at that location. Values for variables were in the top 15 % of those experienced at the same time of year over the whole record. The same holds for the 6th to 8th weeks prior to an outbreak, perhaps setting up initial conditions for later meteorological conditions to have a greater impact. While it is understood that there must be additional factors allowing sediment- and contaminant-loaded source water to enter the drinking water distribution

system for an outbreak to occur, this limited sampling of outbreaks indicates more extreme events (although not absolute extreme events) generally preceded waterborne disease outbreaks.

4.3.3. Links between weather and endemic gastrointestinal disease

4.3.3.1. Risk factors for hospitalizations for acute gastrointestinal disease in southern Alberta

This case study explored the links between hospitalizations for acute gastrointestinal illness in southern Alberta and variables representing land use, demographics, and weather, for the period 1992-1998. Findings indicate that climate variables significantly affect the risk of hospitalization for gastrointestinal illness. Specifically, the quantities of rain and extreme precipitation events 42-days prior to a case or control affect the outcome. Additionally, the quantity of 'special degree-days' representing moderate daily temperature appreciably impacts the probability of hospitalization. Finally, an indicator variable identifying a higher-than-normal quantity of rain days 42-days prior to case or control event is important.

Analysis preceded according to a step-wise multiple logistic regression methodology in SAS (proc logistic). Fifteen variables (Appendix K) were selected from the approximate 400 variables available.

An increase in the number of days with rain greater than 0 mm ultimately increases the probability of disease. With each extra day of rain within the 42-day time span there was a 1.004 (1.002, 1.007) increase in the risk of hospitalization for gastrointestinal illness (Figure 23).

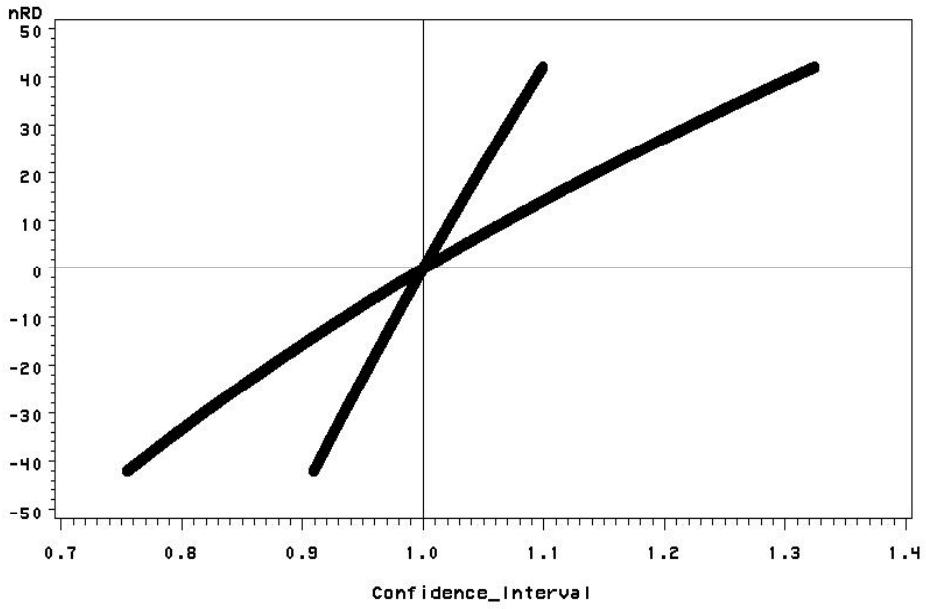


Figure 23: The effect of changes to the number of rain days on the relative risk of hospitalization for acute gastrointestinal disease (holding all other variables constant). The Y-axis represents the number of rain days, and the X-axis the relative risk of hospitalization for acute gastrointestinal disease. The lines on the graph represent the 95% confidence interval around the relative risk, which falls between the lines for the various values of nRD.

Extreme precipitation amount is also a significant contributor to the probability of disease. In this case however, an increasing number of extreme weather events decrease the probability of disease. This may be due to a dilution effect, or the cessation of contamination input. Specifically, each unit increase in extreme precipitation (exceeding 50mm) will decrease the log odds of disease by 0.00081. It should be noted that this variable also appears to interact with the water treatment score, which is expected, as an extreme precipitation event could ultimately affect the quality of water treatment. For example, given a water treatment facility with three different treatment methods (rather than simple chlorination), one would see a further decrease in log odds of disease at a rate of 0.0257 (p-value = 0.0044).

Decreased disease risk was found with higher-than-normal number of days of rain over a 42-day period. The odds of hospitalization for gastrointestinal disease were lower by a factor of 1.12 if the number of rain days exceeded the 95^{th} percentile. This appears to capture a washout effect of heavy rain; that is, with a higher than normal expected level of rain days prior to case or control event, pathogens might be diluted or washed away. Our findings - that number of rain days increases the risk of hospitalization for gastrointestinal illness while extreme rain decreases risk - suggest that, while rainfall is important, its effects depend on amount, timing and context, and that there may well be threshold effects that can be utilized for management purposes. Preliminary analysis of similar Ontario data (next section) found the number of precipitation days may slightly decrease risk of hospitalization, and that extreme precipitation may slightly increase the risk of hospitalization. Some of our other work found that extreme rainfall increased the risk of waterborne disease outbreaks. Further study is required to fully explain the role of precipitation in gastrointestinal disease risk.

Special degree-days (SDD), representing the sum of maximum temperatures over a 42-day period where the maximum temperature was less than 15^{o}C, and the minimum temperature was greater than 5^{o}C was the most significant temperature variable (Figure 24). This finding suggests that mild weather, rather than very cold or very hot days, increases the probability of gastrointestinal disease. For every degree increase in the SDD, the risk of disease increases by 1.003 (p-value = 0.001, with 95% confidence interval from 1.001 to 1.005). Although this quantity is small, the cumulative effect can be significant. Consider an average increase in temperature of 2.5^{o}C on the days where the temperature is within 5 and 15 degrees. This mild change represents an overall increase in risk of 35%.

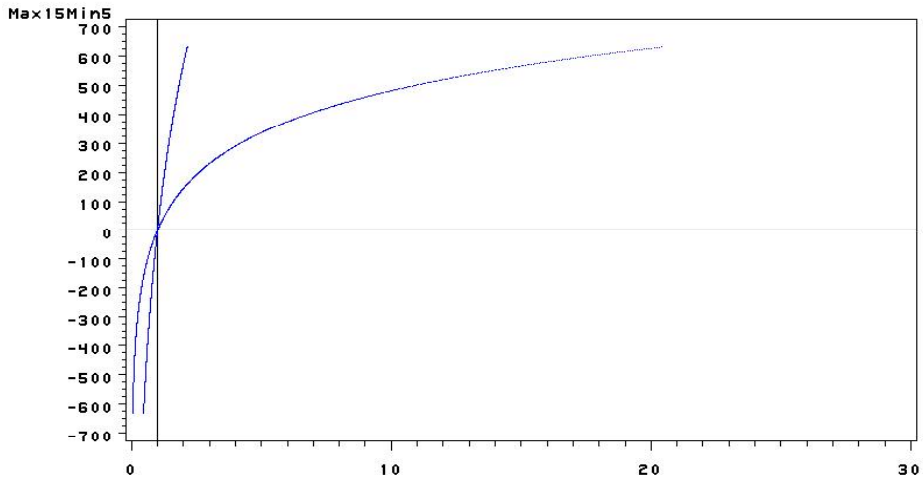


Figure 24: The effect of a range of values for special degree days (SDD), defined as the sum of the maximum temperature on days where the temperature falls between a minimum of 5 and a maximum of 15 on the relative risk of hospitalization for acute gastrointestinal disease (holding all other variables constant). The Y-axis represents the SDD, and the X-axis the relative risk of hospitalization for acute gastrointestinal disease. The lines on the graph represent the 95% confidence interval around the relative risk, which falls between the lines for the various values of SDD.

Patient age and gender were significant risk factors for gastrointestinal illness, and these varied geographically. Females in watershed 13 (Bow River) have a higher relative risk of disease compared to males and to other watersheds. The lowest risk appears to be in watershed 12 (Red Deer River).

By holding all variables constant, one can investigate the effect of land use on the log odds of disease. The analysis indicates that land use classes 4 through 15 (see list in Appendix K) may be at increased odds of hospitalization for gastroenteritis. Land use classes 16 to 25 have decreased odds of hospitalization for gastroenteritis. Interestingly, those that classes which increase the odds of hospitalization for GID are classes that have some level of agricultural application (corn, soy, pasture and high biomass crops). The largest contribution to this increase is related to high biomass crops (land use 14).

This could be a surrogate for agricultural practices, such as type and quantity of surface manure spread. However, this could also be an artifact of where individuals reside, since classes that decrease risk of illness are those that do not have an agricultural application, but tend to be forested or barren lands. Further study is warranted to investigate this relationship.

The model also contained an autoregressive term to account for autocorrelation in the data, latitude, longitude and consolidated census subdivision.

4.3.3.2. Risk factors for hospitalizations for acute gastrointestinal disease in Ontario

Records for Ontario exceeded 1 million cases (hospitalizations for acute gastrointestinal disease) and controls (other hospitalizations, with no gastrointestinal disease). To account for this, the model building process followed that as outlined for Alberta (Appendix K). Variables that significantly improved the fit of the model, including one interaction term, are in Appendix L. Since some of the

Wald Type III p-values indicate non-significant parameter estimates, further research is required to find the appropriate fitting model. However, this analysis provides some interesting results. Similar to the Alberta study, variables investigated are described below, in the event that they differ from those described previously. Of note is the difference in definition of the SDD for Ontario. It should be stated that the final model does not fit the data as well as that of Southern Alberta. However, it is still useful in terms of directing future research, as will be highlighted in the paragraphs below. The Hosmer-Lemeshow Goodness-of-fit test has a significant p-value of 0.0087, which indicates that model fit could be improved. This could occur via the introduction of better variables, or through the use of non-linear or non-parametric modeling techniques.

Ontario data suggests that climate plays a significant role in the spatial and temporal distribution of hospitalizations for gastrointestinal illness. Similar to the results of the southern Alberta study, climate variables representing the number of extreme precipitation events contribute to disease risk. Further, the number of precipitation days appears to reduce the probability of disease (the opposite was found in the southern Alberta study). Additionally, the 42-day average maximum and minimum temperatures are important. These variables were not in the final model from the Alberta study, although they were considered during the model building process. As with Alberta, we see the introduction of a 'special degree-day' playing a significant role in the probability of disease.

Variables explaining precipitation were not as significant in the Ontario model as in the Alberta model. The direction of the association between variables representing number of rain days and extreme rainfall and the outcome were reversed, compared to the Alberta model.

The number of precipitation days in a 42-day period decreases the log odds by 0.00240 (p-value 0.1472) for every extra precipitation day, whereas the same variable increased the odds of hospitalization in Alberta. However, since the p-value indicates the precipitation day count for Ontario is not significant, the impact on log odds is negligible. The variable remains in the model, despite its insignificant parameter estimate, since it was found to improve the model fit. Further study could shed some light on the impact of this particular variable. Additionally, since this variable counts different events (days with total precipitation > 0 mm versus days with rain > 0 mm), it is possible that the overall effect could have the opposite sign as that of the rain day count in Alberta.

When we consider the number of extreme precipitation days (those with total precipitation in excess of 50mm), it appears that log odds increased by 0.0250 (p-value 0.4049). This compares to a decrease in log odds for Alberta. However, as discussed above, the parameter estimate is non-significant and thus its effect on the log odds is negligible. Further investigation could include a non-linear or non-parametric approach to modeling this particular variable. Additionally, redefining the variable might provide a better estimate.

As with Alberta, the 'special degree-day' significantly improved the fit of the model. However, the parameter estimate is not significant. This implies that its effect on the log odds is negligible. The range of temperatures for this variable (min above 5, max less than 20) is wider than that which was important for Alberta.

The 42-day average minimum and maximum air temperatures were not part of the Alberta final model, although they were considered. In Ontario, they appear to significantly influence the

distribution of hospitalizations for gastrointestinal disease. Specifically, average minimum temperature decreases the log odds by -0.0156 (p=0.0030) while the average maximum increases log odds by 0.0159 (p=0.0049) per degree increase. Since parameter estimates are similar, it suggests that an increase in the averages by the same amount would have a small overall effect on the probability of disease. This could suggest that as temperatures increase uniformly, and holding all other variables constant, the risk of disease would change upwardly. For example, an overall 5-degree increase in average maximum and minimum temperatures results in a relative risk of 1.0015 and a 95% confidence interval of (0.884, 1.133), or a statistically non-significant change in risk. This does not imply that a risk change will not occur given other changes in minimum and maximum temperature. To illustrate this, the following two graphs plot the confidence intervals for different combinations of changes to the average maximum and minimum temperatures.

Figure 25 illustrates the range of estimates of risk of hospitalization for acute gastrointestinal illness, for a range of values of minimum temperature, given a one-degree increase in maximum temperature. The average minimum changes between -5 and 5^{o}C. Notice that if the average minimum increases by more than 2^{o}C, there is a decrease in the relative risk of hospitalization for gastrointestinal disease. Cooler minimum temperatures appear to increase gastrointestinal risk.

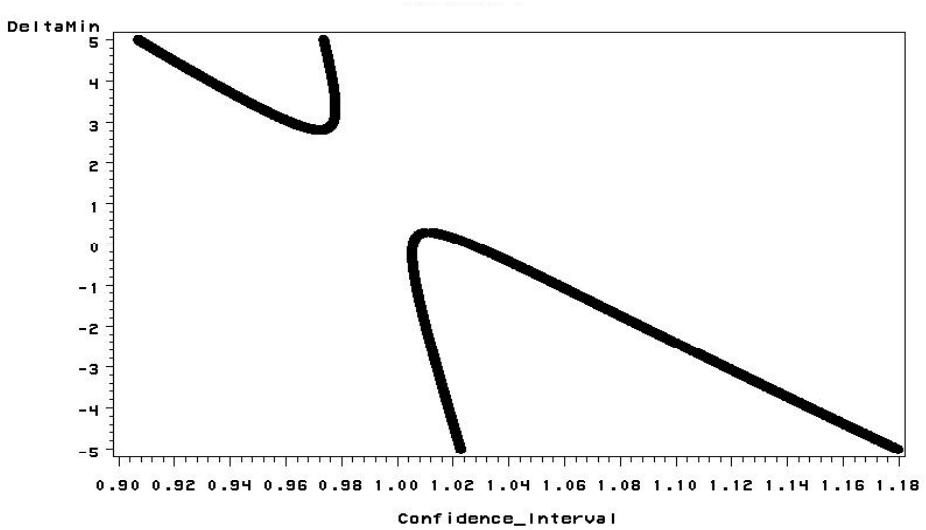


Figure 25: Plot of the 95% confidence intervals for estimates of relative risk of hospitalization for acute gastrointestinal illness (X-axis) versus average minimum temperature (Y-Axis DeltaMin) given a fixed one degree increase in maximum temperature, all else held constant in the model.

In Figure 26, estimates of risk of hospitalization for acute gastrointestinal illness range vary with average maximum is allowed to change in the range of -5 to 5^{o}C, given a fixed one degree increase in minimum temperature. In this situation, cooler maximum temperatures are associated with lower gastrointestinal disease risk. If one considers the obvious seasonal fluctuations in both average maximum and minimum seasonal temperatures, it is easy to see that the temporal aspect associated to the risk of hospitalization for GID is indeed significant.

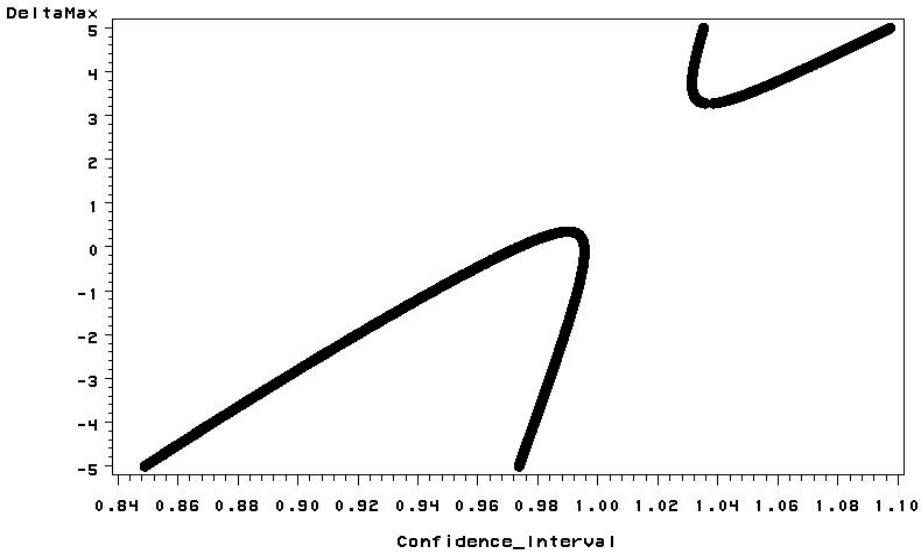


Figure 26: Plot of the 95% confidence intervals for estimates of relative risk of hospitalization for acute gastrointestinal illness (X-axis) versus average maximum temperature (Y-axis, DeltaMax) given a fixed one degree increase in maximum temperature, all else held constant in the model.

As with the southern Alberta study, age group and gender are both relevant factors affecting the probability of hospitalization for GID (Figure 27). Both studies indicate that females have a higher risk of disease than men. Both studies also indicate that there is a significant interaction between age and gender. Further, both studies have each level of interaction providing the same type of effect on the log odds. That is, females in age groups 1 through 4 (children and young women) have an increased risk of hospitalization for GID, and females in age groups 5 through 7 (adults) have a lower risk than children and older people. Each study used age group 8 (people older than 65) as the reference group. Of note, the age group most at risk for both genders and provinces appears to be the youngest group (4 or less years of age). Additionally, the change in probability for each gender and age combination and across provinces follows the same pattern. There appears to be a declining risk as the age group moves from infant to teenager (age groups 1 to 3), but then a sudden increase in risk for those in their 20s. This is followed by a gradual decline in risk, until those aged more than 65 years, which have a pronounced increase in risk. This suggests the populations most affected by a changing distribution of disease risk are the extremely young and old, and those in their twenties.

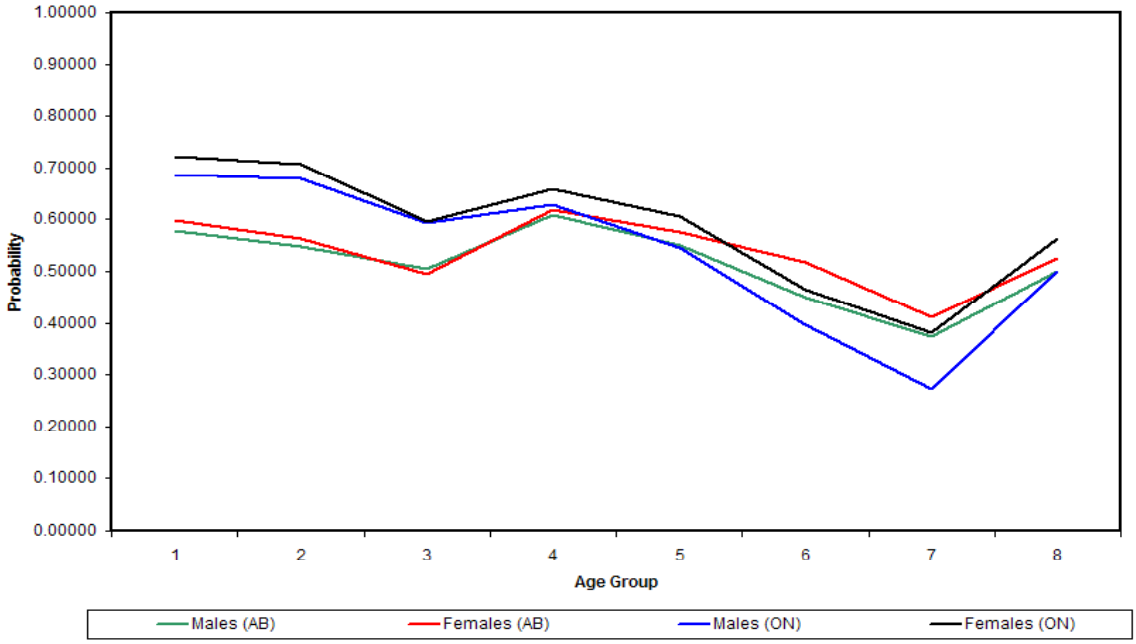


Figure 27: Probability of hospitalization due to gastrointestinal disease given age group and sex for Alberta and Ontario [age groups 0-4, 5-12, 13-19, 20-29, 30-39, 40-49, 50-64, and 65+]

The Ontario study considered the relative distance (as determined by the ArcGIS software; ArcGIS, 2002) between postal code centroids of the case or control and the closest water treatment station. It should be noted that the closest station is assumed to be that which is treating the water for that particular case or control. This of course is not necessarily the case. Nor is water from one tap necessarily sourced from just one treatment plant. Nonetheless, the information provided from this result suggests that the greater the distance to the nearest water treatment plant, the greater the risk of hospitalization for gastrointestinal illness (odds ratio 1.216). That is, for every unit of latitude and longitude distance between the water treatment plant and case or control, the odds of disease increase by 21%.

4.4. Implications of climate change on waterborne diseases

4.4.1. Downscaled climate change scenario data

Tables 10 to 15 (Appendix M) summarise selected features of future climate projections. The data have been generated by statistical downscaling temperature and precipitation outputs from two Global Climate Models (GCMs): the Canadian model CGCM2 and the United Kingdom model HadCM3. These models simulate global climate systems based on inputs of solar radiation, natural and anthropogenic greenhouse gas emission scenarios, atmospheric and ocean circulations and other related phenomena. GCMs simulate climate change at coarse spatial resolutions (typically 300-400km), which are too coarse to be useful in epidemiological models. Downscaled results are based on IPCC greenhouse gas emission scenario A2 (see Section 3.5.1).

Sites listed in the following tables are a subset of the locations for which downscaled data have been generated in this study, and they provide a transect for Canada from west to east. It should be noted that although these projections are plausible, they might not be precise, given the uncertainties

associated with climate change. The uncertainty increases significantly the further we look into the 21st century, and the confidence in these results is higher for temperature than for precipitation.

The 30-year return period refers to the frequency with which a particular event is expected (once in 30 years, on average). An increase in the temperature or precipitation value of the 30-year return period indicates increasing frequency of current extreme events. For example, a daily maximum of 36ºC occurs once every 30 years now, but would occur more frequently in future, given that a maximum temperature of 42ºC (according to HadCM3) becomes the new 30-year value (see Montreal in Table 12). Minimum air temperature would increase in all locations and some areas could encounter values over 30ºC according to HadCM3 (see Table 13). Maximum air temperatures are projected to be highest in interior British Columbia and the Prairies, with Atlantic Canada experiencing up to 6ºC increases from current values while the west coast (e.g. Victoria, BC) would remain least changed (see Table 14).

A 20% increase in annual precipitation amounts would be expected over much of Canada by the 2050s, compared to the baseline period 1961-1990. Small variations are projected for the 30-year return period of maximum 1-day, 5-day and monthly precipitation (Table 10 and 12); however, there would be an increase in the number of days with extreme precipitation events (greater than 50mm per day, Table 15).

In order to gain a general picture of changing meteorological conditions across the country, projections from 5 Canadian cities are presented here.

Victoria, BC, is projected to experience a general increase in precipitation across all seasons, with the average amount in winter increasing by 60 mm. Average precipitation amounts in May, will decrease 20mm by the 2080s. Average maximum temperatures will exceed 10°C in the winter months by the 2080s and spring temperatures will rise by an average 4°C. Average minimum temperatures will increase by approximately 4°C in the winter and spring by the end of the century.

Projections for Lethbridge describe an increase in the number of precipitation days by 2050s, mostly in summer, followed by spring. Heavy rainfall may increase, but there will be less rain in total during the summer. There will be less snowfall in winter. Spring temperatures will be warmer, and summers much hotter by the 2080s.

Climate change projections for Orangeville, Ontario, include generally drier winter and spring months and a rise by more than 20 mm in summer by 2050s, followed by a return to 1961-1990 levels by the end of the century. Average maximum temperatures will increase by 8 °C in the spring and stay above 0°C in winter by the middle of the century. Spring will come much earlier, with average maximum temperatures in March and April rising by 9°C. Autumn will be warmer, with average minimum temperatures rising above 0°C in November at the end of the century.

In Montréal, QC, an increase in average total precipitation is projected to occur, sooner in the winter and spring, increasing also in summer and autumn by the end of the century. Average maximum winter temperatures rose above 0°C 2050s, and are projected to increase by 4-5°C for the preceding years. Winter minimum temperatures will warm by nearly 10°C. The start of winter will be later, with November minimum temperatures well above 0°C by 2080s.

Charlottetown may experience less snowfall in winter and drier spring conditions. However, rainfall in June and November could increase by more than 30mm. Average winter maximum temperatures will rise above 0°C as soon as 2020s, with positive maximum temperatures in January by the 2080s. By the middle of the century, winter will be noticeably shorter, temperatures remaining above freezing in March and November. Summers will be hotter, nighttime temperatures rising by 4°C.

4.4.2. Walkerton

A few more detailed examples of downscaled climate change scenarios are presented for Walkerton, Ontario. Since the Walkerton weather station was closed in 1971, data from Hanover, ON (12 km to the East) were used to supplement the historical record. Figure 28 illustrates a time series plot of extremes of annual 5-day cumulative precipitation using the historical record (1916-2004) and three 30-year scenario periods centered on 2020s, 2050s and 2080s, employing output from the Canadian GCM (upper graph) and the United Kingdom (UK) GCM (lower graph). It is clear from these graphs that the precipitation events in May 2000 that preceded the *E. coli* O157 outbreak in May 2000 were exceptional, but not the most severe historically (late 1960s was more severe). The Canadian model projects fewer events of this severity over the coming century. The UK model projects such events with similar frequency to the present, but with substantially greater rainfall when they occur. In May 2000, excess rainfall was identified on May 12 alone. However, the cumulative rainfall over 5 days including May 12 was higher than average (Auld et al., 2001), hence our interest in this 5-day value. Five-day rainfall was shown to be an important contributor to risk of waterborne disease outbreak in Section 4.3.1.

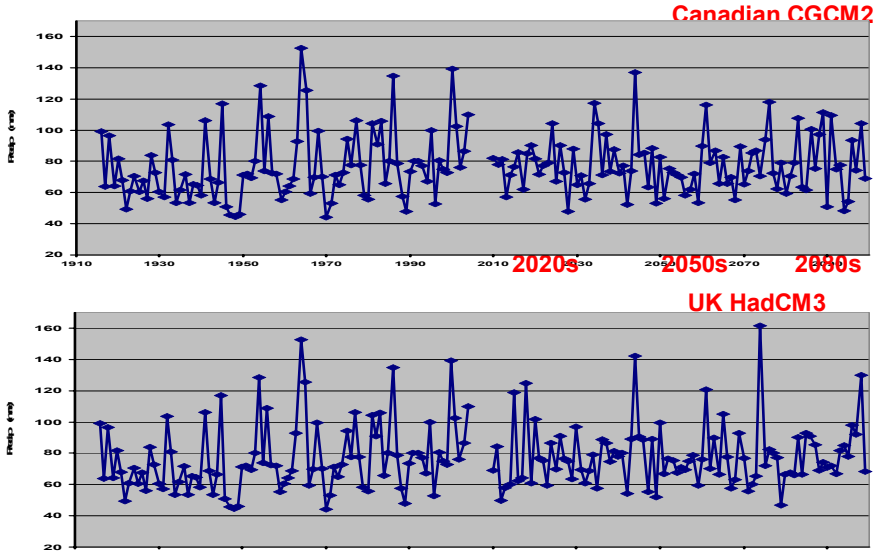


Figure 28. Time series plots of extremes of annual 5-day cumulative precipitation (in mm, Y –axis) near Walkerton, ON, using the historical record (1916-2004) and three 30-year climate change scenario periods centered on 2020s, 2050s and 2080s, employing output from the CGCM2 (upper graph) and the HadCM3 (lower graph).

The monthly long-term average (also called 30-year normal values) of 5-day precipitation extremes is shown in Figure 29 for the baseline climate (1961-1990) and the 2050s. The UK and Canadian models generally agree on the direction of change (increasing or decreasing magnitude of events relative to baseline) although the HadCM3 model projects greater increases in rainfall, particularly in the autumn months. The Canadian model projects greater extreme rainfall in May where the UK model shows greater extremes in March and April. Both models agree on much more precipitation (presumably snow) in January. The UK model projects substantial increases in extreme rainfall in the autumn. This may change the pattern of waterborne disease risk from an historical elevation in spring and summer to an autumn peak with climate change.

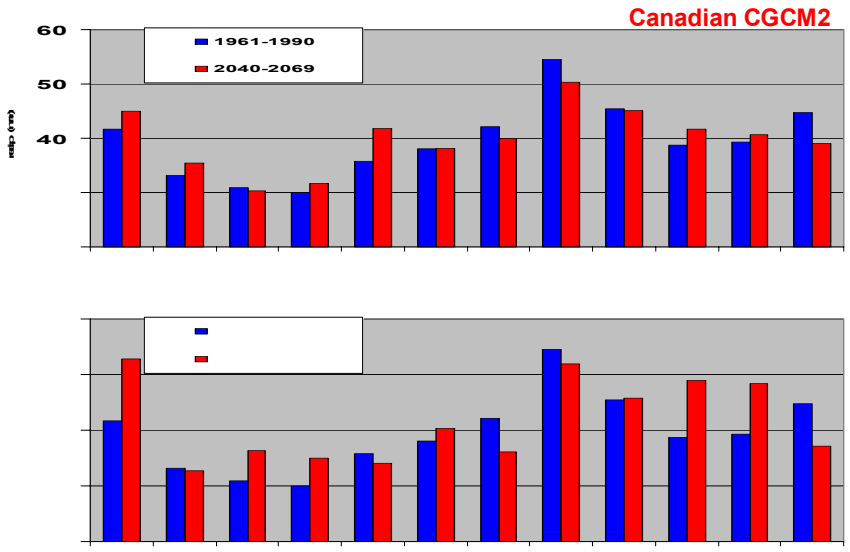


Figure 29. Plot of the average monthly long-term 5-day precipitation extremes (in mm, Y-axis) near Walkerton, Ontario, using the historical record 1961-1990 (the baseline climate) and the downscaled climate change models centered on 2050s, employing output from the CGCM2 (upper graph) and the HadCM3 (lower graph). The historical long-term average is used for reference and is also called 30-year normal.

Figure 30 demonstrates the annual time series of the maximum monthly precipitation, using the historical record (1916-2004) and three 30-year scenario periods centered on 2020s, 2050s and 2080s, employing output from the Canadian GCM (upper graph) and the UK GCM (lower graph). These time series show how monthly precipitation fail to capture events such as those in May 2000. Again, the Canadian and UK models tend to agree on the increased frequency of extreme monthly rainfall, and on the increased variability of rainfall.

Mean seasonal precipitation has increased in all seasons near Walkerton, ON over the period 1921-2000 (Figure 31). These increases have been incremental over the period in all seasons but spring. Climate change projections for mean seasonal precipitation for Walkerton, when compared to the historical record, identify trends for substantial increases in winter and autumn (UK and Canadian models) over the twenty-first century. Both models show an increase in spring precipitation, particularly toward the end of the century.

Taken together, the projected precipitation levels for near Walkerton tell us that the weather preceding the devastating *E. coli* outbreak of May 2000 was an exceptional event by historical standards. Five-day precipitation events of this nature are projected to occur with approximately the same frequency in future, but with perhaps greater severity when they do occur. In terms of waterborne disease hazard, the projected increases in mean monthly and mean seasonal precipitation for winter and autumn raise concerns regarding increased risk of drinking water contamination.

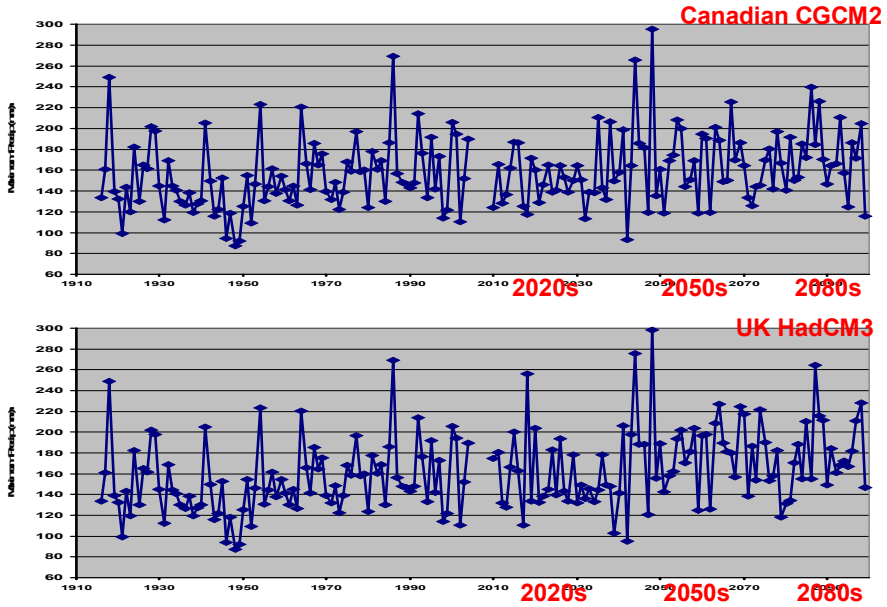


Figure 30. Time series plots of the maximum monthly precipitation (in mm, Y –axis) near Walkerton, Ontario, using the historical record (1916-2004) and three 30-year climate change scenario periods centered on 2020s, 2050s and 2080s, employing output from the CGCM2 (upper graph) and the HadCM3 (lower graph).

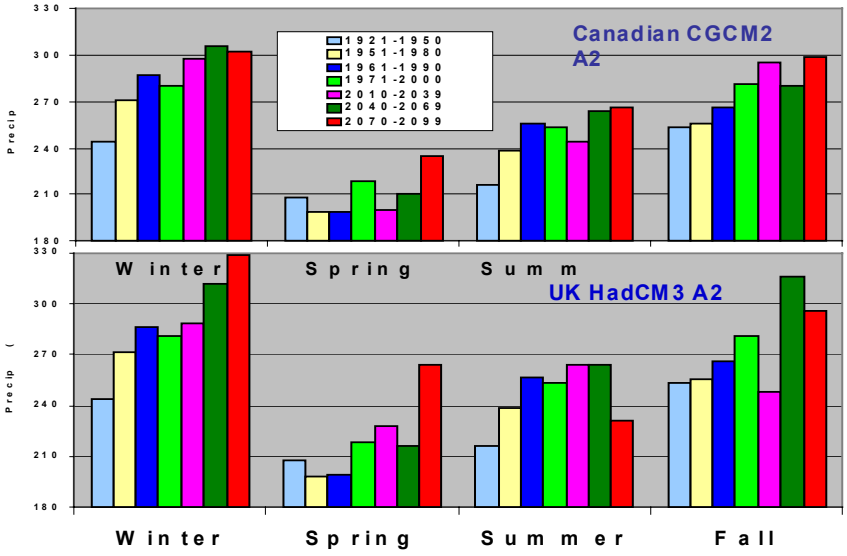


Figure 31. Time series of mean seasonal precipitation (in mm, y-axis) near Walkerton, Ontario, using historical data from 1921-2000, and three 30-year climate change scenario periods centered on 2020s, 2050s and 2080s, employing output from the CGCM2 (upper graph) and the HadCM3 (lower graph). Seasons defined as follows: winter (December-February); spring (March-May); summer (June-August); autumn (September-November).

4.4.3. Southern Alberta

Tables 16 to 18 (Appendix N) outline the different climate change scenarios considered for southern Alberta. The scenarios are based on the Canadian CGCM2 and UK HadCM3 global climate models, and the IPCC A2 greenhouse gas emissions scenario. The tables represent standard projection periods centered on the 2020s, 2050s and 2080s. Each table is divided by model type (CGCM2 versus HadCM3) and season. Within each model-season group are the estimates of the weather parameters, as related to the southern Alberta hospitalizations for the gastrointestinal disease statistical model reported in Section 4.3.3.

Each of the period-model-season scenarios within Table 16 to 18 is represented graphically via maps (Figures 32 to 34). The maps provide a graphical representation of the effects of climate change on the spatial and temporal distribution of hospitalizations for acute gastrointestinal illness in southern Alberta, given the variables for rainfall, precipitation and temperature, and other covariates (see Section 4.3.3 for details). The models provide a direct measure of the change in the number of rain days, and precipitation days above 50mm per season (a 42-day average) compared to the baseline 1969-1990 values.

Analysis of changes in projected maximum and minimum degree-days (Max15Min5) provided values for special degree-days. Simulations were created to derive special degree-days from maximum and minimum degree-days, and summed to a 42-day value.

Table 16 outlines seasonal scenarios for the period centered on the 2020s. When comparing two climate change models, the CGCM2 shows a bigger change from the 1990s than the HadCM3 model. In fact, the HadCM3 model shows no change except for the autumn months. The Canadian model projected southern Alberta could experience wetter springs, autumns and winters, but drier summers (when compared to the baseline values).

The modelling suggested that the number of rain days increased the risk of hospitalization while extreme precipitation over 50mm reduced the risk. Also that greater frequency of mild days (special degree-days) increased the risk of hospitalization for acute gastrointestinal disease. The impact of climate change on these precipitation and temperature variables is illustrated in the series of maps shown in Figure 32. The left-most map is the modeled distribution of hospitalizations for 1992-1998. The remaining two maps represent the springtime distribution based on the projections provided for the 2020s from the Canadian CGCM2 and UK HadCM3 model respectively. Note that the bright red sections located in the northwest corner of the study regions do not accurately represent a high risk of hospitalization for gastrointestinal disease in any of the maps. Rather, it is a statistical artifact called ‘edge effects’ and should be disregarded.

a) 1990s b) 2020s CGCM2 c) 2020s HadCM3

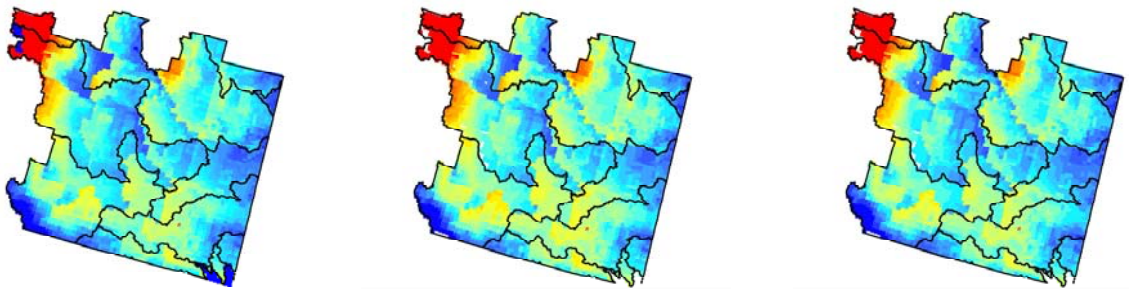


Figure 32. (a) Distribution of gastrointestinal disease risk in spring, in the 1990s and two climate change scenario periods centered on 2020s, (b) CGCM2 and (c) the HadCM3 (N.B. The colour scale ranges from blue for areas of low risk through green, yellow, orange and red for areas of high risk. The elevated risk of hospitalization shown in red in the northwest corner is a statistical artifact.)

As can be seen with Figure 32, the effect of predicted changes during the spring of the 2020s is relatively small compared to baseline distribution. However, if one looks closely, the CGCM2 model does indicate regions of increased risk. Specifically, this can be seen in the northern region of CCS Cardston No. 6 (lower left side of map). Since the maps reflect variation in hospitalization risk over the entire study region, local variation tends to be washed out. The maps should be considered a rough estimation of the projected impacts of climate change. A more focused example of the impacts on climate change on GID hospitalization risk is given for Lethbridge, Alberta below.

Climate change model scenarios for the period centered on the 2050s are given in Table 17. The values shown represent the projected change from the baseline, and are determined in the same was as described for the period of the 2020s (Table 16).

Both the Canadian and UK models project large changes in precipitation throughout the year. Using the CGCM2 model, it shows that the spring, autumn and winter will be wetter than the baseline and that the summer will not change significantly. In contrast, the HadCM3 model suggests that the spring and winter will be wetter, but the summer will be much drier. The autumn will remain unchanged.

In terms of extreme precipitation events (greater than 50mm), the CGCM2 suggests all seasons except the summer can expect an increase. The HadCM3 shows increases during the spring and winter, no change in the autumn, and a decrease in the summer.

Finally, given increasing seasonal average maximum and minimum temperature, both models show large changes to the measure of the special degree-day. They do of course vary in terms of the magnitude of this change. The CGCM2 model tends to give more special degree-days than the projections of the HadCM3 model. The spring and summer show the largest increase in Max15Min5 values, while both models show a large decrease in the summer months.

Figure 33 shows the baseline map with the 2050s scenario maps for the spring (based on the CGCM2 and HadCM3 models respectively). The maps show considerable increases in the distribution of hospitalizations for disease compared to the baseline. The two models also differ from each other. As with the previous scenario centered on 2020s, the Canadian model shows a large increase in the probability of disease. The area known as feedlot alley appears to have a huge increase in the probability of disease. The HadCM3 model also shows slight increases in the probability of disease.

a) 1990s b) 2050s CGCM2 c) 2050s HadCM3

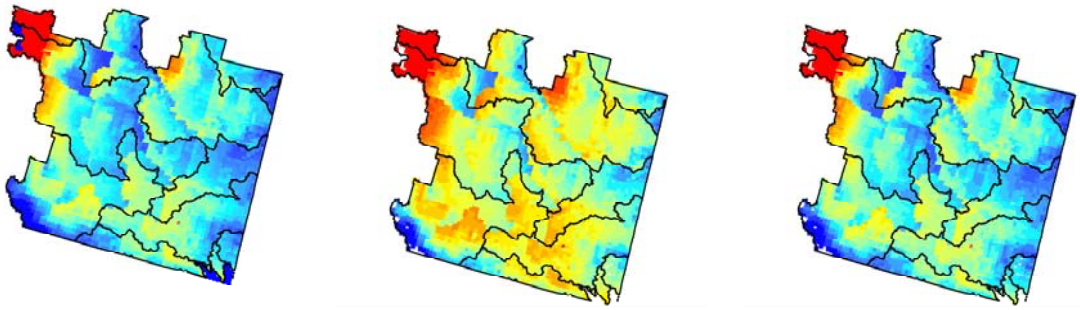


Figure 33. (a) Distribution of gastrointestinal disease risk in spring, in the 1990s, and two climate change scenario periods centered on 2050s, (b) CGCM2 and (c) the HadCM3. (N.B. The colour scale ranges from blue for areas of low risk through green, yellow, orange and red for areas of high risk. The elevated risk of hospitalization shown in red in the northwest corner is a statistical artifact.)

The climate change projections for the period centered on the 2080s are outlined in Table 18. Again, the Canadian model appears to show larger changes when compared to the baseline models and to the UK HadCM3 projections.

Spring rains are projected to increase further in both Canadian and UK models, as well as a relatively large increase in the number of extreme precipitation events in spring. Additionally, the summer continues to be drier, with hotter temperatures. The resulting increase in temperature has the effect of greatly reducing the special degree-day value (far fewer mild days). The Canadian model projects different results for autumn than the HadCM3 model. The CGCM2 projects much wetter autumns with very large increases in mild days (Max15Min5). By contrast, the UK model shows a smaller increase in the amount of rain days, and a decrease in the Max15Min5 value. This is due to a projected increase in the average minimum and maximum temperature for this season, meaning hotter weather and fewer mild days.

Figure 34 shows the baseline map with the 2080s period scenario maps for the spring (based on the CGCM2 and HadCM3 models respectively). The CGCM2 map shows a considerable increase in the distribution of hospitalizations for disease compared to the baseline (1990s).

a) 1990s b) 2080s CGCM2 c) 2080s HadCM3

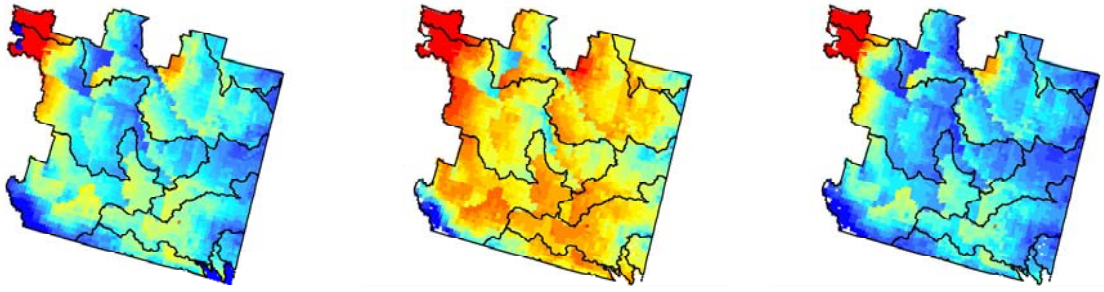


Figure 34. (a) Distribution of gastrointestinal disease risk in spring, in the 1990s, and two climate change scenario periods centered on 2080s, (b) CGCM2 and (c) the HadCM3. (N.B. The colour scale ranges from blue for areas of low risk through green, yellow, orange and red for areas of high risk. The elevated risk of hospitalization shown in red in the northwest corner is a statistical artifact.)

The divergences between the two climate change models (CGCM2 and HadCM3) are most evident for projections late in the 21st century. The Canadian model shows a further increase in the probability of hospitalization for gastrointestinal illness, while the UK model indicates that the probability will slightly decrease.

Additionally, if one investigates the summer months, it appears that both models show an increase in probability of hospitalization for gastrointestinal disease (Canadian model projects a greater increase). The autumn months for both climate change models show an almost uniform reduction in probability of hospitalization for gastrointestinal illness.

The statistical model of hospitalization for gastrointestinal disease risk in southern Alberta and downscaled data from the Canadian model (CGCM2) (Section 3.5) were used to project the temporal shift in probability of hospitalizations for gastrointestinal disease for the city of Lethbridge, Alberta, as an example of a model application.

The climate variables for the model include the number of rain days (nRD), the special degree-days (Max15Min5), the 95th percentile of rain days (highRD) and the interaction between nPD50 and the water treatment score. Details of this model and of the projected seasonal values for each variable are given in Tables 19 to 21 (Appendix N). The values for number of rain days and special degree-days were incorporated into each age-sex specific group analyses for the two different land uses. Figure 35 illustrates the seasonal change in probability of hospitalization for gastrointestinal disease averaged over the sexes, all age groups and land classes 8 and 11 (mixed and soybean-corn, respectively). The modeling indicates a large change in the distribution of disease in spring and summer, with an overall annual increase in the risk of gastrointestinal hospitalizations by the end of the 21st century. Lethbridge may experience a 20% increase in the spring risk of hospitalization for GID, relative to the 1990s. No change is expected in risk in autumn and winter, but summer risk of hospitalizations for gastrointestinal disease may decrease, due to hotter, drier weather. There is no impact of climate change on gender or age-specific risk of hospitalization, assuming no change in age and sex distribution in the population.

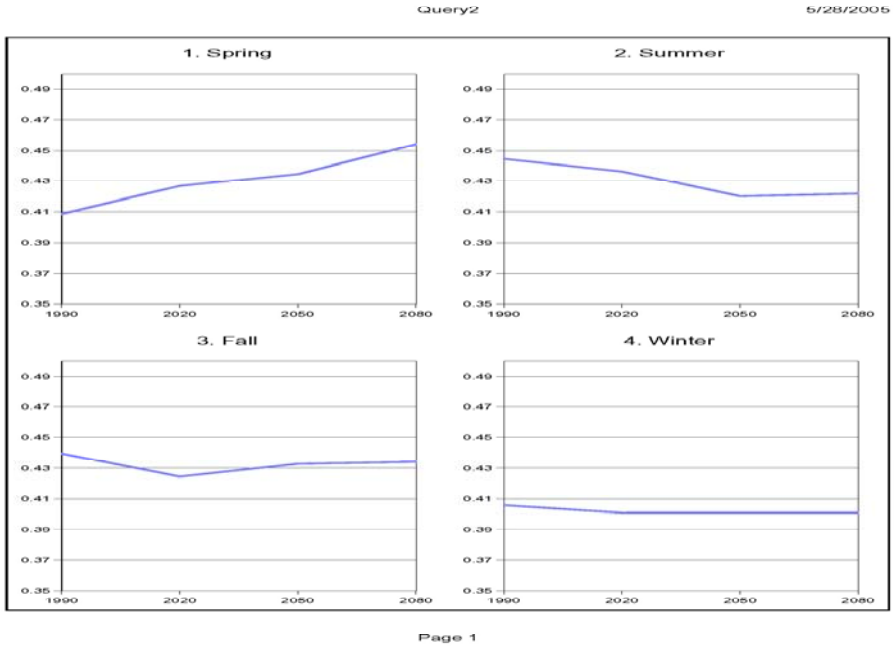


Figure 35. Seasonal probability of hospitalizations for gastrointestinal disease (GID) in Lethbridge, AB, averaged over the sexes, age groups and the two different land uses considered (DEFINE), under conditions of climate change, modeled using CGCM2 (IPCC A2 scenario). Note that the horizontal axis represents time while the probability of hospitalization for GID is displayed along the vertical axis.

4.4.4. Projected impact of climate change on climate thresholds for waterborne outbreak risk

Downscaled climate change data was used to assess the projected impacts of climate change on temperature and precipitation threshold values found in Section 4.3.2. Percentiles on precipitation, and maximum and minimum temperature data 8 weeks prior to a waterborne outbreak were determined using climate normals of 1961-1990 as comparison. However, only 9 outbreaks of the original 23 were chosen because of their links to weather events. The subset of 9 outbreaks was determined by the availability of downscaled data. However, it is not the purpose of this analysis to quantify or empirically verify this contribution.

Downscaled daily meteorological data from the HadCM3 and CGCM2 (IPCC scenario A2) for the periods 1920-1939, 1940 - 1969 and 1970-1999 were then used to rank the pre-outbreak weather variables based on future climate. The goal was to explore the possibility that historically severe weather might be more frequent in future because of climate change.

It is immediately apparent that weather conditions prior to these selected outbreaks often fell in the extreme range of normal. With climate change, it is expected that extremes of temperature will become warmer (maximum and especially minimum temperatures). For some places, heavy rainfall is expected to become more frequent while in others, it may become less frequent (Table 3 and 4). This would suggest that fewer of the weather conditions preceding the outbreaks should be ranked beyond the extreme cut-points. Yet, the weather events preceding the selected outbreaks generally

remain exceptional (ranked beyond the extreme cut-points) with little change in the number of outbreaks ranked beyond the extreme cut-points.

Table 3. A comparison of the number of outbreaks exceeding given percentile sand how that changes in the future (CGCM2 scenario A2)

Meteorological Variable	**1961 - 1990**		**2020s**		**2050s**		**2080s**	
	>99th	**>90th**	**>99th**	**>90th**	**>99th**	**>90th**	**>99th**	**>90th**
Max 1 day Precip (1-2 weeks prior)	4	7	4	7	5	7	5	7
Max Daily Tmax (1-2 weeks prior)	3	7	4	8	4	7	4	6
Max 1 day Precip (6-8 weeks prior)	3	9	5	9	5	9	5	9
Max Daily Tmax (6-8 weeks prior)	6	8	6	8	5	8	5	8
	<5th	<10th	<5th	<10th	<5th	<10th	<5th	<10th
Min Daily Tmin (1-2 weeks prior)	3	7	3	8	4	9	4	9
Min daily Tmin (6-8 weeks prior)	4	5	7	8	8	8	8	8

Table 4. A comparison of the number of outbreaks exceeding given percentile sand how that changes in the future (HadCM2 scenario A2)

Meteorological Variable	**1961 - 1990**		**2020s**		**2050s**		**2080s**	
	>99th	**>90th**	**>99th**	**>90th**	**>99th**	**>90th**	**>99th**	**>90th**
Max 1 day Precip (1-2 weeks prior)	4	7	4	7	3	7	4	7
Max Daily Tmax (1-2 weeks prior)	3	7	3	5	3	5	3	5
Max 1 day Precip (6-8 weeks prior)	3	9	3	9	5	9	9	9
Max Daily Tmax (6-8 weeks prior)	6	8	5	8	5	8	9	9
	<5th	<10th	<5th	<10th	<5th	<10th	<5th	<10th
Min Daily Tmin (1-2 weeks prior)	3	7	5	9	6	9	6	9
Min daily Tmin (6-8 weeks prior)	4	5	6	6	7	8	7	8

4.5. Adaptation to climate variability and change: Tobacco Creek Case Study

Previous sections of this report have presented complex and elaborate statistical models of the relationship between climate variables and waterborne diseases, and of the projected impact of climate change on various measures of gastrointestinal risk. For analytical expediency, all of these models have assumed no additional effort or response to reduce the impacts of climate change on gastrointestinal disease risk. Yet, Canadians have been adapting to harsh and variable climatic conditions since the time of the earliest human settlements. More recently, communities have made changes to lessen their vulnerability to climate phenomena, often in response to extreme weather events. For example, Ontario implemented new drinking water regulations in the aftermath of the *E.*

coli outbreak in Walkerton, Ontario. Armed with some foreknowledge of the projected impacts of climate change, it is possible to make changes in advance that may lessen the impact of climate change on gastrointestinal disease risk.

In this section, a farming community's self-driven program of alterations to the landscape in response to extreme weather is used as a case study of community-based adaptive capacity with implications for adaptation to climate change.

Two broad approaches to adaptation are currently promoted in the literature: integrated impact assessment scenarios and a vulnerability assessment approach. In the first approach, climate change is taken to be the sole driver of change (Figure 36). The second approach begins with an assessment of current vulnerability and adaptive capacity, and then assesses future vulnerability by projecting possible climate changes via GCM scenarios.

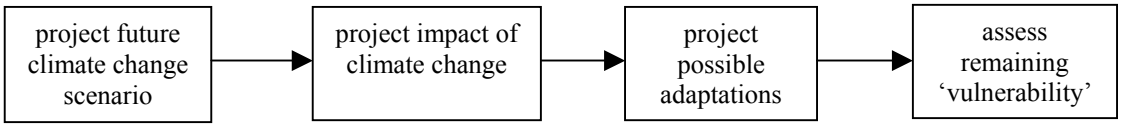


Figure 36. The steps involved in an integrated impact assessment scenario

Unfortunately, the challenges of a complex system, such as climat, forces a radical change to the traditional assumptions driving adaptation - because of complexity and uncertainty we cannot predict with any degree of certainty what the impacts of climate change will be in a particular time and place. Therefore, complexity and uncertainty (should) fundamentally change our understanding of the 'starting point' for the process of adaptation. We cannot predict with any certainty *what* the precise impacts of climate change will be in a specific local context, we can only speak in generalities. Furthermore, climate change is not a 'once off' proposition - we will not wake up one day and find that our climate has 'changed' so that we can assess that change and 'adapt'. Rather, it will be an ongoing process of change over a period of decades to centuries. It is likely that we cannot identify a 'particular and identifiable climate threat' to which we can adapt. Therefore, we end up at a very different starting point for the actual process of adaptation for rural communities.

Adaptation to climate change, in health and in all sectors, will be an ongoing process of reducing vulnerability to the effects of weather and increasing our capacity to cope with impacts. This research demonstrates that vulnerability can be reduced and adaptive capacity increased by building ecological and social resilience to climatic variability and extreme events.

This research investigated social and ecological basis resilience to climate variability and extreme events on the Canadian prairies. Current and past soil and water conservation activities of several agricultural communities were examined as adaptive responses to environmental change and climatic stress, in order to understand how this experience may translate into climate change adaptation strategies for rural Prairie communities. The specific context of this research was a study of the Deerwood Soil and Water Management Association (DSWMA), a local farmer's group, in the South Tobacco Creek watershed, south-central Manitoba (see Figure 37).

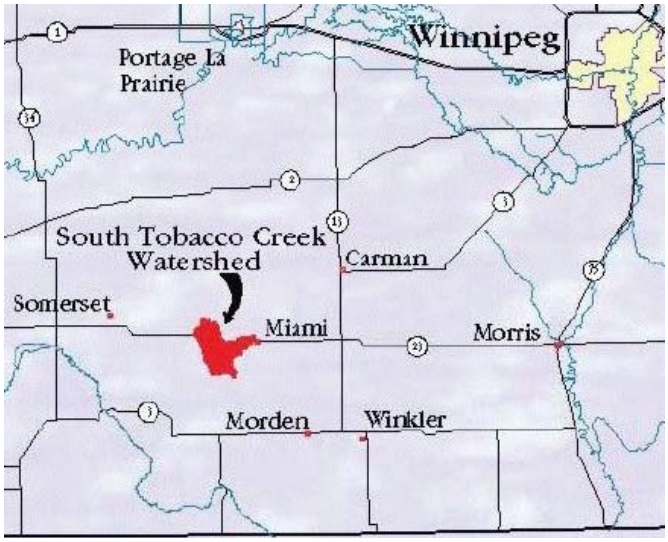


Figure 37. South Tobacco Creek Watershed, Manitoba

The research sought to answer four key questions:

a. How are rural communities on the Canadian Prairies currently organizing to adapt to soil and water problems caused by too much (spring flooding and summer storms) and / or too little precipitation (drought)?
b. What conservation actions are farmers taking?
c. How are farmers addressing local concerns?
d. What questions are raised for managing health outcomes associated with waterborne disease?

Climate change projections for the Canadian Prairies generally suggest that warmer temperatures, drier conditions, greater incidence and severity of both drought and extreme precipitation events, and reductions in water availability and quality will prevail by the end of the 21st century (CGCM2). Drought is already the most significant and distinguishing climate feature on the Prairies. Farmers have developed coping strategies to address this kind of climate variation.

The research focused on three aspects of vulnerability and resilience:

1. How the adaptive cycle metaphor may be used to understand the process of responding to environmental change over time (not presented here);
2. How the notion of vulnerability can be used to understand the set of conditions that precipitate organizational restructuring; and
3. How seven features of a resilient system, can be used as a framework for evaluating a community response to extreme events.

DSWMA is a unique example of community-based management on the Prairies. Farmer-led since its inception over 20 years ago and supported by all farmers in the watershed, DSWMA formed to address local concerns with soil erosion and flooding during extreme precipitation events, particularly the spring runoff and summer storms. Working in the South Tobacco Creek (STC) watershed, the farmers designed and built a network of 26 small check dams in the upper reaches of the watershed. Past research has demonstrated that the dams reduce peak flow runoff by as much as 90%. Equally important is the network of partnerships that DSWMA has formed with over 20 other groups including provincial and federal agencies and other local NGOs.

In addition to the primary case study of the DSWMA, 3 secondary case studies were conducted to provide a richer picture of the local context and provide a baseline with which to compare the primary DWSMA case. The neighbouring North Tobacco Creek (NTC) watershed is topographically similar to STC and experiences similar climatic conditions, but has not been managed to address soil erosion and flooding. Thus, NTC serves as a useful control case where the impact of extreme precipitation events on the biophysical environment of an unmanaged watershed may be seen. The Pembina Valley Conservation District (PVCD) has been working since 1999 to try to establish similar soil and water conservation activities in the NTC. The case study will examine this emerging attempt to replicate the Deerwood model, in terms of building local institutions. Pilot Mound, MB is a community west of the watershed, which has been experiencing drinking water quality issues and asked PVCD in 2003 to develop soil and water conservation activities following the Deerwood model. Taken together, the three case studies will provide a very clear picture of the potential of community-based soil and water conservation to build the eco-social resilience of a Prairie watershed as a climate change adaptation strategy.

Major Findings

DWSMA has gone through two major organizational cycles since its inception in 1984 as an informal farmers' group. The organization first received government funding to build water retention structures in the watershed, winning the required changes in legislation that allowed for water retention on farmland. At the end of the government funding for such projects, DWSMA reinvented itself as an academic research steering organization, generating further opportunities for understanding hydrological dynamics in the watershed, and funding to manage water flow. An understanding of the processes by which DWSMA was organized serves as a model for adaptation to climate change. In the context of this study, vulnerability consists of crises and crashes that precipitate a major reorganization of some aspect of the system (in this case DWSMA). Figure 38 illustrates some of the key vulnerabilities.

There were also a number of key 'adaptive capacities' that were part of the overall picture of vulnerability at the time of the emergence of Deerwood in 1980. All of the founding Deerwood members were young farmers at the time, in their 20s and 30s, and most started farming during 1979 to 1982 with strong horizontal social networks. They were young and very enthusiastic with a 'we can do anything' type of attitude, according to several of the members interviewed. The founding members also all owned small mixed farms which were in very close proximity – dotted along two or three side roads off the major highway passing through the area - within 10 or 15 minutes driving distance. The small size of farm, from about 500 to 1000 acres, translated into a relatively high density of local people in the area. The group also had strong vertical cross-scale linkages - one founding member was on the local Rural Municipality council, another worked for the Manitoba Department of Agriculture - so both of these members had access to information and decision-makers inside the government hierarchy.

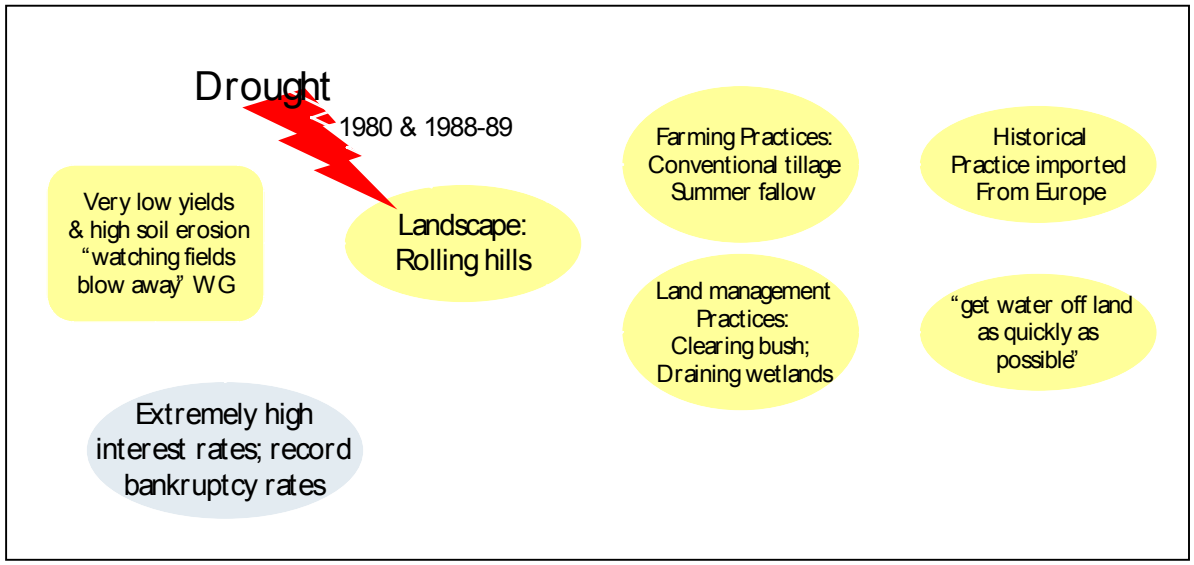


Figure 38. Key Vulnerabilities of South Tobacco Creek from the beginning.

The Deerwood group had a number of built-in coping mechanisms that helped it reorganize in times of crisis. All the founding Deerwood members were young farmers with strong social networks. Their farms were small and tended to be of mixed type. Small farm size meant a relatively high density of people in the area. The group was well connected with government agencies at various levels, which helped them achieve their goals.

In addition to building the network of small dams, Deerwood promoted a number of soil and water conservation activities to farmers in the watershed including:

1. Conservation tillage including zero and minimum tillage practices.
2. Shelter belt construction to prevent wind erosion and trap snow on fields.
3. Grassed waterways – planting of grasses along the banks of waterways and in natural watercourses on the landscape to prevent soil erosion.
4. Gulley stabilization – stabilizing natural gullies in fields through reshaping and planting grasses.
5. Forage planting – taking marginal farmland out of annual production and sowing down to annual forages.

The dam network reduces peak flows during extreme precipitation events by up to 25%. Further, they retain sediments and nutrients and act as artificial wetlands, directly improving water quality. As a result, there has been a marked decrease in the turbidity in the creek after heavy rainfall. Turbid water reduces the efficiency of drinking water treatment, and has been linked to increases in gastroenteritis in the community (Aramini et al., 2000). Since the STC water eventually reaches the Red River, an important source of drinking water downstream, improvements in turbidity levels in the STC watershed will reduce health hazards to downstream populations.

The research shows that successful adaptation to climate variability relies upon:

1. Strong leadership, particularly at the local level, as well as within government and industry. Commitment within government and industry to community-based organizations

2. A regulatory and legislative environment that minimizes barriers to the effective local implementation of adaptation strategies.
3. Commitment by governments to fund adaptation initiatives.
4. Long term monitoring of current conditions, changes in condition, and of the results of interventions.
5. Innovative arenas for sharing information among stakeholders from local to national. Particularly, to provide a forum where the community can interact with the scientists and decision makers toward achieving a common goal.

5. Policy Implications

5.1. Policy context

The Government of Canada continues to build a comprehensive environmental vision by launching, for example, Project Green in 2005, which comprises a set of policies and programs aimed at supporting a sustainable environment and a more competitive economy. Project Green's first installment, "Moving Forward on Climate Change," is a comprehensive plan of challenges and opportunities for honouring Canada's Kyoto commitment to reduce its greenhouse gas emissions to 6 percent below 1990 levels (www.climatechange.gc.ca). Along with climate change, Project Green will also address a range of environmental issues, including biodiversity, water, contaminated sites and clean air.

Canada's Second National Assessment of Climate Change Impacts is also underway (to be completed in 2006) and will provide comprehensive information on the health implications of climate change and climate variability at national, regional and local levels. The health agenda is being addressed through Health Canada's Assessment of Health Vulnerabilities to Climate Change (also due in 1996). The Government has contributed to, and is able to draw on, international work such as the Arctic Climate Impact Assessment (2004, available at http://www.acia.uaf.edu/) and ongoing work for the Fourth Assessment Report on Climate Change by the Intergovernmental Panel on Climate Change (www.ipcc.ch).

Public and political responses to climate change are often driven by health concerns, and the health impacts of climate change are now beginning to influence climate change policy. Results of this project provide new information on the projected health burden from global climate change, and highlight some generic aspects of adaptation strategies geared toward managing water on the Prairies. For example, Canadians who rely on untreated drinking water (private wells and surface water supplies) are at higher risk from climate change-mediated impacts on source water quality. The segment of the population relying on these private water systems does not benefit from legally enforceable standards and national drinking water policies, even though guidelines, such as the Guidelines for Canadian Drinking Water Quality (Health Canada, 1996) were developed for application to both public and private water systems. Results from this research benefit this subpopulation by helping to locate, protect and maintain safe drinking water sources. The findings will therefore support the integration of climate change considerations into federal drinking water policy under the auspices of the Federal-Provincial-Territorial Committee on Drinking Water.

The federal government created the Public Health Agency of Canada (PHAC) in September 2004, to promote and protect the health of Canadians through leadership, partnership, innovation and action in public health. PHAC researchers investigate the impacts of climate change on disease risk, while the Agency as a whole helps protect Canadians from emerging disease threats, some of which may be due to climate change. PHAC's support of this research helps ensure the findings will be disseminated Agency-wide, to those who investigate outbreaks of waterborne disease and other risk factors associated with enteric disease.

5.2. Policy implications from the research

Policy implications arise from five main empirical conclusions of our work:

1) Waterborne diseases are a burden to Canadians now.
   - **a) Outbreaks of waterborne disease are not infrequent in Canada.**
     There were 288 disease outbreaks in Canada between 1971 and 2001, all with at least one possible link to a treated drinking water source. The number ill varied, from members of a single household, to larger proportions in urban centres (e.g. Vancouver, Edmonton, Walkerton). The adequacy of epidemiological records was an issue of concern for us, as there were certainly more than 288 outbreaks of waterborne disease spanning our period of study; it is suspected additional disease records were incomplete, lost, or destroyed.
   - **b) Sporadic gastrointestinal illness affects many more Canadians than were affected by outbreaks linked to a source.**
     - i) Sporadic gastrointestinal illness is defined as the totality of individual cases of disease that are not linked to other cases through a common source of infection. Such sporadic cases are used to estimate the background level of illness, also known as endemic illness. National notifications of laboratory confirmed infections and hospitalizations for acute gastrointestinal illness are used to assess rates of sporadic illness.
     - ii) The highest numbers of notifications for major enteric pathogens occurred in the most populated provinces: Ontario, Quebec, Alberta and British Columbia. These data were subject to provincial differences in laboratory submission rates, testing, reporting, and targeted surveillance, making inter-provincial comparisons problematic. *Campylobacter* was the most frequently reported pathogen in all provinces, followed by *Salmonella* and *Giardia*, except in the Territories, where *Giardia* or *Salmonella* were more often found (*Campylobacter* testing may not be as frequent).
     - iii) In Canada from 1988 to 2001, the incidence of some nationally notifiable pathogens known to be waterborne some of the time (*Salmonella* 18.37, *Giardia* 16.29 cases per 100,000) decreased. Verotoxigenic *E. coli* incidence had, generally, remained constant, averaging between 6 and 8 cases per 100,000, except for the increase attributable to the Walkerton, Ontario outbreak in 2000. The rate of *Campylobacter* was highest of all (still just below 30 per 100,000), but appears to be declining, yet was subject to considerable variability.
     - iv) Hospitalization data for acute gastrointestinal illness are not subject to the same inter-provincial biases as notifiable disease data, but are subject to standard hospital data biases, differences in hospital record-keeping protocols, and hospital contributions to the Canadian Institute for Health Information (CIHI) database. In the CIHI database, it was

not possible to differentiate cases of waterborne disease from cases of severe acute gastrointestinal disease, as in more than 75% of the cases, no pathogen was identified.

v) Between 1993-1998, there were, on average, 68,415 hospitalizations per year in Canada, for which a diagnosis of acute gastrointestinal illness was made (Appendix G), based on data from (approximately) 85% of hospitals and long-term care facilities across Canada, except in Quebec (one long-term care facility) and Manitoba (six long-term care facilities). Females displayed consistently higher rates of hospitalization for gastrointestinal illness than males, across all years.

vi) The largest number of hospitalizations occurred in individuals aged 20-49, followed by the elderly and children under five. Given those 55 and older represent a rapidly growing segment of the North American population, it can be inferred that hospitalizations rates may not continue their decline, but rather increase, as the population ages.

vii) In cases with confirmed aetiology, viral agents were most frequently found in children and young adults, whereas bacterial aetiologies were more frequent in adults and the elderly. There was a slight decline in hospitalization rates for severe acute gastrointestinal illness from 278 per 100,000 in 1993 to 246 per 100,000 in 1997.

viii) Alberta Case Study

- There was a slight decline in hospitalization rates for gastrointestinal illness in Alberta, with 142 cases in 1993 to 121 in 1997 (per 100,000). Females were 1.12 times more likely to be hospitalized for acute gastrointestinal disease than males. The elderly accounted for the largest absolute number of hospitalizations for acute gastrointestinal illness, but the disease was over-represented among the 20 - 29 age group (accounting for the largest proportion of illness in this age group). Variability across the south of the province, with the Red Deer River watershed having the lowest risk of hospitalization for GID and the Bow River watershed having a high risk, was evident, especially for females. However, analysis based on census divisions found Calgary having a lower rate of hospitalization for GID relative to the rest of the study area.
- Areas with a high concentration of corn, soy, pasture and expansive biomass crops appeared to increase the rate of acute GID hospitalizations in southern Alberta. This could have been a surrogate for agricultural practices, such as type and quantity of surface manure spread, or may have reflected greater human population (relative to forested areas).

ix) Ontario Case Study --Endemic Disease

- Risk of hospitalization for gastrointestinal disease in Ontario was similar to that of Alberta. There was a slight decline in hospitalization rates associated with gastrointestinal illness, falling from 183 per 100,000 in 1993 to 156 per 100,000 in 1997, and females were slightly more likely to be hospitalized in Ontario, relative to Alberta (female to male ratio 1.28 to 1). Gastrointestinal illness in young children (age 1 - 4) accounted for 25% of those admitted to hospital in this age group and also accounted for the largest number of gastrointestinal hospitalizations relative to other age groups.
- Risk of disease increased as the distance to nearest water treatment plant increased.

x) Atlantic Case Study --Endemic Disease

- Nova Scotia, Newfoundland-Labrador and Prince Edward Island had similar incidence of hospitalizations for acute gastrointestinal illness (all sources) of, on average, 3 cases per 10,000 per person-month. New Brunswick had a higher

incidence, at 17 cases per 10,000 per person-month. Incidence peaked in late spring to early summer (March to June) in all 4 Atlantic provinces.

- The incidence of acute gastrointestinal disease is highest in children under 5, remained high in older children, then lowered between the ages of 20-49, where the incidence began to climb for people aged 50 and older.
- Clusters of gastrointestinal disease in space and time in the Atlantic Provinces are clearly present, requiring further research to address contributing factors.
- Although differentiation of waterborne illness from other sources of endemic gastroenteritis has only been possible in those situations where good epidemiological evidence has been collected, it appears that trends in endemicity of predominantly waterborne (and other enteric) pathogens are generally declining.

c) **The quality of disease surveillance data is inadequate.**

i) Lack of a national standardized integrated surveillance system for disease outbreaks hampered research. Historical outbreak records often failed to include data on the number of cases, the number of people at risk, the exact date, the exact location, microbiological test results, or other evidence used to link the outbreak to a drinking water source. PHAC is currently developing the Canadian Network for Public Health Information, a system that should address some of these failings.

ii) There is a need for better epidemiological and microbiological data for sporadic cases of enteric disease and for hospitalizations for acute gastroenteritis, to ascertain the likelihood of a drinking water source of infection.

iii) Prevalence and modes of transmission of enteric viruses, including Noroviru,s is needed, since few data are available on the burden of such viruses.

iv) Molecular markers that may help differentiate waterborne enteric illness from other modes of transmission (food, inter-personal) would be of great use, when developed.

d) **The costs of waterborne illness are considerable.**

i. Although the financial costs of outbreaks and endemic cases of waterborne diseases have not been adequately described, and were not an explicit part of our research program, results from other studies indicate they are substantial.

ii. Walkerton's outbreak, estimated to be $90.5 million in health care dollars, carried an additional $64.5M in tangible costs (Livernois, 2002a and 2002b).

iii. A study of acute gastrointestinal illness in Hamilton, Ontario, (Majowicz et al., Submitted) found the estimated mean annual cost per case was $1,089 (range $257 to $15,221), with 73% of this cost attributed to paid sick leave from work. These findings are consistent with other reports. For example, the cost for medical treatment per case of waterborne illness in the United States ranges from $200 for mild cases to $8000 or more for more extreme cases, not including lost productivity.

Mortality was most likely in children, pregnant women, those over 55, and immune-compromised people (such as those with AIDS, and those receiving radiation treatment or heavy doses of antibiotics). Today, these vulnerable populations represent over 25% in both the USA and Canada.

Summary: Waterborne diseases are a burden to Canadians now.
Many Canadians, particularly the young and elderly, are affected by gastrointestinal disease annually, at considerable cost to society. Some of this disease burden was waterborne, but it was not possible to determine at what rate. Outbreaks of waterborne disease are not a rare occurrence in Canada. In addition, thousands of Canadians are hospitalized each year with gastrointestinal illness. There is a need for improved integration of disease surveillance systems, in order to improve our ability to assess the occurrence of endemic and epidemic gastrointestinal illness in Canada. Improvements are urgently needed in epidemiological data and microbiological techniques, to facilitate the attribution of disease to a waterborne or other source, and to enable development of targeted control measures.

2) Waterborne disease risk is related to ambient temperature and rainfall.
   a) **Extreme precipitation and warmer temperatures increased risk of waterborne outbreaks.**
      i) In general, severe weather, close proximity to animal populations, treatment system malfunctions, poor maintenance and treatment practices were associated with the reported disease outbreaks resulting from drinking water supplies.
      ii) Extreme rainfall was found to increase the likelihood of waterborne disease outbreak in Canada by a factor of two.
      iii) Warm temperatures also contributed to a higher risk of waterborne disease outbreak.
   b) **In Alberta, climate variables significantly affect the risk of hospitalization for gastrointestinal illness.**
      i) An increase in the number of days with rain greater than 0mm ultimately increased the probability of disease. The impact translated into an increased risk of 1.004 (1.002, 1.007) for every extra day of rain in a 6-week period.
      ii) Paradoxically, increased frequency of heavy rain or extreme precipitation events (while controlling for the number of rain days) decreased the probability of disease. This may be due to a dilution effect, or cessation of the contamination input, but may also be an artifact of model specification (i.e. modeling both number of rain days and number of extreme events).
      iii) Mild (but not hot) weather significantly impacts the probability of disease. For example, an increase in temperature of 2.5^{o}C on days where the temperature lies between 5 and 15 degrees represented an increase in risk of disease of 35 percent over the study period.
   c) **In Ontario, weather has an impact on hospitalizations for gastrointestinal disease, similar to Alberta (but not identical).**
      i) The number of precipitation days (and not rain days as with the Alberta study) increased the probability of disease. As with Alberta, mild but not hot days contributed to increased risk of enteric disease.

Summary: Waterborne disease risk is related to ambient temperature and rainfall.
There is now substantial evidence that various types of weather affect gastrointestinal disease risk in many parts of Canada. Extreme precipitation increased the risk of epidemic waterborne disease twofold. Precipitation also contributed to the risk of endemic gastrointestinal illness, implying that some portion (as yet inestimable) of endemic gastrointestinal illness must be waterborne. Epidemic waterborne illness was linked to heat accumulation over a 6-week period – perhaps representing thawing conditions during cold months or heat waves in summer. Warm (but not hot) weather

conditions over a 6-week period (suggesting spring or autumn conditions) were found to be the most significant contributors to hospitalizations due to gastrointestinal illness in Alberta and Ontario.

3) Climate change will alter the distribution and risk of gastrointestinal risk in parts of Canada.
   a) Downscaling Global Climate Model data was useful for modeling health impacts of climate change.
      i) Climate change projections from Global Climate Models (GCM) generate data at too coarse resolution to be useful in modelling enteric disease. This project showed that both the LARS-WG and SDSM downscaling techniques could be used to generate future weather data, based on GCM output and historical weather data. The downscaling process required considerable time and computer processing capacity.
      ii) Based on downscaled climate change projections from a series of weather stations selected on an east-west transect through Canada, we calculated a 20% increase in annual precipitation amounts over much of Canada by the 2050s, compared to the baseline period 1961-1990. There will be an increase in the number of days with extreme precipitation events (greater than 50mm per day). Maximum air temperatures will be highest in the Prairies, but Atlantic Canada will experience the greatest warming (due to the rapid increase in minimum temperature).
      iii) Simple examination of total precipitation, maximum and minimum temperature data was not sufficient to understand the impact of climate change on future patterns of weather. The detailed study of future weather for Walkerton, Ontario clearly showed the precipitation events in May 2000, that preceded the *E. coli* O157 outbreak, were exceptional, but not the most severe historically. Five-day precipitation events of this nature may occur with approximately the same frequency in future, but with greater severity. Increases in mean monthly and mean seasonal precipitation for winter and autumn raise concerns regarding increased risk of drinking water contamination.
      iv) Southern Alberta case study: Downscaled GCMG A2 climate data was used to model the future risk of enteric disease in southern Alberta. In general, increased hospitalizations with a diagnosis of acute gastroenteritis may be expected with climate change by the end of the 21st century. The increase was mostly found in spring. The largest increases appeared to be in the area known as feedlot alley, located in the south-central part of the study area. The Canadian GCM data calculated greater increase in precipitation, and lower maximum temperatures, thus yielding higher projected hospitalization rates. A more detailed model of future gastrointestinal disease hospitalizations for Lethbridge, Alberta, showed a marked increase -- by 20% -- in spring (compared to 1961-1990 average), and little change in winter. Summer risk of hospitalization for gastrointestinal disease may decrease, due to hotter, drier weather.

Summary: Climate change will alter the distribution and gastrointestinal risk in parts of Canada.

Downscaling techniques allowed for the consideration of climate change projections in epidemiological models of disease risk. Such downscaled data should be widely available to allow for widespread applications in research in health and other sectors. Better regional climate change models would increase future abilities to include climate change projections into disease models.

4) Some Canadian populations have developed adaptive responses to extreme weather events.
   a) **South Tobacco Creek group managed soil erosion and water shortages for over 20 years**
      i) Given there was good evidence supporting the premise that waterborne illnesses have a significant impact on the health of Canadians, that these illnesses will be impacted by climate change in Canada, and that mitigation of climate change may have long-term beneficial effects, policies need to be directed at facilitating adaptation. The South Tobacco Creek, MB, project identified a number of important aspects to adaptation to extreme weather. The organization was begun by of mainly young adults, who owned small mixed farms that were in close proximity to one another, who had strong social networks, and established connections to political and government bodies (decision makers). The organization showed the ability to be socially adaptive, even as it promoted ecological resilience in watershed management.
      ii) From 1985 to 1995, the Deerwood Soil and Water Management Association constructed a network of 26 small dams in the upper reaches of the South Tobacco Creek watershed. The group also promoted a number of soil and water conservation activities to farmers. The dam network has been shown to reduce peak flows during extreme precipitation events by up to 25%. The dams hold back sediments, nutrients, and act as artificial wetlands, directly improving water quality. As a result, there was a marked decrease in the turbidity of the water in the creek after heavy rainfall. Turbidity in the source water decreases the efficiency of drinking water treatment, a problem for communities downstream from South Tobacco Creek.

Summary: Some Canadian populations have developed adaptive responses to extreme weather events.
A number of important policy implications emerged from this work. In particular, successful adaptation relied upon strong leadership, locally and from government; strong social networks; successful interventions; and a regulatory and legislative environment that supported community action and leadership. Lack of long-term funding was a limiting factor, hampering extended monitoring of ecological conditions into the future.

5) What does all this mean?

On April 18, 2005, research scholars and policy makers attended a one-day symposium to review results of this research and engage in a structured discussion on its policy implications. Some general themes emerged, including: the recognition that our understanding of the complex interactions among climate, environmental change, and health outcomes was uncertain; the need for clearer and more effective communication between scientists, the general public, and policy-makers in several government departments; and the need to act now, given the considerable knowledge we already have, particularly on source water protection. Indeed, to wait for additional certainty, when we already know, with a high degree of probability, that not protecting source waters will have strong negative impacts on the health of Canadians, would be behaving irresponsibly.

a) Action items proposed.

i) The Walkerton Inquiry Report drew a map toward safeguarding Canadians from waterborne disease. The implementation of the O'Connor recommendations must continue, to enhance Canada's resilience to risks posed by a changing climate.

ii) Water supply, water treatment, and sewage treatment system upgrades must be designed with climate change projections in mind, such that they continue to be effective. The multi-barrier approach is key to this resilience. Climate change projections can be downscaled to a geographical scale more meaningful to water and public health planning.

iii) Continue to develop and build a strong, coordinated and integrated disease surveillance system, which is key to detecting and responding to the health impacts of climate change.

iv) Local stakeholders have many good ideas and valuable insight – they must be included in the development of plans and projects aimed at improving water quality now and under climate change.

v) Risk assessments used for public health policies for waterborne diseases should include climate change projections. Using links between specific rainfall thresholds and the likelihood of waterborne disease outbreaks, we need to develop warnings and action lists, as we currently have regarding air quality, for instance.

vi) Develop and implement adaptive and proactive policies that are coordinated across government sections, such as Environment Canada, Health Canada, Public Health Agency of Canada, and Agriculture Canada.

vii) Develop national policies that facilitate local activities (such as the Deerwood Soil and Water Conservation Organization), particularly in under-serviced areas.

viii) Engage scientists in programs of public communication and discourse, so issues are planted firmly in the public agenda, and decisions made are informed by the best, most recent science available.

6. Consolidation of Knowledge Gained

6.1. Conferences

6.1.1. Presentations

- **Global Climate Change: Implications for Enteric Diseases Surveillance and Targeted Research at Health Canada.**
  D. F. Charron. *National Enteric Disease Surveillance Steering Committee.* Québec City, Québec. June 2002. (Oral Presentation)

- **Climate Change and Waterborne Diseases: Implications for a Shared Resource.**
  D. F. Charron. *Managing Shared Waters International Conference.* Hamilton, Ontario. June 2002. (Oral Presentation)

- **Excessive Rainfall and Waterborne Diseases in Southern Ontario, Canada.**
  D. F. Charron. *International Conference on Water and Health.* Ottawa, Ontario. September 2002. (Poster Presentation)

- **Water Quality and Human Health.**
  J. E. Valcour. *Bathurst Sustainable Development: Fresh Water for Atlantic Canada Emerging Issues for the 2stCentury*. Bathurst, New Brunswick. October 2002. (Oral Presentation)

- **Eco-social Resilience, Vulnerability and Climate Change on the Canadian Prairies.**
  C. Neudoerffer, D. Waltner-Toews, D. F. Charron. *Rural Canada: Issues and Insights, Conference sponsored by the Rural Development Graduate Students' Association, Department of Rural Development*. Brandon University, Brandon, Manitoba. March 2003. (Oral Presentation)

- **Eco-social Resilience, Vulnerability and Climate Change on the Canadian Prairies.**
  C. Neudoerffer, D. Waltner-Toews, D. F. Charron. *On the Edge 2003, 53rd Annual Conference of the Canadian Association of Geographers*. Victoria, British Columbia. May 2003. (Oral Presentation)

- **Are High Impact Weather Events Related to Waterborne Disease Outbreaks in Canada?**
  M. K. Thomas, D. F. Charron, D. Waltner-Toews, C. J. Schuster, A. R. Maarouf and J. D. Holt. *Canadian Meteorological and Oceanographic Society*. Ottawa, Ontario. June 2003. (Oral Presentation)

- **Impact of Global Climate Change on the Incidence of Waterborne Diseases in Canada.**
  C. J. Schuster and J. Valcour. *Canadian Institute of Public Health Inspectors, Ontario Branch: Annual Educational Conference*. Waterloo, Ontario. September 2003. (Oral Presentations)

- **Are High Impact Weather Events Related to Waterborne Disease Outbreaks in Canada?**
  M. K. Thomas, D. F. Charron, D. Waltner-Toews, C. J. Schuster, A. R. Maarouf and J. D. Holt. *15th Conference of the International Society for Environmental Epidemiology*. Perth, Australia. September 2003. (Oral Presentation)

- **Building Eco-Social Resilience of a Rural Watershed on the Canadian Prairies – A Climate Change Adaptation Strategy.**
  C. Neudoerffer, D. Waltner-Toews. *Open Meeting of the International Human Dimensions of Global Environmental Change (IHDP) Research Community.* Montreal, Québec. October 2003. (Oral Presentation)

- **Are High Impact Weather Events Related to Waterborne Disease Outbreaks in Canada?**
  M. K. Thomas, D. F. Charron, D. Waltner-Toews, C. J. Schuster, A. R. Maarouf and J. D. Holt. *Second Annual Graduate Student Appreciation Day, Ontario Veterinary College / University of Guelph*. Guelph, Ontario. November 2003. (Oral Presentation)

- **Adapting to the health impacts of climate change: Getting past GO.**
  D. F. Charron. *CCIARN Ontario workshop*. Guelph, Ontario. March 2004. (Oral Presentation and Panelist)

- **Climate Change, Infectious Diseases and the Public Health Response Challenge.**
  D. F. Charron. *Laboratory for Foodborne Zoonoses, Health Canada.* Guelph, Ontario. April 2004. (Lecture)

- **Logistic Analysis of Space-Time Data Investigating Potential Climatic Risk Factors of Waterborne Enteric Illness.**
  D. Gillis. *Statistical Society of Canada*. Montreal, Québec. May 2004. (Oral Presentation)

- **The Potential Role of High Impact Weather Events in Waterborne Disease Outbreaks in Canada 1975-2001.**
  M. K. Thomas, D. F. Charron, D. Waltner-Toews, C. J. Schuster, A. R. Maarouf, J. D. Holt. *Canadian Meteorological and Oceanographic Society*. Edmonton, Alberta. May 2004. (Oral Presentation by Kate Thomas)

- **A Forensic Analysis of Waterborne Disease Outbreaks – the Relationship with Weather Events.**
  C. J. Schuster, A. G. Ellis, D. F. Charron, W. J. Robertson, J. J. Aramini, B. J. Marshall, D. T. Medeiros. *Canadian Meteorological and Oceanographic Society*. Edmonton, Alberta. May 2004. (Oral Presentation)

- **Impact of Climate and Agriculture on Enteric Illness in Atlantic Canada: Implications of Climate Change.**
  J. E. Valcour, D. Waltner-Toews, D. F. Charron, T. Edge, O. Berke, A. R. Maarouf. *38th Canadian Meteorological and Oceanographic Society Congress: Human dimensions of weather and climate*. Edmonton, Alberta. May - June 2004. (Oral Presentation)

- **The Possible Role of High Impact Weather Events in Waterborne Disease Outbreaks in Canada, 1975-2001.**
  M. K. Thomas, D. F. Charron, D. Waltner-Toews, C. J. Schuster, A. R. Maarouf and J. D. Holt. *Canadian Water Resources Association (CWRA) Conference*. Montreal, Québec. June 2004. (Oral Presentation)

- **Excessive Rainfall and Waterborne Diseases in Southern Ontario, Canada.**
  D. F. Charron. *Canadian Scientific Writers Association*, Ryerson University. Toronto, Ontario. June 2004. (Poster Presentation)

- **Bridging the Eco-Social Divide – A Resilience Approach to Climate Change Adaptation in a Rural Watershed on the Canadian Prairies.**
  C. Neudoerffer, D. Waltner-Toews. *Annual Conference of the International Society for Ecological Economics.* Montreal, Québec. July 2004. (Oral Presentation)

- **A Study of Potential Climate Risk Factors of Enteric Waterborne Disease in Southern Alberta & Ontario**
  D. Gillis, D. F. Charron, J. D. Holt, D. Waltner-Toews, A. R. Maarouf. *16th Conference on Biometeorology and Aerobiology*. Vancouver, British Columbia. August 2004. (Oral Presentation)

- **A Forensic Analysis of Waterborne Disease Outbreaks – Exploring Techniques to Identify Thresholds**
  M.K. Thomas, D. F. Charron, J. Klaassen, A. R. Maarouf, H. Auld, D. MacIver. *American Meteorological Society (AMS) 16th Conference on Biometeorology and Aerobiology*. Vancouver, British Columbia. August 2004. (Oral Presentation by M.K. Thomas)

- **Impact of Climate and Agriculture on Enteric Illness in Atlantic Canada: Implications of Climate Change.**
  J. E. Valcour, D. Waltner-Toews, D. F. Charron, T. Edge, O. Berke, A. R. Maarouf. *American Meteorological Society 16th Biometeorology and Aerobiology Conference*. Vancouver, British Columbia. August 2004. (Oral Presentation)

- **The Possible Role of High Impact Weather Events in Waterborne Disease Outbreaks in Canada 1975-2001.**
  M. K. Thomas, D. F. Charron, D. Waltner-Toews, C. J. Schuster, A. R. Maarouf and J. D. Holt. *American Meteorological Society 16th Biometeorology and Aerobiology Conference*. Vancouver, British Columbia. August 2004. (Oral Presentation)

- **The Possible Role of High Impact Weather Events in Waterborne Disease Outbreaks in Canada, 1975-2001.**
  M. K. Thomas, D. F. Charron, D. Waltner-Toews, C. J. Schuster, A. R. Maarouf and J. D. Holt. *Health Canada Science Forum*. Ottawa, Ontario. October 2004. (Poster Presentation)

- **Infections Disease Outbreaks Related to Drinking Water in Canada, 1975-2001.**
  C. J. Schuster, A. G. Ellis, D. F. Charron, W. J. Robertson, J. J. Aramini, B. J. Marshall, D. T. Medeiros. *Health Canada Science Forum*. Ottawa, Ontario. October 2004. (Poster Presentation)

- **Spatial and Temporal Risk of Enteric Waterborne Illness as Related to Climate Variables.**
  D. Gillis, J. D. Holt, D. F. Charron, A. R. Maarouf, D. Waltner-Toews. *Hawaii International Conference on Statistics, Mathematics and Related Fields*. Honolulu, Hawaii. January 2005. (Oral Presentation)

- **Impacts of Climate Change on Waterborne Disease in Canada.**
  A. R. Maarouf. *Climate Change Scenarios Workshop by the Adaptation and Impacts Research Group, Environment Canada.* Ottawa, Ontario. January-February 2005. (Oral Presentation)

- **Lessons from the Past – Lessons for the Future: A case study of community-based adaptation on the Canadian Prairies.**
  C. Neudoerffer, D. Waltner-Toews. *Climate Change Adaptation and Canadian Agriculture: Impacts and Capacity. Invited workshop sponsored by CCIARN Agriculture*. Edmonton, Alberta. February 2005. (Oral Presentation)

- **Lessons from the Past – Lessons for the Future: A case study of community-based adaptation on the Canadian Prairies.**
  C. Neudoerffer, D. Waltner-Toews. *Adapting to Climate Change in Canada 2005: Understanding Risks and Building Capacity, sponsored by CCIARN and Natural Resources Canada*. Montreal, Québec. May 2005 (Oral Presentation).

- **The Possible Role of High Impact Weather Events in Waterborne Disease Outbreaks in Canada, 1975-2001.**
  M. K. Thomas, D. F. Charron, D. Waltner-Toews, C. J. Schuster, A. R. Maarouf and J. D. Holt. *Adapting to Climate Change in Canada 2005: Understanding Risks and Building Capacity, sponsored by CCIARN and Natural Resources Canada*. Montreal, Québec. May 2005 (Oral Presentation).

- **Climate Risk Factors of Enteric Waterborne Illness.**
  D. Gillis, J. D. Holt, D. F. Charron, A. R. Maarouf, D. Waltner-Toews. *Adapting to Climate Change in Canada 2005: Understanding Risks and Building Capacity, sponsored by CCIARN and Natural Resources Canada*. Montreal, Québec. May 2005 (Oral Presentation).

- **A Possible Role of High Impact Weather Events in Waterborne Disease Outbreaks in Canada, 1975-2001.**
  M. K. Thomas, D. F. Charron, D. Waltner-Toews, C. J. Schuster, A. R. Maarouf and J. D. Holt. *Animal Determinants of Emerging Disease Research Unit National Rounds*, Guelph, Ontario. May 2005 (Oral Presentation).

- **A Possible Role of High Impact Weather Events in Waterborne Disease Outbreaks in Canada, 1975-2001.**
  M. K. Thomas, D. F. Charron, D. Waltner-Toews, C. J. Schuster, A. R. Maarouf and J. D. Holt. *Abstract submitted to Canadian Meteorological and Oceanographic Society of Canada 39th Annual Conference ~ Sea to Sky*, Vancouver, Canada. Accepted for presentation June 2005.

- **The Application of Climate Thresholds for Waterborne Disease Outbreaks to Climate Change Scenarios in Canada.**
  C. J. Schuster, D. F. Charron, A. R. Maarouf, J. Klaassen, H. Auld, D. McIver. *Abstract submitted to the 17th International Society of Environmental Epidemiology Conference*. Johannesburg, South Africa. Accepted for presentation September 2005.

- **A Possible Role of High Impact Weather Events in Waterborne Disease Outbreaks in Canada, 1975-2001.**
  M. K. Thomas, D. F. Charron, D. Waltner-Toews, C. J. Schuster, A. R. Maarouf and J. D. Holt. A*bstract submitted to the 17th International Society of Environmental Epidemiology Conference*. Johannesburg, South Africa. Accepted for presentation September 2005.

- **A Possible Role of High Impact Weather Events in Waterborne Disease Outbreaks in Canada, 1975-2001.**
  M. K. Thomas, D. F. Charron, D. Waltner-Toews, C. J. Schuster, A. R. Maarouf and J. D. Holt. *Abstract submitted to Mapping the future of public health: People, Places and Policies*, Ottawa, Canada. Accepted for presentation September 2005.

6.1.2. Attended

- February 2003. Freshwater Forum by The Manitoba Clean Environment Commission, Fisheries and Oceans Canada (Freshwater Institute), Manitoba Conservation (as part of Canadian activities to mark the International Year of Freshwater). Winnipeg, Manitoba. (C. Neudoerffer)

- February 2003. Meeting the Challenges from Climate Change Workshop, CCIARN Agriculture, Winnipeg, Manitoba (C. Neudoerffer)

- March – April 2003. Climate Change and Water on the Prairies. Water Wisdom Public Forums, Winnipeg, Manitoba (C. Neudoerffer)

- May 2003. 53rd Annual Meeting, Canadian Association of Geographers, Victoria, British Columbia. (C. Neudoerffer)

- May 2003. International Forum 2003: Ecosystem Approaches to Health, Montreal, Québec. (D. F. Charron)

- June 2003. CREM Symposium: The changing profile of food- and waterborne pathogens: Environmental and hygiene connections, Ottawa, Ontario. (M.K. Thomas)

- June 2003. Understanding Climate Change Impacts on Manitoba's Water Resources. Conference sponsored by Manitoba branch of the Canadian Water Resources Association, with PARC (Prairie Adaptation Research Collaborative), and C-CIARN Water Resources, Winnipeg, Manitoba (C. Neudoerffer)

- June 2003. CMOS Conference: Impacts and Innovations, Ottawa, Ontario. (M.K. Thomas)

- Sept 2003. 15th Conference of the International Society for Environmental Epidemiology, Perth, Western Australia, Australia. (D. F. Charron, M.K. Thomas)

- Sept 2003. 1-day Climate Change & Health Symposium and 3-day short course by Australian National University, Canberra, ACT, Australia (D. F. Charron)

- September 2003. Guide to Climate Change Research in Manitoba, (sponsored by Prairie Adaptation Research Collective and Climate Change Connection), Winnipeg, Manitoba. (C. Neudoerffer)

- October 2003. Young Human Dimensions Researchers Pre-Conference, Montreal, Quebec. (C. Neudoerffer)

- October 2003. Human Dimensions of Global Environmental Change Conference, Montreal, Québec. (C. Neudoerffer, D. Waltner-Toews)

- October 2003. Presentation to "High Impact Weather Group," Environment Canada Meteorologists, Alberta. (C. Soskolne)

- November 2003. Presentation to Cuba Delegation on Climate Change Impacts and Adaptations Research in Health Canada, Havana, Cuba. (D. F. Charron)

- December 2003. Canada Climate Change and Health Vulnerability Assessment: Natural Hazards and Extreme Events Workshop, Ottawa, Ontario. (D. F. Charron)

- December 2003. Climate Change Scenarios Workshop and Statistical Downscaling Tutorial. Hosted by C-CIARN, Ottawa, Ontario. (A. R. Maarouf)

- January 2004. Climate Change and Health Workshop in Cuba. (D. F. Charron, D. Waltner-Toews)

- March 2004. "Bridging Scales and Epistemologies: Linking Local Knowledge and Global Science in Multi-Scale Assessments," part of the Millenium Ecosystem Assessment, Alexandria, Egypt. (D. Waltner-Toews)

- March 2004. Climate Change and Health Presentation for York University graduate class, Toronto, Ontario. (A. R. Maarouf)

- March 2004. Climate Change, Infectious Disease, and the Public Health Response Challenge. (D. F. Charron, P. Sockett)

- March 2004. Climate Change and Infectious Diseases Lecture, Ryerson School of Occupational and Public Health, Toronto, Ontario.

- March 2004. Climate Change and Public Health Issues, CCIARN, Ontario. (D. F. Charron)

- March 2004. Adaptation to the Health Impacts of Climate Change: Getting Past Go! C-CIARN, Ontario (D. F. Charron, W. Galatianos)

- March 2004. The health impacts of Climate Change. Health Canada, Safe Environments Program Lecture Series, Ottawa, Ontario. (D. F. Charron, P. Sockett)

- March 2004. Communities and the Impact of Climate Change Conference. Sponsored by CUSO, Winnipeg, Manitoba. (C. Neudoerffer)

- May 2004. SAS User Groups International, Montreal, Québec (D. Gillis)

- August 2004. Missing Data Workshop, Fields Institute, Toronto, Ontario (D. Gillis)

- August 2004. Joint Statistical Meeting, Toronto, Ontario (D. Gillis)

- November 2004. Fields Institute Workshop on Mathematical Education, Toronto, Ontario (D. Gillis)

6.2. Media Events

- D. F. Charron. Interview with Geoff McMaster, Alberta writer for *The Health Journal*, a free national publication distributed through pharmacies, on climate change and infectious diseases

- D. F. Charron. Live interview for August 31, 2003 climate change and infectious diseases article in *The Globe and Mail: Focus Section, Weekend Edition* by Lydia Dotto (published August 31st 2003)

- J. E. Valcour. "Examining the influence of climate change." At Guelph News, February 2004.

- M. K. Thomas, D. F. Charron, D. Waltner-Toews, C. J. Schuster, A. R. Maarouf and J. D. Holt. "The possible role of high impact weather events in waterborne disease outbreaks in Canada, 1975-2001." Your Health and a Changing Climate Newsletter, Health Canada. October 2004; 2:3.

- C. J. Schuster, D. F. Charron, A. R. Maarouf, H. Auld, J. MacIver and J. Klaassen. "A Forensic Analysis of Meteorological Thresholds with Increased Risk of Waterborne Disease in Canada." Your Health and a Changing Climate Newsletter, Health Canada. October 2004; 2:6.

- J. E. Valcour. "Impact of Climate and Agriculture on Enteric Illness in Atlantic Canada: Toward a Climate Change Adaptation Strategy." Your Health and a Changing Climate Newsletter, Health Canada. October 2004; 2:6.

- D. Gillis. "A Study of Potential Climate Risk Factors of Enteric Waterborne Disease in Southern Alberta (1992-1998)." Your Health and a Changing Climate Newsletter, Health Canada. October 2004; 2:7.

6.3. Peer-reviewed Journal Publications

6.3.1. Published, In-press or Submitted

Charron DF, Thomas MK, Waltner-Toews D, Aramini JJ, Edge T, Kent RA, Maarouf AR, Wilson J. 2003. Vulnerability of Waterborne Diseases to Climate Change in Canada: a review. Proceedings of the International Conference on Water and Health, September 23-25 2002, Ottawa, Canada. Institute for Risk Research, University of Waterloo, Waterloo, Ontario, Canada. 476pp.

Thomas MK, Charron DF, Waltner-Toews D, Schuster CJ, Maarouf AR, Holt JD. 2003. Extreme weather and waterborne disease outbreaks in Canada, 1974-2000. Epidemiology 14(5) Supp: S133.

Charron DF. 2003. Canada's response to the potential health threats of climate change. Epidemiology 14(5) Supp: S138.

Charron DF, Thomas MK, Waltner-Toews D, Aramini JJ, Edge T, Kent RA, Maarouf AR, Wilson J. 2004. Vulnerability of Waterborne Diseases to Climate Change in Canada: A Review Part A. Journal of Toxicology and Environmental Health, 67:20-22.

Maarouf AR. 2005. Impacts of climate change and waterborne disease. In "Adaptation Science," the Newsletter of Adaptation and Impacts Group, Environment Canada, Downsview, Ontario, Issue #3:10-11.

Schuster CJ, Ellis A, Robertson WJ, Aramini JJ, Charron DF, Marshall B, Medeiros D. 2005. Drinking Water Related Infectious Disease Outbreaks in Canada, 1974-2001. (Submitted to Can J Public Health)

Schuster CJ, Ellis AG, Charron DF, Aramini JJ, Marshall B, Robertson W. 2005. Infectious Drinking Water Related Disease Outbreaks, 1974-2001. (Accepted for publication in Can J. Pub Health summer/autumn 2005)

Thomas MK, Charron DF, Waltner-Toews D, Maarouf AR, Holt JD, Schuster CJ. 2005. Case Crossover Examination of Waterborne Disease Outbreaks and Extreme Precipitation Events. (Under revision for publication)

Neudoerffer RC and Waltner-Toews D. 2005. Beyond Vulnerability: a resilience approach to climate change adaptation. Submitted to Global Environmental Change. (Under revision for publication)

Maarouf A, Ramay F, Charron D, Waltner-Toews D, Schuster C, et al., 2005. Utilizing climate change scenarios in waterborne disease research. (In preparation).

Neudoerffer RC, Waltner-Toews D, Charron DF. Lessons from the Past – Lessons for the Future: A case study of community-based adaptation on the Canadian Prairies. In Climate Change and Canadian Agriculture: Understanding Impacts and Capacity. E. Wall, B Smit, J. Wandel (editors). Invited book chapter for publication by UBC Press in 2006. Note: this proposed book is the first Canadian publication where twenty years of climate change and Canadian agricultural impacts and adaptation research will be presented in a comprehensive manner.

6.3.2. Reports and Theses

Charron D.F., Waltner-Toews, D. "A synopsis of known and potential diseases and parasites associated with climate change". Compiled by Sylvia Greifenhagen and Thomas L. Noland, Ontario Forest Research Institute, Forest Research Information Paper No. 154.

Gillis, D. PhD Thesis. Department of Mathematics and Statistics, University of Guelph. Expected submission 2006. Working Title: Spatial and Temporal Risk of Enteric Waterborne Illness as Related to Climate Variables.

Thomas MK. MSc project, Department of Population Medicine, University of Guelph. 2004. The Role of High Impact Weather in Waterborne Disease Outbreaks in Canada.

Neudoerffer, RC. PhD Thesis. Rural Studies, School of Environmental Design and Rural Development, University of Guelph. Expected submission 2005. Working Title: Building social-ecological resilience of a rural watershed on the Canadian Prairies: a climate change adaptation strategy.

Valcour, J. PhD Thesis. Department of Population Medicine, University of Guelph. Expected submission 2006. Working Title: Impact of Climate and Agriculture on Enteric Illness in Atlantic Canada: Implications of Climate Change.

6.3.3. Forthcoming

- The Role of Weather in Endemic Enteric Disease in Southern Ontario.
  D. Gillis, D.F. Charron, J. Holt, D. Waltner-Toews, A.R. Maarouf

- Simulating Future Daily Meteorology Data for Use in Climate Change Health Impact Studies.
  A.R. Maarouf, F. Ramay

- Defining Parameters for Weather Events Which Precede Waterborne Disease Outbreaks in order to Predict Future Vulnerability.
  C.J. Schuster, D.F. Charron, A.R. Maarouf, H. Auld, D. Waltner-Toews

- A Canadian Comparison to U.S. Waterborne Disease Outbreaks and Extreme Precipitation Events.
  C.J. Schuster, D.F. Charron, J. Holt

- Examining Social Adjustment to Flood Events in a Small Farming Basin, Manitoba.
  C. Neudoerffer, D. Waltner-Toews, D. F. Charron

- The Theoretical Application of Concepts of Vulnerability and Adaptation to Climate Change.
  C. Neudoerffer, D. Waltner-Toews, D. F. Charron

- Endemic Waterborne Disease in Southern Alberta and its Relationship to Weather Events.
  D. Gillis, D.F. Charron, J. Holt, D. Waltner-Toews, A.R. Maarouf, V. Edge

- Interpolation Techniques Used to Examine Meteorological Data.
  D. Gillis, J. Holt, V. Edge, D. F. Charron

- Thin-plate Methodology for Spatially and Temporally Correlated Data.
  D. Gillis, J.D. Holt, D.F. Charron, A.R. Maarouf, D. Waltner-Toews

- Potential Climate Risk Factors of Enteric Waterborne Disease – Southern Alberta.
  D. Gillis, J.D. Holt, D.F. Charron, A.R. Maarouf, D. Waltner-Toews

- A Climate Risk Model for Southern Alberta.
  D. Gillis, J.D. Holt, D.F. Charron, A.R. Maarouf, D. Waltner-Toews

- The Future of Endemic GastroIntestinal Disease Under Changing Climate Scenarios.
  D. F. Charron, A.R. Maarouf, M.D. Fleury, K. Thomas, J. Holt

- The Impact of Climate Change on Waterborne Disease in Canada: Scenarios, Vulnerability and Adaptation.
  D. F. Charron, D. Waltner-Toews, A.R. Maarouf, F. Ramay, J.J. Aramini, T. Edge

- A Review of the Distribution of Endemic Disease in Atlantic Canada.
  J. Valcour, D. F. Charron, D. Waltner-Toews, C. J. Schuster, T. Edge, O. Berke

- Relationship between weather parameters, agricultural intensity indicators, water quality and quantity and the incidence of enteric illness in Atlantic Canada: A Comparison of Modelling Techniques.
  J. Valcour, D. F. Charron, O. Berke, D. Waltner-Toews, T. Edge

- A Comparison of Spatial Statistical Manipulations and Their Effect on Mapping Endemic GastroIntestinal Disease in Atlantic Canada.
  J. Valcour, O. Berke, D. Waltner-Toews, D. F. Charron

- Weather and Endemic Disease: A Study of (the West Coast?,) the Prairies, Central Canada and the Atlantic Provinces.
  J. Valcour, D. Gillis, D. F. Charron, D. Waltner-Toews, A.R. Maarouf, J. Holt

- Potential Effects of Climate Change on the Risk of Enteric Disease in Canada.
  C.J. Schuster, D. F. Charron, J. Valcour, D. Gillis, A.R. Maarouf, F. Ramay, J. Holt, D. Waltner-Toews

- Return Periods, Odds Ratios and Thresholds.
  M.K. Thomas, D. Waltner-Toews, D.F. Charron, A.R. Maarouf, J. Holt

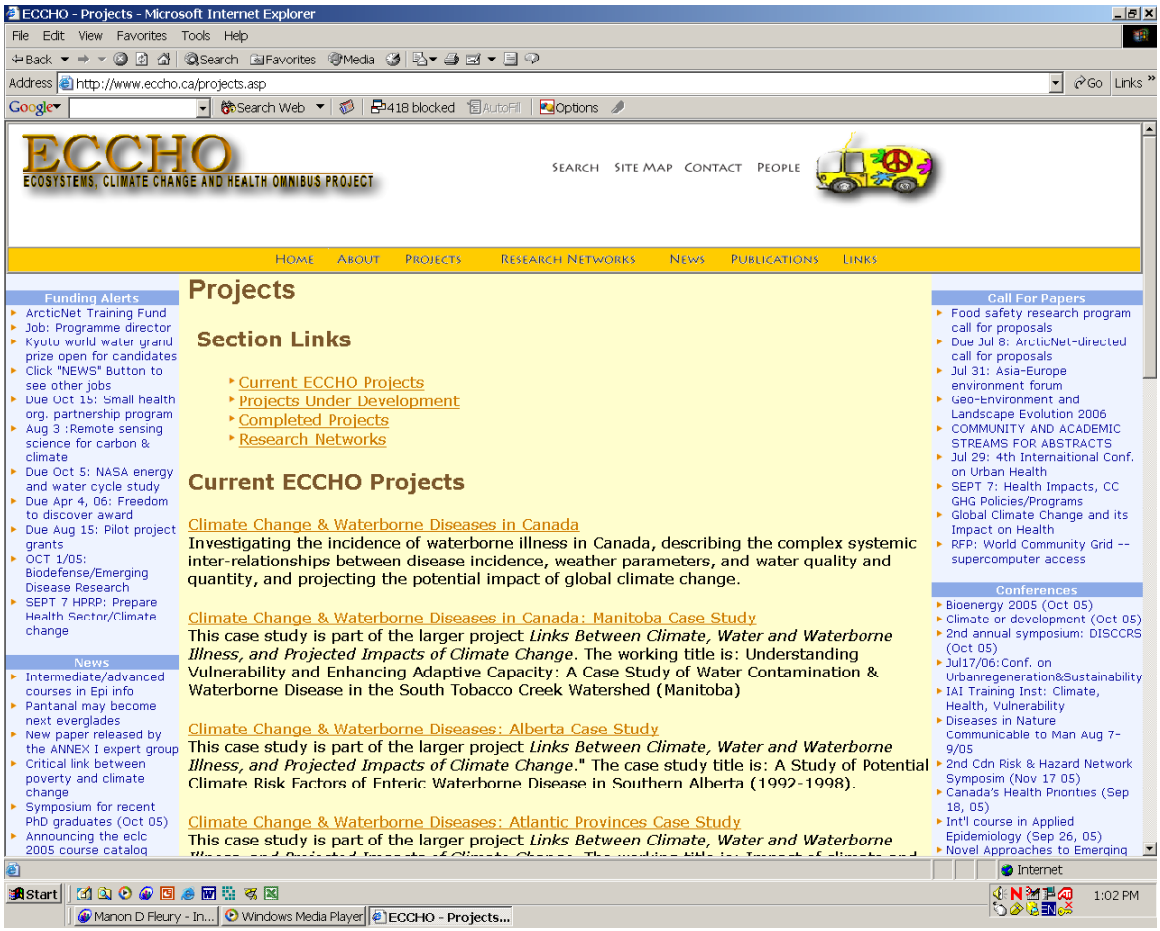
- Outbreak Thresholds and Climate Change.
  C.J. Schuster, D. Charron A.R. Maarouf, M.D. Fleury, H. Auld, J. Klaassen, D. McIver

- Utilizing Climate Change Scenarios in Waterborne Disease Research.
  A.R. Maarouf, F. Ramay, D.F. Charron, D. Waltner-Toews, C.J. Schuster

6.4. External communications

6.4.1. Website

The website http://www.eccho.ca provides visitors with information about project groups, project listings, newsletters, upcoming events and contacts. See examples below.



6.4.2. Newsletters

Most ECCHO newsletters are available from the www.eccho.ca website, in both official languages.

Newsletters published include:

- Canada Climate Change, Food and Water-borne Contaminants Research News. Volume 1, Number 1, February 2002.
- Canada Climate Change, Food and Water-borne Contaminants Research News. Volume 2, Number 1, April 2003.
- Canada Climate Change, Food and Water-borne Contaminants Research News. Volume 2, Number 2, March 2004.

6.5. Soliciting expert advice from stakeholders – workshops

6.5.1. Interim HPRP Workshop, October 2003

"Waterborne Illness and Climate Change in Canada -- The Guelph HPRP Project -- Interim Workshop Proceedings – October 20, 2003"

Symposium presentations and findings are available, in complete form, upon request. Topics presented at the symposium include:

- Links between extreme weather events and waterborne disease outbreaks (Kate Thomas)
- A Review of Waterborne Disease Outbreaks in Canada – 1971-2000 (James Valcour, on behalf of Corinne Schuster)
- Building social and ecological resilience to reduce vulnerability and enhance adaptive capacity on the Canadian Prairies: A case study of water contamination and waterborne disease in the South Tobacco Creek watershed (Cynthia Neudoerffer)
- Impact of climate and agriculture on enteric illness in Atlantic Canada: Toward a climate change adaptation strategy (James Valcour)
- Investigation of potential climatic risk factors of waterborne gastrointestinal disease in southern Alberta, 1992-1998 (Dan Gillis)
- Next Steps: Completion of phases I and II (Dominique Charron)
- Next Steps: Phase III (Abdel Maarouf)

6.5.2. Final HPRP Workshop, April 2005

"Waterborne Illness and Climate Change in Canada -- The Guelph HPRP Project --
Final Workshop Proceedings -- April 18, 2005"

Symposium presentations and findings are available, in complete form, upon request. Topics presented at the symposium include:

- Participants' Experiences:
    - What is the most important research issue or challenge relating to water, climate and health in Canada?
    - What is the most important policy issue or challenge?
- Research Reports:
    - Climate thresholds for waterborne disease outbreaks – potential policy implications (Corinne Schuster)
    - A possible role of high impact weather events in waterborne disease outbreaks in Canada, 1975-2001 (Kate Thomas)
    - Climate risk factors of enteric waterborne disease (Dan Gillis)
    - Impact of climate and agriculture on enteric illness in Atlantic Canada: Implications of climate change (James Valcour)
    - Lessons from the past – lessons for the future: A Case Study of community-based adaptation on the Canadian prairies (Cynthia Neudoerffer)
- Policy and Research Challenges – Where Do We Go From Here? (discussion)

6.6. Links

In 2001 and 2002, through Health Canada's participation in ENDS -- the Enteric Diseases Surveillance Steering Committee -- the project team communicated with Agriculture Canada, Canadian Food Inspection Agency, Association of Medical Officers of Health, provincial health ministries, provincial environment ministries, First Nations, and stakeholders in the water

industry. ENDS acted as the national stakeholder forum for epidemiological research and surveillance of waterborne disease, and included representation from the above agencies and groups, as well as other bureaus within Health Canada, Environment Canada, and academia. ENDS developed numerous policy-oriented studies of waterborne disease, and played an advisory role project during the first half of this project, until disbanded. It is currently being reformed. Members of the Federal-Provincial-Territorial Committee on Drinking Water also provided guidance to the team. This provided an excellent basis on which to continue further collaborations.

The initial core project team expanded to include many additional collaborators. Within the University of Guelph, faculty members in the Department of Mathematics and Statistics, the Department of Population Medicine, the Canada Research Chair of Global Environmental Change within the Department of Geography, and the Coordinator of CCIARN Agriculture participated. A faculty member with the University of Ottawa also provided data.

Early in the research process, professionals shared information on waterborne disease outbreaks across Canada – information that had not previously been published. Access to data and in-kind contributions were forthcoming from the Public Health Agency of Canada, which included support and data sharing from the Foodborne, Waterborne & Zoonotic Infections Division, Meteorological Services, the National Water Research Institute and Monitoring Science and Strategies (within Environment Canada). The Canadian Forest Service (within Natural Resources Canada) also supported our efforts.

In Miami, Manitoba, links with the Deerwood Soil and Water Management Association, South Tobacco Creek Project Steering Committee, Coleman (North Tobacco Creek) Watershed Steering Committee, and the Prairie Farm Rehabilitation Administration, and Pembina Valley were made. The Manitoba case study benefited from additional funding through a SSHRC (Social Sciences and Humanities Research Council) post-doctoral fellowship.

Expert guests attending the two workshops included the Associate Dean of Environmental Sciences from University of Guelph, a leader of the Guelph Water Management Project, a member of the Canada Water Network and School of Planning from the University of Waterloo, an Environmental Management Specialist and a Policy Analyst from the Ontario Ministry of Agriculture and Food, an epidemiologist and statisticians from the Foodborne, Waterborne and Zoonotic Infections Division, Health Canada, and several climatologists/meteorologists from Environment Canada. Other invited guests included other Researchers/Managers such as the NSERC Chair in Water Treatment, a physician, a representative from Environmental Studies at York University, the Canada Research Chair in Water Supply Security, a lawyer from the Canadian Environmental Law Association, a scientific evaluator from the Water Quality and Health Bureau, an epidemiologist from the Laboratory for Foodborne Zoonoses, Health Canada, and a research associate from the Department of Civil Engineering.

We were especially pleased to have the participation of the Director for the Research Management & Dissemination Division of Health Canada, the Head of Targeted Studies for the Public Health Agency of Canada, the Director of the Foodborne, Waterborne and Zoonotic Infections Division, Public Health Agency of Canada and the manager of the Climate Change and Health Office, Health Canada.

All experts provided invaluable insight into their specialties and excellent discussion about current challenges to tracking and preventing waterborne diseases in Canada, along with the additional challenge of potential climate change impacts.

Several collaborative proposals have been written as a result of links made through this project, and are highlighted below:

"Improving Resilience of Water Infrastructure and Health Response Systems against Waterborne Diseases" (Funded)

Funding for the project "*Improving Resilience of Water Infrastructure and Health Response Systems against Waterborne Diseases"* is secured and falls under the Joint Infrastructure Interdependences Program (JIIRP), managed by NSERC (Natural Sciences and Engineering Research Council). The Principal Investigator is the Canada Research Chair in Water Supply Security, based at the School of Engineering, University of Guelph. Research will identify how to improve and obtain increased understanding on delivery of capabilities for infrastructure throughout Canada. Four overlapping program objectives aim to:

1. Expand and leverage academic, industrial, and government research activities in the area of infrastructure interdependencies to develop relevant new knowledge, techniques, and policies.

2. Build Canadian research capacity in area of infrastructure interdependencies.

3. Raise awareness of infrastructure interdependency research issues and promote Canadian academic interdependency research, education, and training.

4. Build linkages, networks, and partnerships across Canada and among relevant disciplines to facilitate effective transfer and dissemination of research results to the private and public sectors.

Collaborators include Health Canada, Environment Canada, the Red Cross, Emergency Management Ontario, Federation of Canadian Municipalities, Canadian Council for Professional Engineers, and three case study partners in Peterborough, Ontario, Greater Vancouver Regional District, British Columbia and City of Guelph, Ontario. Advisory committee members will be involved in workshops and webcast seminars, for provision of advice and data assembly for evaluations, to encourage and participate in initiatives to explore the applicability of the findings of the three case studies.

RésEAU Partnership Fund Proposal (Funded)
Project: An Infectious Disease Application for RésEAU

The goal is to develop a functional, responsive, health information application for RésEAU. The federal and provincial governments produce aggregate health statistics. Also, relevantCanadian health information is published in scientific journals. Although such data can be mapped, their relationship to water-related hazards is not always clear. The Principal Investigator will be Dominique Charron, Senior Epidemiologist, Public Health Agency of

Canada. This project will collate publicly available health information with direct connections to water quality, quantity and meteorological conditions, augment these data with analyses on existing data that further delineate relationships between water and health, and contribute these and supporting information (interpretive information) for the RésEAU web portal. Goals are as follows:

1. In consultation with RésEAU stakeholders, collate, summarize, and map publicly available health information with direct connection to water quality, quantity, or meteorological conditions.

2. Where a connection to water quality, quantity, or meteorological conditions is hypothesized, but not clear, perform analyses to determine the nature of the connection, if any, and add these findings to data in 1)

3. Stakeholder consultation within Environment Canada, federal-provincial-territorial partners, and academia through a small one-day workshop by invitation, and by telephone and email consultation

4. Draft interpretive information to accompany the health information on the RésEAU website.

It is likely that new links between water and health outcomes will be discovered through the analyses planned in this project. At present, few health data in Canada are formally connected to a contaminated water source. In this project, we will use epidemiological and statistical methods to strengthen the evidence between poor water quality, high and low water quantities, and several meteorological conditions (extreme precipitation, drought, heat) and infectious disease. In addition, we will network with groups doing primary research on molecular markers for waterborne organisms, to better identify the proportion of enteric infections that are waterborne.

Partners include Meteorological Services, Environment Canada; National Water Research Institute, Environment Canada; Health Canada's Water Quality and Health Bureau, Climate Change and Health Office; Public Health Agency of Canada; and the Ecosystems, Climate Change and Health Omnibus project, University of Guelph.

Letter of Intent: CIHR Team Grant Program (Rejected)

Collectively, this team of scholars and practitioners has the capacity to generate innovative and synergistic responses to emergent infectious diseases and their socio-ecological contexts on its own behalf, as well as to train a new generation of scholars and practitioners in interdisciplinary and trans-disciplinary approaches to the collaborative development of theory and practice.

Objectives:

1. To characterize relationships between the changes in microbial populations, human and animal populations, and social and ecological contexts relevant to emerging infectious diseases.
2. To identify possible points of intervention based on qualitative and quantitative analyses for: key decisions in identifying and tracking the emergence of infectious diseases, optimal time and space coordinates for effective interventions, and sustainability- based criteria for allocation of resources and assessment of impacts.
3. To develop integrated assessment models that can serve as a hub around which stakeholders, researchers and decision makers can better understand each other's perspectives, so as develop appropriate responses.
4. To characterize selected socio-ecological systems in terms of their health or resilience in general, and the implications of different systemic organizations for patterns of health and disease.
5. To identify feasible, adaptive, ecologically and socially resilient and equitable policy and management responses to emerging disease threats, which also foster broader improvement in social-ecological sustainability, based on our best understanding of the changes and relationships we have documented in 1-3.
6. Public engagement, knowledge translation, policy development and management interventions are all inherent in some of the latest methods developed to integrate across scales and disciplines (Walker et al., 2001; Waltner-Toews et al., 2004). However, we have separated this out as an important objective, so it is treated with the same scholarly seriousness as other objectives.

An Advisory Committee will ensure both peer review and accountability. A Steering/Coordinating Group will be responsible for overall intellectual direction of the project, key decision-making and management. We envisage the overall team subdivided into several overlapping streams, led by key investigators; these would be linked to an overall integrative team. The decision-making structure will reflect this multi-faceted team approach. Each team will have post-doctoral and research associates as part of the team, as well as graduate students.

Teams include:

- Epidemiology of infectious disease emergence
- Socio-cultural and governance issues
- Environmental and climate change related to emerging diseases
- Responding to infectious disease emergence: prevention and adaptation policies and actions.

An Analysis of Peterborough's Municipal Infrastructure Design Following An Extreme Precipitation Event: Reflecting the Associated Burden of Waterborne and Water-related Diseases in a Global Climate Change Reality (CCIAP –NRCan – Submitted)

Changes in intensity and frequency of precipitation events in response to the global warming reality are of major concern among Canadian communities. Changes are ongoing, although

largely not quantified, from long-term precipitation and temperature records. Growing evidence links such trends to global warming. Simultaneously, incidents of waterborne diseases, including cryptosporidiosis, giardiasis, and infections due to other pathogens, have troublesome implications to vulnerable communities across Canada. Although not strictly waterborne but of extreme importance to municipal infrastructure, mosquito-borne infections, such as West Nile virus, are affected by changes in temperature, precipitation levels, and infrastructure design. The effectiveness of municipal infrastructure's capacity to respond to more frequent and intense storms is critical. In July of 2004, the City of Peterborough, Ontario, experienced an extreme precipitation event that impacted the city's municipal infrastructure (water, wastewater and storm water) and left residents vulnerable. The City of Peterborough is demonstrative of the potentially enormous impact that climate change may inflict among Canadian communities.

This project will investigate how climate change scenarios will influence potential hazards from waterborne and mosquito-borne diseases in relation to municipal infrastructure vulnerabilities, focusing in particular on the July 2004 extreme precipitation event in Peterborough, Ontario. In addition, it will focus on how improvements in the design of municipal infrastructure systems will minimize associated health risks to Canadians. An understanding of the inter-relationships between water-related and health response infrastructures in response to an extreme precipitation event will be developed, learning from the experiences in Peterborough, Ontario.

Objectives:

1. Establish the performance response of water, wastewater and storm water infrastructures and water-related disease exposures experienced during the July 2004 extreme precipitation event in Peterborough, Ontario;

2. Determine how infrastructure systems will perform under climate change; and,

3. Generalize findings to relate to infrastructure and water-related disease exposures to other Canadian municipalities in response to climate change.

Collaborators include the Public Health Agency of Canada, Meteorological Service of Canada-Ontario, the City of Peterborough, and the involvement of the Ontario Federation of Canadian Municipalities will be invited.

7. Deliverables

7.1. Literature review

In the past, waterborne diseases were thought of only as problems for those in developing countries and common waterborne diseases of the 19th century are now almost unknown in developed countries. However, it is vital that vigilance is maintained at a high level because these diseases are still common in many parts of the world (Fawell and Nieuwenhuijsen, 2003). Modern agricultural practices, increased global trade and rapid forms of transportation facilitate the transmission of

various parasites from developing regions to urban areas (Gajadhar and Allen, 2004). Recent waterborne disease outbreaks have increased the public's awareness to the risks inherent to contaminated water. Canadians realize that safe water is a concern for them also. Nearly 300 outbreaks of waterborne disease have been reported in Canada since 1975, including the outbreak of *Escherichia coli* O157:H7 in Walkerton, Ontario, in 2000, and an outbreak of gastroenteritis in North Battleford, Saskatchewan, in 2001. Increases in human and animal populations and alterations to natural landscapes are factors that can lead to local water contamination (Mallin et al., 2001). Combined with fiscal reform for public services, this had lead to a decline in national water safety (O'Connor, 2002). Weather has also played a significant historical role in triggering a number of reported waterborne disease events in Canada (Hrudey, 2003).

In light of the results from the O'Connor report (2002), combined with concern following the outbreak in North Battleford, Saskatchewan, in 2001, new public health initiatives related to drinking water quality commenced in 2002. Policy and decision makers are now assessing the potential health impacts of global climate change. Understanding of the possible water-related health implications of pronounced climate change is growing. Given that existing wells and water and sewage treatment systems were designed to operate within expected levels of precipitation, ambient temperature, snow cover, snow melt, water levels, sea level, and coastal dynamics, substantial changes to what was once considered the meteorological norm could have a detrimental effect on water safety. Public health professionals and water managers need as much information as possible about these potential changes in order to take the necessary steps at this time to protect public health now and in the future.

7.1.1. Waterborne diseases in Canada

The Canadian burden of waterborne illness is thought to account for a significant proportion of enteric illness. Payment et al. (1991) estimated that 35% of enteric diseases in Montreal were due to preventable waterborne illness. There were 4015 cases of giardiasis and 599 cases of cryptosporidiosis reported in Canada in 2003 (Public Health Agency of Canada, 2004). The incidence of these diseases is probably much higher than what is captured by these data (Majowicz et al., 2004; Frost et al., 1996). Infective *Giardia* cysts have been shown to be widespread in raw surface waters for some time in Canada (Wallis et al., 1996). Although many cases are known or presumed waterborne, other cases are not. For example, persons with HIV are over-represented among the cases of cryptosporidiosis, for reasons including compromised immunity, community and zoonotic exposure, and behavioural factors (Hunter and Nichols, 2002). Nonetheless, Hunter and Nichols (2002) suggest unboiled tap water is an important source of exposure for this group. Majowicz et al. (2004) found that 5% of cases of cryptosporidiosis reported in Ontario occurred in persons with HIV. Both giardiasis and cryptosporidosis are more frequently reported in children (Majowicz et al., 2004; Greig et al., 2001), in whom community exposure and behavioural factors likely play a role. Payment et al. (2000) found *Cryptosporidium*, *Giardia* and enteric viruses in samples taken at each of 45 water treatment plants along the St. Lawrence River. They were able to model a measurable risk of giardiasis in some of these communities, depending on water temperature and treatment practices.

Waterborne cases and outbreaks have been associated with *E. coli* O157:H7 and *Campylobacter* noroviruses, occasionally *Shigella*, and a number of other enteric pathogens (i.e. Lee et al., 2002; Grey-Bruce-Owen Sound Health Unit, 2000; Levy et al., 1998). Of cases of enteric illness that are

reported, often the source is not identified and may be any of travel, waterborne, foodborne, or person-to-person transmission. A few cases of cholera are reported in Canada annually, including three indigenous cases (Health Canada, 2002; WHO, 2001; WHO, 2002). Other pathogens, such as hepatitis A (385 cases reported nationally in 2003; Public Health Agency of Canada, 2004), leptospirosis (rare, not notifiable) and Legionnaire's disease (44 cases reported nationally in 2003; Public Health Agency of Canada, 2004), can be waterborne but do not cause gastrointestinal illness. Some cases of enteric illness may have been acquired outside Canada. Canada's native peoples may be at particularly increased risk of waterborne enteric illness due to poor availability of safe drinking water in remote areas (Rosenberg et al., 1997). Likewise, Canada's rural population may potentially be more vulnerable as they often depend on groundwater sources, but have little access to historical water quality data (Rudolph et al., 1998).

Occasionally, outbreaks of gastrointestinal illness occur where, by epidemiological investigation, water is unquestionably implicated: these events provide a reasonable starting point for assessing the scope of the Canadian waterborne illness problem. Preliminary results from an analysis of a subset of nearly 300 Canadian historical reported waterborne disease events include outbreaks reported from 9 provinces and 1 territory (Schuster et al., In Press). *Giardia* was the most frequent cause of these outbreaks, followed by *Cryptosporidium* (diagnosed since 1993 only) and *Campylobacter*. Most involved a surface water source (usually a rural watershed). Mechanical problems with treatment were implicated in some outbreaks where water treatment information was known (in less than half of all outbreaks in this subset). Outbreaks in this subset frequently occurred in the spring. Snowmelt and heavy spring rainfall may be significant factors contributing to many such spring outbreaks. In Ontario, four outbreaks were linked to heavy snowfall, snowmelt, or heavy rainfall along with resulting turbidity. B.C. and Québec each had two outbreaks linked to heavy rainfall.

An analysis of passive surveillance data in the National Notifiable Disease Records (1987-2001, www.hc-sc.gc.ca/pphb-dgspsp/dsol-smed/, and Health Canada, 2002), which captures laboratory confirmed endemic cases and those linked to outbreaks, suggests there has been a distinct drop in both the rate and the number of reported cases of giardiasis and campylobacteriosis in recent years. Cases of verotoxigenic *E. coli* have peaked and fallen twice since reporting began in 1990 (mean near 1400 cases per year). Cryptosporidiosis has only been captured in this database since 2000 (573 cases in 2000, 1643 cases in 2001 including the North Battleford, Saskatchewan, outbreak, (Public Health Agency of Canada, 2002). Majowicz et al. (2004) found the mean incidence of cryptosporidiosis in Ontario in 1996-97 to be 2.13 per 100,000 people, but suspected substantial under-reporting of the disease due to sporadic testing for the pathogen. In Ontario, males, children under 5 years of age, and rural residents were at elevated risk. Of the cases where a suspected source was reported, 48% listed water, livestock exposures was a factor in 21% of cases, person-to-person transmission in 15% of cases, and travel outside of the province a factor in 22% of cases. In a similar study of *Giardia* reported in Ontario, Greig et al. (2001) found a mean annual age- and sex-adjusted rate of 26 cases per 100,000 people. Again, higher rates were found in males and children, and in urban populations. Incidence peaked in late summer or early autumn.

7.1.2. Waterborne pathogens

Cryptosporidium and *Giardia* spp.

Cryptosporidium and *Giardia* are protozoan parasites. Van Leeuwenhoek first observed *Giardia* in the late 1600's. *Giardia lamblia* can infect human and a variety of animals (i.e. cattle).

Cryptosporidia was described over 100 years ago, but it was not until the mid-1950's that it was seen as a pathogen of animals. The first case of human related cryptosporidiosis was not seen until 1976. *Cryptosporidium parvum* is able to infect both humans and certain livestock. Infection with either organism requires the ingestion of 10-100 oocysts. In healthy adults, infection is often subclinical or results in self-limited diarrhea. In infants, the elderly, and immuno-compromised patients, these organisms can cause severe and, in some cases, fatal diarrhea.

C. parvum and *G. lamblia* are obligate parasites that are only able to replicate within an infected host. Cysts and oocysts are shed in the host's feces in high numbers (10^7 – 10^{10} cysts/oocysts depending on the host species). Contamination of surface waters with cysts and oocysts can result in concentrations of 1 – 10^6 cysts / 100 litres. There is considerable seasonal and geographical variation in surface water contamination with *C. parvum* and *G. lamblia*.

Several waterborne outbreaks of cryptosporidiosis and giardiasis have been documented (Hunter, 1997). The largest outbreak occurred in Milwaukee in 1993. Contamination of the city's water supply with *C. parvum* resulted in an estimated 403,000 cases of cryptosporidiosis. The treated water met all of federal water quality standards at that time (Steiner et al., 1997).

C. parvum cysts and *G. lamblia* oocysts are highly resistant to the chlorination process. Due to the small size of the cyst (8-15 μm) and oocysts (4-6 μm) and low infective dose, filtration processes need to be highly refined to eliminate their presence. Filters can become overloaded during heavy precipitation events, allowing for contamination of localized water supplies.

Shiga-toxin producing Escherichia coli (STEC)

Shiga-toxin producing *E. coli* was first recognized as a pathogen of humans in 1982. The number of reported cases has steadily increased since this time (Szewzyk et al., 2000). Infection can cause hemorrhagic colitis with bloody diarrhea. In some cases, disease can progress to hemolytic-uremic syndrome, a potentially fatal condition characterized by acute renal failure (Griffin and Tauxe, 1991). Young children, immuno-compromised people and the elderly are particularly susceptible to infection.

Cattle and other ruminants are considered the major reservoir for this organism. Infection typically occurs through the ingestion of contaminated food products, but direct and indirect contact with an infected person has also been demonstrated as a route of infection (Wilson et al., 1996; Michel et al., 1999). More recent studies indicate that direct and indirect exposure to cattle is a potential source of infection (Wilson et al., 1996; Michel et al., 1999; Valcour et al., 2002). Infections can also occur via swimming in contaminated recreational waters (Hunter, 1997).

Rural populations tend to be at a higher risk of infection than urban populations due to a strong association between cattle density and the incidence of human STEC infection (Michel et al., 1999; Valcour et al., 2002). The spreading of manure to the surface of agricultural land was also found to be a risk factor of human STEC infections (Valcour et al., 2002), attributed to contamination of well water and locally produced food products contaminated with agricultural runoff (Cliver and Atwill, 1997; Valcour et al., 2002).

STEC has been responsible for several large outbreaks of enteric disease. Unpasteurized apple juice was implicated as a source of an outbreak in California when apples contaminated with manure were used in production (Guan and Holley, 2000). Several large waterborne outbreaks have also been linked to contamination of water sources with STEC. An outbreak of STEC at a New York county fair was linked to manure-laden water that was used for making beverages and ice (Patz et al., 2000). In May 2000, Canada experienced their worst outbreak of *E. coli* O157:H7. Agricultural run-off contaminated the municipal water supply in Walkerton, Ontario (Bruce Grey Owen Sound Health Unit, 2000). This combined with a breakdown in operating procedures resulting in over 2000 cases of illness and 7 deaths.

Campylobacter spp.

Campylobacter was discovered as an animal pathogen in the first half of the 20th century. It wasn't until 1970's that its pathogenic potential for humans was seen. The infectious dose for the campylobacters is relatively low. Birds, both wild and livestock species, are the typical reservoir, but other habitats include pigs, cattle, dogs and cats.

High numbers of *Campylobacter* spp. can be found in raw sewage (10-10^5 colony forming units/100 ml) and in contaminated surface waters (10-10^2 colony forming units/100 ml) (Szewzyk et al., 2000). Contamination of surface water has been correlated with contamination from poultry and wild birds and contamination of ground water has been linked to dairy cattle (Szewzyk et al., 2000).

Campylobacter bacteria are able to survive short periods of time in the environment. Survival is negatively correlated with temperature, with survival times at cooler temperatures (4°C) of several days (Szewzyk et al.*.,* 2000). Infection from water is typically through untreated sources because *Campylobacter* spp. are sensitive to chlorination and typical chlorination treatments at water treatment facilities can eliminate the bacteria from drinking water. The presence of biofilms in the environment enhances the survival of *Campylobacter* (Szewzky et al., 2000). It is felt that *Campylobacter* spp. can enter a viable but non-culturable state (VBNC) that makes detection in the environment difficult (Skelly and Weinstein, 2003).

Several outbreaks due to *Campylobacter* spp. have occurred worldwide. They were responsible for the greatest number of outbreaks in private well systems in the UK (Szewzyk et al., 2000) and Prince Edward Island ranks third for cases of campylobacteriosis in Canada (Peterson, 2001). Campylobacteriosis is typically mild and self-limiting, but secondary conditions, such as Guillain-Barre Syndrome can have longer lasting effects (Peterson, 2001).

Salmonella spp.

Salmonella spp. has been causing disease for hundreds of years. From the late 1800's to the mid-1900's, *Salmonella* typhi was the leading cause of infection in the United States (Tauxe, 1991). Improvements in sanitation and hygiene practices have reduced the number of infections due to *Salmonella* typhi (Olsen et al., 2001). As a result, infections due to non-typhoidal strains have become more important.

Poultry and swine are the major livestock reservoirs for *Salmonella*, but the different strains of *Salmonella* are quite ubiquitous and seen in or on most animals. Infections with *Salmonella* spp.

have been steadily decreasing over the past few decades (Khakhria et al., 1997). Despite this, salmonellosis is still an important public health issue.

7.1.3. How do people become ill from water?

Waterborne pathogens are spread through contaminated drinking water, exposure to contaminated water while swimming or other activities, or secondarily through food contaminated with bad water. All of these transmission patterns may be affected by climate variability and thus, potentially, by climate change.

For drinking water to be a source of illness, the water must first become sufficiently contaminated, escape treatment, or treatment must fail. Human sewage, leaking septic systems, manure runoff from agricultural lands, and wild animal wastes may all contaminate surface water later used for drinking water. Ground water may become contaminated by surface contamination of wells, sub-surface inflows, improperly situated septic fields, or leaking dumps (chemical contamination). Drinking water may also become contaminated during or after the treatment process. A persistent threat to public health, antiquated combined sewer systems (CSS) carry both storm water and raw sewage to the sewage treatment plant. When the flow of water is too great for the system (heavy rainfall, snowmelt, etc) the sewers overflow directly into a surface water body (river, lake). Thus pathogens, industrial wastes, and city street contaminants run untreated into water, contaminating downstream drinking water sources, beaches, fish and shellfish. For example, more than 67 municipalities in Ontario have CSS (at least since 1956), providing service to millions of people. Seventy-five percent of residents of large cities in Ontario are served by these systems (Tufgar et al., 2001).

Waterborne pathogens generally have a human or animal reservoir. A study of sewage effluent found that *Cryptosporidium* oocysts were present in sewage effluent and surface waters, with likely sources including septic tank leakage, recreational bathing, and agricultural runoff (Madore et al., 1987). Human waste is often a source of water contamination (Hafliger et al., 2000 Stirling et al., 2000; Lungstrom and Castor, 1992). *Cryptosporidium* is found in a wide range of mammals, particularly cows (Howe et al., 2002; Jellison et al., 2002; Kistemann et al., 2002; Rose, 1997). In the Walkerton, Ontario, spring of 2000 outbreak, *E. coli* O157:H7 and *Campylobacter* originated from cattle manure on a nearby farm (O'Connor, 2002). Deer and elk were thought to be the source of *E. coli* O157:H7 in an outbreak in Alpine, Wyoming in 1998 (Olsen et al., 2002). In a toxoplasmosis outbreak associated with a municipal water supply in Victoria, British Columbia, in 1995, both cougars and domestic cats were implicated (Aramini et al., 1999). Thus, there are many sources of contamination in Canadian watersheds.

Weather is often a factor in triggering waterborne disease outbreaks. The impact of heavy rainfall on waterborne illness may be widespread. Curriero et al. (2001) found that more than half the waterborne disease outbreaks in the United States during the last half-century followed a period of extreme rainfall, with 68 percent of the outbreaks following storms of a severity that ranked in the top 20 percent for that region. Excess rainfall resulted in surface contamination of ground water and contributed to the Walkerton outbreak of *E. coli* O157:H7 (Auld et al., 2001); drought followed by heavy rainfall preceded a large waterborne outbreak of *E. coli* O157:H7 in New York in 1999 (Patz et al., 2001). Extreme precipitation preceded the massive outbreak of *Cryptosporidium* in Milwaukee in 1993 (MacKenzie et al., 1994) and preceded several other outbreaks of waterborne illness (Rose et al., 2001). A study of the Delaware River found a positive association between amount of rainfall

and concentrations of *Cryptosporidium* oocysts and *Giardia* cysts (Alterholt et al., 1998). A large waterborne outbreak of toxoplasmosis in Victoria BC was associated with extreme precipitation (Bowie et al., 1997). Elevated turbidity caused in part by rainfall has been associated with a significant proportion of physician visits and hospitalizations for non-specific gastroenteritis in some urban areas (Aramini et al., 2000; Schwarz et al., 2000). Kistemann et al. (2002) found that floods make extremely large contributions to the bacterial and parasite loads of drinking water reservoirs. Their results showed that substantial shares of the total microbial loads in watercourses and in drinking water reservoirs result from rainfall and extreme runoff events. The dynamics of floods during runoff events correspond well with drastic increases in turbidity. Peak occurrences of leptospirosis have been associated with high precipitation levels (Vinetz et al., 1996), and outbreaks of leptospirosis have been linked to recreational exposure to infected water (rafting, boating, swimming, Morgan et al., 2002; Trubo, 2001).

Ambient temperatures may also affect drinking water quality. For example, in St. John's, Newfoundland, elevated bacterial levels in a surface drinking water reservoir overburdened the water treatment system in July 2001. This bacterial overgrowth was blamed on elevated water temperature, and resulted in a boil-water order for the city, though no cases of disease were noted (CBC, Aug 2, 2001).

If weather is a determinant of waterborne disease outbreaks, it is likely also a contributing factor to endemic cases of disease. As the weather changes in the coming decades, we may be faced with new public health challenges.

7.1.4. Climate change in Canada

Projections of global climate change models suggest that the globally averaged surface temperature will increase by 1.4 to 5.8C over the period 1990 to 2100 due to the accumulation of greenhouse gases in the atmosphere (IPCC, 2001). Some climate models project more extreme weather, such as intense rainstorms, thunderstorms, high winds, tornadoes, ice and snowstorms (Francis and Hengeveld, 1998; Groisman et al., 1994). Increased precipitation frequency and intensity have been noted in recent years in North America (Karl et al., 1995). The risk of waterborne illness in Canada could, hypothetically, be affected by excess precipitation, floods (increased run-off, decreased effectiveness of treatment), high temperatures (survival and replication of some bacterial pathogens), and drought (water availability, water pressure, and compaction contributing to run-off when rains eventually fall). There may be increased risk that heavy rain or snowmelt may flush manure, human sewage, wildlife and pet droppings into surface drinking water reservoirs or ground water, leading to contamination of drinking water sources. In truth, the future risk to Canadians of waterborne illness will be the result of highly complex interactions between changing weather, ecosystem changes, microbial and parasitic evolution, and technological and societal adaptations. A first step in understanding these potential impacts is the identification of existing vulnerabilities to climate variability.

Climate change projections for Canada predict that most of Canada may expect longer summers, milder winters, and increased summer drought (Government of Canada, 2002). Canada is likely to experience a higher than average increase in temperature and a decrease in summer soil moisture, due to its northern latitude. Northern areas are expected to have a greater increase in winter temperatures and more precipitation than currently experienced, especially in the winter.

Although national summaries have some use, climate change projections vary regionally. The Pacific Coast is vulnerable to sea level rise. Low-lying coastal areas would be threatened and this, combined with increased precipitation, may lead to an increase in flooding and erosion, and may affect the location and effectiveness of water treatment plants.

The Prairies frequently experience periodic drought; projected higher temperatures and evapotranspiration would propagate drought conditions. Irrigation may become more widely necessary, with potential increases in soil salinity and degradation of soil quality. Warmer temperatures and low flow/low volume situations will create brackish conditions that favour the survival and sometimes the growth of some pathogens. Large accumulations of contaminants may pose a risk to surface water during extreme precipitation following drought. Available surface water will become scarcer, ground water levels may drop, and water pressure for sewage and water treatment may be inadequate.

The projected average temperature for the densely populated Great Lakes - St. Lawrence Basin region could increase by up to 4.5^{o}C by 2055, with a slightly higher increase in the winter than in the summer. Great Lakes water levels could decrease by 0.5 to 1.0m, which may necessitate dredging, and outflow of the St. Lawrence River could decrease by 20%. This would have detrimental effects on water quality and quantity, affect water treatment plant intake, and potentially require the relocation of treatment plants. This region will also experience more unpredictable winters with an overall decrease in snowfall. Warmer temperatures favour bacterial and algal growth in lakes, which contribute to water quality problems. New demands may be placed on the Great Lakes, for example, to supply New York City if increasing sea level disallows its current source of drinking water.

Floods associated with increasing sea level would threaten the low-lying areas of the Atlantic Coast. Salt-water intrusion can contaminate ground water aquifers, disturb estuaries and displace fresh water fish populations. Such intrusions may have impacts on drinking water supply and on sewage and water treatment in the Maritimes. The effects of warmer climate on ocean circulation, wave patterns and frequency of tropical storms are still unknown.

A rise in sea level would flood northern coastal regions of Canada. The gradual melting of permafrost will alter water runoff and destabilize the land. An increase in precipitation mostly in the autumn and winter would result in a great accumulation of snow, which may lead to increased run-off and flooding with spring thaw.

7.1.5. Enteric illness and agriculture

The public is becoming increasingly more suspicious of the impact that agriculture may have on the environment in which they live. Outbreaks in Walkerton, Ontario, and North Battleford, Saskatchewan, have been linked to agricultural practices. Recent fish kills in the Atlantic provinces were linked to pesticide run-off from agricultural land following heavy rainfalls (CBC News, 2001).

The 4 main areas of concern for impact of agricultural manure management on the environment include: bacterial contamination of surface and groundwater, phosphorous run-off into surface water and unpleasant odours (Mussell and Martin, 2000). Unpleasant odours typically are not a health concern, although they can impact on the quality of life (from an enjoyment stand point) of those living in the vicinity of agricultural lands. Phosphorous can cause eutrophication of rivers and lakes,

disrupting the ecological balance of these waters. While this is not a direct health threat to humans, it does have longer-term consequences for the surrounding ecosystem.

Nitrate from manure can leach through the topsoil and into groundwater. From there, it can find its way into tapped wells and is subsequently consumed by humans. Nitrate is converted to nitrosamine in the stomach. Nitrosamines are toxic to pancreatic β-cells. Nitrate contamination has been linked to insulin dependent diabetes mellitus (IDDM) (Parslow et al., 1997).

Run-off from agricultural land can contaminate surface waters with bacteria. This can lead to beach closures, fish kills and pose a health risk if the water is consumed. Few studies of rural well water quality have been conducted in the past 25 years (Mussell and Martin, 2000). Studies that have been done indicated that bacterial contamination of rural wells is quite high, ranging from 7-68% (Goss et al., 1998). A comparison of rural well water from 1955 to a similar survey done in 1992 shows that nitrate contamination has remained relatively steady, but bacterial contamination has increased sharply (15% in 1955 vs. 25% in 1992) (Mussell and Martin, 2000). This increase is surprising, considering that wells in 1955 were dug, as opposed to bored, and were more susceptible to contamination (Mussell and Martin, 2000). During this time period, there has been a substantial intensification in agricultural activities and a movement toward factory farming practices.

A 1977 study of wells in southern Ontario found that 20% of wells surveyed contained bacteria that originated from animal manure (Conboy and Goss, 1999). Water on farms where manure was applied showed significantly higher levels of bacterial and nitrate contamination compared to farms that did not use manure as fertilizer (Goss et al., 1998). Recent studies have shown a relationship between cattle density and human STEC infections (Michel et al., 1998; Valcour et al., 2002). Vertical transport of pathogens into groundwater from manure is also a concern. A study examining the transport of *E. coli* in soils demonstrated that there is a risk to groundwater of contamination after the application of manure to soil (Gagliardi and Karns, 2000). Transportation was dependent on soil type and the rate of rainfall.

E. coli O157:H7 present in cattle manure is quite resilient and can survive at a wide variety of temperatures (Guan and Holley, 2000). *Salmonella* and *Cryptosporidium* have also demonstrated an ability to survive a wide range of temperatures. *Campylobacter* and *Giardia* were not quite as resilient, but could still survive several days to a couple of weeks in manure, water and soil. Long time survival of pathogens in manure has implications for water quality, as run-off from agricultural land that has had manure applied to it can contaminate surface water and increase the potential for human infection. A recent study demonstrated a relationship between the application of certain types of manure to agricultural land and the incidence of human STEC infections (Valcour et al., 2002). A study conducted in 1999 and 2000 of the Oldman River basin in Alberta, an area associated with intensive livestock operations, showed fecal coliform counts that exceed the Guidelines for Canadian Recreational Water Quality by a factor of 5 or more (Environment Canada, 2004). In July of 2000, over half of the monitoring sites tested positive for one or more pathogens.

A comparison of two watersheds in British Columbia showed higher levels of *Giardia* cysts and *Cryptosporidium* oocysts in water samples collected downstream from ranches than in upstream samples, during peak calving activities on the ranch (Ong et al., 1996). There were also differences seen between the two watersheds. One watershed allowed free access to the water supply, whereas

the other watershed never penned animals near the surface water supply and if cattle need to cross the watercourse, it was done at specific fenced in locations.

7.1.6. Climate change: Implications for waterborne illness

Every region of Canada is likely to be affected by climate change. Alterations in risk of waterborne illness, in particular, may be associated with heavy precipitation, drought, flooding, and coastal erosion. Increases in precipitation could intensify flooding and increase erosion, with potential for surface and ground water contamination by enteric pathogens, and decreased effectiveness of water treatment. During flood events, contamination of wells and surface water is widely assumed, and boil water advisories are generally issued (for example, in south-eastern Manitoba). Drought increases the demand for water when the supply is significantly reduced and vulnerable. Heavy rain following drought can lead to more severe run-off and risk of water contamination. The rise in sea level may displace Canadians in coastal communities, resulting in temporary disruptions in water supply and a need for new fresh water sources.

Climate change may affect the worldwide distribution of cholera and other waterborne diseases, altering risk of disease to visitors going to and from Canada. Cases of illness acquired elsewhere but necessitating treatment in Canada add to the overall burden on the health care system, and may pose a public health threat unless resilient and adaptive public health infrastructure is maintained within the country.

7.1.7. Measuring the impact in Canada

Our understanding of the links between waterborne illness and climate change will always be fraught with uncertainty, reflecting an uncertainty in the knowledge base as well as inherent uncertainties in the complex socio-ecological systems within which these events occur. Science for policy-makers requires us to reduce the level of uncertainty in the basic knowledge base as well as to identify the boundaries of the inherent uncertainty.

Given the continued importance of climate change issues in Canada and increasing international collaboration on climate change internationally, this research is timely and pertinent. Further research is required to better understand the potential impacts of climate change on waterborne illness, and how best to adapt policy and practice to these impacts. Such research requires a broad inter-disciplinary approach, innovative research methods, and ongoing dialogue with decision makers and policy makers.

National research networks, such as those coordinated by the Climate Change and Health Office, Health Canada, and specifically the "Climate Change, Food- and Water-borne Contaminants Research Network" (http://www.eccho.ca/hirn-fwc.asp), facilitate the formation of teams of researchers with the required skills to deal with these types of complex issues.

With funding from Health Canada's Health Policy Research Program, we have put together a collaborative team from the University of Guelph, Health Canada and Environment Canada in order to fill in some of the important gaps in our knowledge base for these important questions. Drawing on available Health Canada and Environment Canada databases and with the participation of provincial and territorial departments of health and environment, and additional federal partners outside the project team, the project we have undertaken assessed the nature, frequency and

geographic distribution of water-related diseases in Canada, both in terms of outbreaks and sporadic or endemic cases. The links between these disease occurrences and those weather-related events most likely to be affected by climate change, and most plausibly causing waterborne illness (extreme rainfall, soil conditions, drought), were closely examined. In a selection of communities from different ecological regions of Canada, our research team studied, in some depth, how weather affects potentially waterborne health outcomes. This research has also enabled a greater understanding and identification of preventive actions and adaptive responses that might be undertaken in Canadian communities more generally.

7.2. Inventory of data

7.2.1. Meta-database

7.2.1.1. Health Data

Health data were from the Canadian Institute for Health Information (CIHI) hospital admission database. This patient-specific database hospital discharge information contains a number of fields including demographic and administrative data on patient discharge: most responsible physician/diagnosis, principal procedure, patient age and gender, residential postal code, institution number, admission date, discharge date, and other. With the exception of Quebec (only includes one long-term hospital) and Manitoba (only includes 6 hospitals), all provinces and territories fully participate. Information from the years 1992 to 1998 were used for the southern Alberta, Ontario, and the Atlantic regions. A case of gastrointestinal illness was defined using the primary and secondary diagnosis fields, which are coded using ICD-9-CA codes, as outlined in Aramini et al. (2000). The data were linked to a geo-locator file to group the data into Consolidated Census Subdivisions (CCS). The records were filtered to exclude cases of enteric illness that were not related to waterborne disease (i.e. Crohn's Ulcerative Colitis). The data was further filtered to remove any duplicate visits from a patient within 40 days after their first visit. Each of the patients also had to be linked to a specific postal locator for spatial analysis capabilities.

7.2.1.2. Meteorological Data

Meteorological data were from Environment Canada. The data consisted of seven climate variables: minimum daily temperatures, maximum daily temperature, mean daily temperature, total daily rain, total daily snow. There were a number of weather stations used across Canada for the analyses.

For the outbreak data, each weather station was selected in proximity to the outbreaks. A numeric identifier, station name, latitude and longitude coordinates and elevation identified the stations. More than 120 stations were selected. The daily data for rainfall (mm), minimum air temperature ($^{\circ}$C) and maximum air temperature ($^{\circ}$C) were extracted from the selected stations. In the event of missing data, data from nearby comparable stations were substituted.

For research in the Alberta, Ontario and the Atlantic regions, the data was extracted from weather stations that met the following criteria: adequate spatial distribution and temporal distribution with no missing data.

7.2.1.3. Hydrology

The Environment Canada HYDAT database (HYDAT, 2003) was used to provide data on stream flow. Each station was identified by a numeric identifier, station name, latitude and longitude coordinates, size of drainage area (km^2), and whether the stream at the station location was classified as regulated or non-regulated. This classification refers to the impact of upstream river control structures, diversions or impoundments on the magnitude and timing of the water levels. Selection criteria for stream flow stations were set to obtain the most accurate and unadulterated measurement for daily stream flow, that would also be representative of the flow conditions at the outbreak location. These stations were found on non-regulated streams (i.e. zero or negligible impact from upstream river control structures, diversions or impoundments to the natural magnitude and timing of the water levels), with drainage basins less than 10 000 km^2, as geographically close as possible to the site of the outbreak. The daily average stream flow (m^3/s) data were obtained for each selected station.

7.2.1.4. Outbreak

In Canada, public health authorities are responsible for investigating and documenting waterborne disease outbreaks. Data on 288 drinking waterborne disease outbreaks, occurring throughout Canada from 1974 to 2001, were compiled for Health Canada by Schuster and colleagues (In Press). The definition of a waterborne disease outbreak was two or more cases of disease, occurring at the same place and time, linked to a drinking water supply. Records for many outbreaks were incomplete and not suitable for the present analysis. Outbreaks were excluded if location in either space or time was ambiguous.

A subset of 168 outbreaks of waterborne disease was used in this analysis. For each outbreak, we obtained the following information: the year, month and, when available, date of onset, the location (city and province), the number of cases of disease (when available), the agent responsible (when known), the population served by the water source (i.e. community, restaurant, etc., when known), a description of the water system (i.e. private well, municipal water supply etc., when known) and the reported contributing factors to the outbreak (when known). Outbreaks were classified as possible (n=76), probable (n=34) or definite (n=58), depending on how strongly they were linked to water as the source of the outbreak. Latitude and longitude co-ordinates of each outbreak location were taken from the Atlas of Canada website (Natural Resources Canada, 2004). For outbreaks where only the year and month were known, the last day of the month was selected as the onset date for analytical purposes. This ensured that all of the weather data for the onset month would be included.

7.2.1.5. Agriculture

Agricultural data was obtained from two separate sources. The first is the Agricultural Census (1996). The data includes CSD specific information including various animal livestock densities, as well as agricultural treatment levels. Animal densities cover cattle (bull, calve, cow, etc), pigs and chickens. Agricultural treatment includes various types and quantities of manure spread. The second source of agricultural information was obtained from the Agricultural Land Use Survey. This file combines SPOT4 satellite imagery with the Agricultural Census (1996). The merged information

contains a finer resolution regarding location and intensity of agricultural land use, as well as various other vegetative regions.

7.2.1.6. Geographical

The geographical shape files were provided by DMTI from 1992-2000. The shape files contained, for all of Canada, postal code conversion, health regions, water resources, watersheds, drinking water distribution areas, water treatment plants, sewage treatment plants, administrative boundaries, street information, digital flow data and livestock at the watershed level. Only certain parameters were available in each province.

For the research on outbreaks and extreme weather events, it was important to identify the ecozones of each outbreak. Canada is divided into 15 terrestrial ecozones based upon soil type, vegetation, climate and landforms. Ecozone was included as a categorical variable and provided a surrogate for soil type. The map of the outbreaks was overlaid on the map of the ecozones (Figure 39). Each outbreak was classified by the ecozone within which it was located, based on latitude and longitude coordinates.

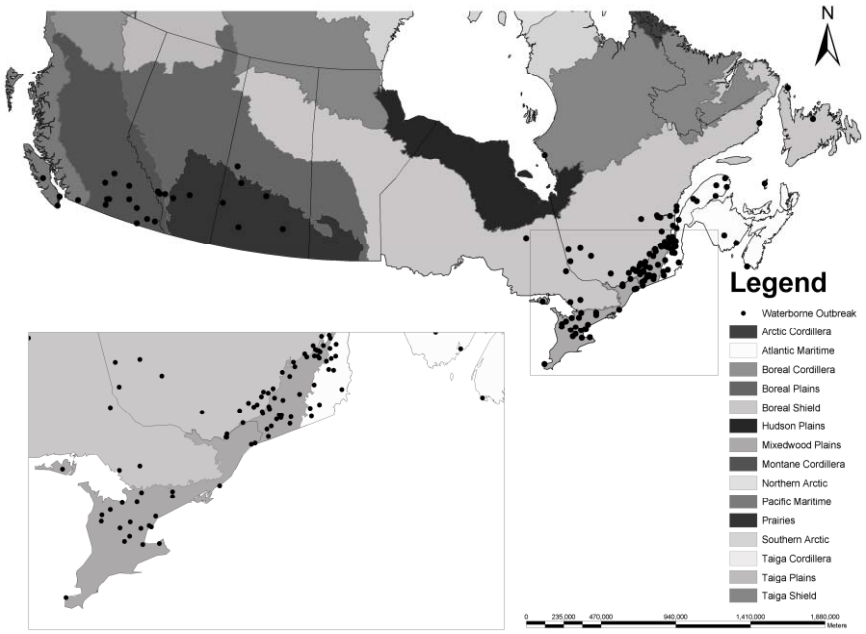


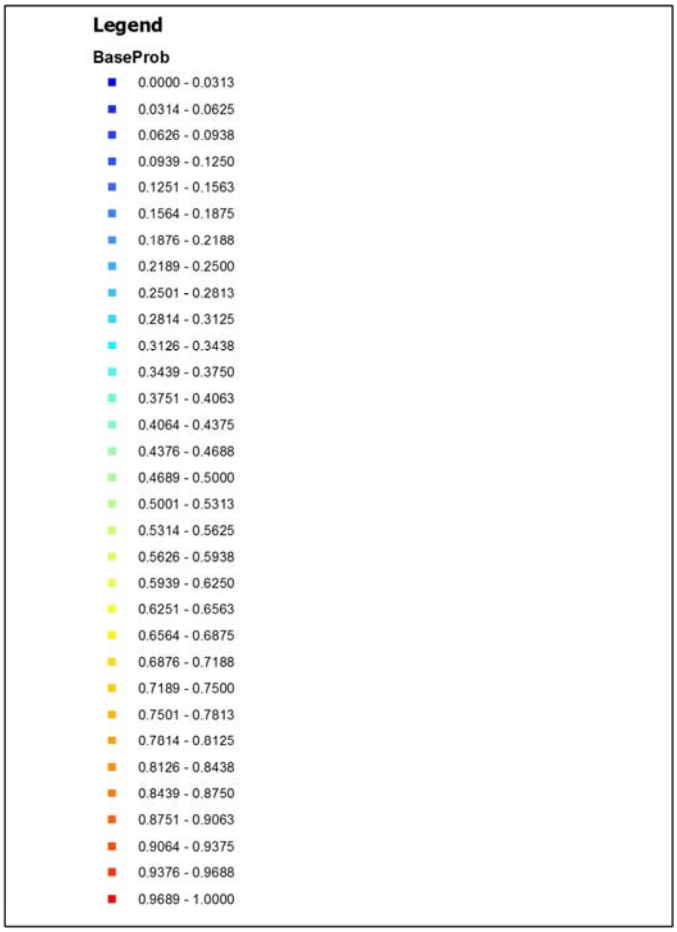
Figure 39. One hundred and sixty-eight waterborne disease outbreaks (1975-2001) distributed across 8 of Canada's 15 ecozones.

8. Maps

8.1.1. Southern Alberta

The following maps outline the change in probability of disease given various climate change scenarios. These are based on downscaled data from the HadCM3 and CGCM2 climate change models for the 2020's, 2050's and 2080's. The maps represent the change in spatial distribution of

disease for each of the four seasons. There are a total of 24 maps in all. A legend explaining the probabilities associated with each colour is included below.

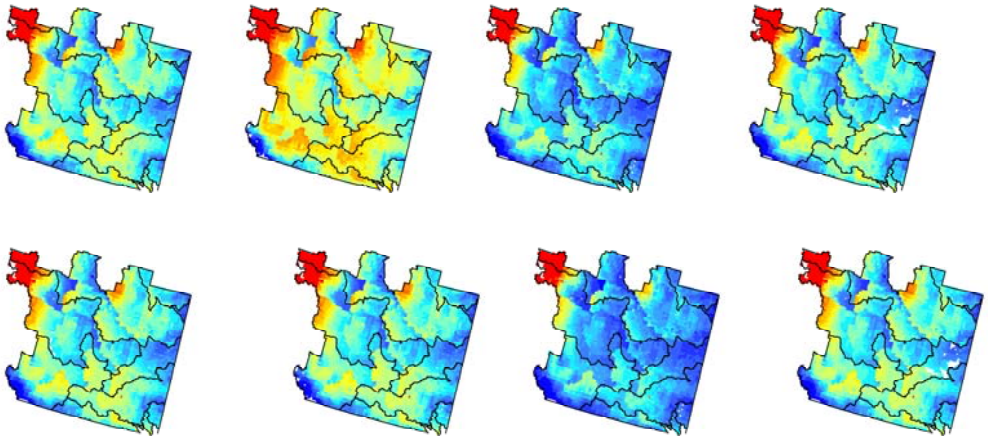


From left to right we have spring, summer, autumn and winter maps. Top maps are based on the CGCM2 model, while the lower maps are from the HadCM3 model.

Projections for the 2020's do not differ significantly from the current probability distribution of disease within the study area.

2050s

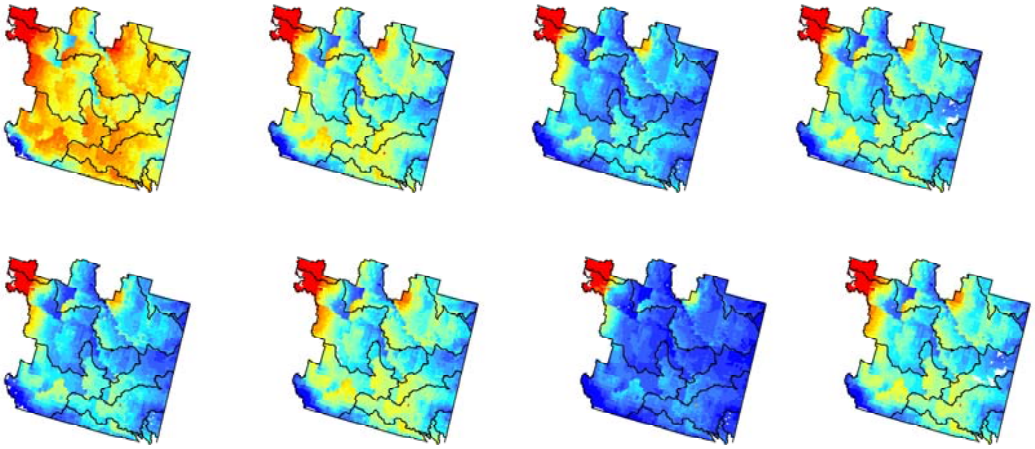
The maps below represent the probability distribution of disease given the projections for the 2050's. They are from left to right, spring, summer, autumn and winter. The upper maps are generated using predictions from CGCM2, while the bottom maps are from HadCM3. It is important to note the obvious significant visual changes in distribution, specifically in the spring months. There is a marked increase in probability of disease (via CGCM2), as noted by the spectral shift from blue to orange, yellow and red. There is a high concentration of increased probability within feedlot alley.



The two models generally agree except for the spring months. This is due to the difference in proposed levels of rain/precipitation during this time. An interesting note is that both models indicate a decrease in probability of disease within the autumn months.

2080s

Distribution maps for the 2080's are below. Again, they are organized from left to right as spring, summer, autumn and winter. The top maps are CGCM2, and the bottom maps are HadCM3.



9. Conclusions

This project has made an important contribution to the growing body of knowledge on the incidence of waterborne diseases in Canada, the inter-relationships between water, weather and health outcomes, the health impacts of climate change, and the social mechanisms that build community resilience.

The research found that waterborne diseases are a burden to Canadians now, that waterborne disease risk is related to ambient temperature and rainfall, and that climate change will alter the patterns of gastrointestinal disease risk over the next several decades. The project also investigated how some Canadian populations have developed adaptive responses extreme weather events.

While the research findings are being disseminated widely in scientific forums, they have also been presented to audiences more interested in health and environmental policy, as well as to decision-makers. This research is ongoing. Several new projects will build upon this effort, to help strengthen the body of evidence available to policy and decision-makers striving to protect the health of Canadians.

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Appendix A: Bayesian Estimation Methods for Spatial Analysis

The following information has been summarized from Waller and Gotway (2004). Several different modeling procedures have been outlined for normally distributed data, but public health data often do not follow a normal distribution. Although transformation of data may allow for the use of a Gaussian distribution, often model assumptions are violated and spatial autocorrelation in the data may cause problems with the transformed data.

One way to deal with this is through the use of generalized linear models (GLM). Instead of assuming the mean response of the data is a linear function of our covariates, some function of the mean is linearly related to our covariates such that

$$g(\mu) = g(E(Y)) = \mathbf{X}\beta$$

(Waller and Gotway, 2004)

There are typically two different functions utilized for public health data, the log link for count data (Poisson model) or the logit link for binary/binomial data (Logistic model). Assumptions about the variance of these models are needed. For both links, the variance is dependent on the mean. For the Poisson model:

$$v(\mu) = \mu \qquad \text{(Waller and Gotway, 2004)}$$

And for the Logistic model:

$$v(\mu) = \mu(1-\mu) \qquad \text{(Waller and Gotway, 2004)}$$

When dealing with a model that only contains fixed effects we are dealing with what are referred to as *marginal* models. But our data often contains an underlying spatial process on which we *condition* the outcome. To achieve this we utilized random effects in our model and the model equation becomes:

$$g[\mu(s) = g[E(Y) \mid S(s)] = X(s)\beta + S(s) \qquad \text{(Waller and Gotway, 2004)}$$

where *S(s)* represents a random component to the expected mean of our outcome. We are trying to estimate the fixed effects in our model conditioned on the spatial effect of our underlying spatial process. These models that incorporate both a fixed and random component are referred to as Generalized Linear Mixed Models (GLMM).

Maximum likelihood estimation is used in the estimation of parameters for GLMs, direct calculation is complicated by effects of the underlying spatial process. When data contain spatial autocorrelation the marginal likelihood cannot be easily determined. To address this complication we use multivariate distribution for the mean-variance relationship, but such distributions are difficult to parameterize and few have been evaluated for their usefulness in spatial modeling. This can be bypassed by using the fact that when we condition on the random effect the data are *conditionally independent* and thus use the hierarchical nature of the data to build a multivariate

distribution. Yet this also results in problems when trying to define a likelihood function that encompasses all stages of the model.

To avoid the above problems two different approaches can be used, quasilikelihood and pseudolikelihood estimation. Quasilikelihood estimation is based on the first two methods of a distribution. An iterative estimating equation is used to formula a method that can be used with spatial data. Pseudolikelihood methods use Taylor series expansion to allow for inference of spatial data. Lastly, Bayesian methods can also be utilized. Bayesian methods avoid the limitations of pseudo and quasi likelihood methods.

To model the random effects in pseudo and quasi likelihood some assumptions are made about the distribution of the random effects. The vector of random effects is assumed to be a multivariate normal (MNV) $(\mathbf{0}, \Sigma_\xi, \theta)$ with $\Sigma_\xi(\theta)$ modeled with a parametric covariance model (Waller and Gotway, 2004). A conditional autoregressive (CAR) or simultaneous autoregressive model (SAR) can be used to model ξ (the vector of random effects). SAR utilizes and iterative approach where an initial estimate for β is obtained and then based on those estimates, maximum likelihood estimation is used to obtain values for the variance and autocorrelation parameters. The method of generalized least squares is then used to obtain new estimates for β. Estimation of the variance, autocorrelation and β parameters continues iteratively until convergence is met (Bailey and Gatrell, 1995). The only difference between a SAR model and a CAR model is in the specification of the autoregressive parameter. In the case of GLMM the semivariogram is used to suggest a parametric model for $\Sigma_\xi(\theta)$. Overdispersion parameters can also be incorporated into the estimation methods. Spatial autocorrelation and overdispersion can impact both the estimate of β parameters and their standard errors, therefore it is important that we take into account the impact that these will have on model estimation.

Answers to our question will dictate what type of model, conditional or marginal to be used. Marginal models are also referred to as population averaged because β describes the change in the function of E(Y) with changes in the covariates. On the other hand, conditional models are subject-specific models as random effects are estimated for each "subject" and β represents the covariate effect at the subject level. How the models are applied will also direct which type of modeling procedure should be used. If we want to simply smooth out disease rates adjusted for our covariates than a conditional (GLMM) model would be more appropriate.

An alternative to the above methods is a Bayesian approach. Complications may arise in the inference of parameters in likelihood methods by the inclusion of random effects. Particularly assumptions about the distribution of random effects may not allow for fully specified random effects that better describe underlying spatial processes. Bayesian inference allows for the fitting of complicated hierarchical models with spatially correlated random effects. The underlying theory of Bayesian statistics and Markov Chain Monte Carlo algorithms will be left to the reader. Some good resources are Besag et al. (1991, 1995), Cressie (1993), Clayton and Bernardinelli (1992) and Wakefield et al. (2000).

In Bayesian statistics a probability model is built linking the distribution of the data to the parameters in the model. Model parameters are then treated as random effects and estimated using simulation methods. Inference stems from interpretation of the posterior distribution of a parameter that is conditional on the data that was obtained. The posterior distribution is proportional to the

product of the likelihood function and the prior distribution of the parameters, which are defined by the analyst. The posterior distribution can be mathematically represented by:

$$f(\theta_\psi, \psi, \beta \mid Y) \propto f(Y \mid \beta, \psi) f(\psi \mid \theta_\psi) f(\beta) f(\theta_\psi)$$

(Waller and Gotway, 2004)

where $\boldsymbol{\beta}$ is a vector of fixed effects, $\boldsymbol{\psi}$ is a vector of random effects and θ_ψ is a vector of spatial correlations (variance-covariance matrix) of the random effects. Since θ_ψ enters the model at the second level of the hierarchy they are often referred to has hyperparameters and a hyperprior distribution is assigned to them. The fixed effects ($\boldsymbol{\beta}$) are typically assigned a non-informative prior distribution such as a Normal or Gaussian distribution because $\boldsymbol{\beta}$ is often well estimated from the data. Bayesian inference differs from quasi and pseudolikelihood methods in how the spatial random effects are incorporated in to the model. Spatial random effects for each area ($\boldsymbol{\psi_i}$) are assigned a joint multivariate Gaussian prior distribution that incorporates spatial covariance that is estimated for a parametric semivariogram. An alternative is to conditionally specify a prior spatial structure via a conditionally autoregressive (CAR) prior. Lastly, the hierarchy is completed by defining a hyperprior for $\boldsymbol{\nu_\psi}$. This prior distribution is usually based on an inverse gamma distribution. Markov Chain Monte Carlo algorithms are used to estimate the posterior distributions. Summaries of the posterior distribution of each estimated parameter will yield an estimate and a 95% *credible interval*. This interval differs from a *confidence interval* in that a confidence interval represents an interval that 95% of intervals constructed from an identically distributed data sets would contain the true parameter value. Whereas a *credible interval* represents an interval having 95% posterior probability of containing the parameter of interest.

Appendix B: Kriging Interpolation Method

Covariance Function

Kriging relies on the covariance function, C(h), of the data. The covariance function is a vector of differences between point's s_i and s_j; that is, the direction and distance of separation. If the underlying spatial dependence in a geostatistical data process is isotropic then spatial dependence is purely a function of the distance between data points and not related to how the points are orientated with respect to each other. The covariance function is one measure of spatial autocorrelation.

Semivariogram and Variogram

The quantification of the autocorrelation between spatial points was measured using the semivariogram. If the data exhibit intrinsic stationarity which was defined as a constant mean and variance (intrinsically stationary) in the differences between value at locations separated by a given distance and direction than the function that represents the autocorrelation is called the variogram. The semivariogram and varigram are related in that the semivariogram is one half the variogram.

A graph of the semivariogram versus the separation distance between points conveys the continuity and spatial variability of the process. The graph starts at the x-intercept of a distance of zero. If points close together are more alike than ones further apart the graph will increase with increasing difference until it eventually levels off to a constant value called the sill. At the sill observations are uncorrelated as reflected by the constant variance in their differences. If there is no autocorrelation than the graph semivariogram will be a straight horizontal line. The shape of the curve also gives clues as to the underlying spatial process. If there is a vertical jump in the semivariogram at the origin (a distance of zero) this represents has irregular spatial variability and this is referred to as the nugget effect. A large nugget effect indicates that two observations close to each other have different values. This is often due to measurement error, but can also indicate a discrepancy in the spatial process that defines the data.

Covariance and the Correlogram

The semivariogram is related to the covariance in the following manner:

$$\gamma(\mathbf{h}) = C(\mathbf{0}) - C(\boldsymbol{h})$$

where $\gamma(\mathbf{h})$ is the semivariogram, $C(\mathbf{0})$ is the variance of data (referred to as the sill) and $C(\boldsymbol{h})$ is covariogram. The point at which the sill occurs is called the range.

Estimation of the Semivariogram

The semivariogram is easily estimated from the data using the following equation if the assumption intrinsic stationarity is met:

$$\hat{\gamma}(h) = \frac{1}{2|N(h)|}\sum_{N(h)}\left[Z(s_i) - Z(s_j)\right]^2,$$

where $N(\boldsymbol{h})$ is the set of distinct pairs separated by distance $\boldsymbol{h}$. With a regular grid lattice distance and directions are easily obtained. Where data are irregularly spaced there may be only one pair of locations that is of a distance $\boldsymbol{h}$ apart. This can result in poor estimate because averages are based a

$$h \in \Re^2$$

small number of points. Tolerance values can be incorporated into the estimation to allow for a better estimation of the semivariogram. The semivariogram can also be estimated using nonlinear least squares regression or maximum likelihood estimation. Several different routines in SAS, S-Plus and R are available for estimation of the semivariogram.

Spatial Prediction

Interpolation is the process of obtaining values for our spatial process for locations where no sampling had occurred. Kriging is one method that allows for the interpolation of data. There are several different types of kriging. For example:

- *Simple*: linear prediction assuming a known mean.
- *Ordinary*: linear prediction with a constant unknown mean.
- *Universal*: linear prediction with a non-stationary mean
- *Filtered*: smoothing and prediction for noisy data
- *Lognormal*: optimal spatial prediction based on the lognormal distribution
- *Cokriging*: multivariate linear prediction (i.e. linear prediction based on one or more interrelated spatial processes)

Only ordinary kriging will be described below, as it forms the basis for other types of kriging methods that add adjustments to kriging equations.

Ordinary Kriging

For ordinary kriging, we assume that spatial process that gave rise to our data is intrinsically stationary (i.e. that is has a constant unknown mean and a known semivariogram). As with inverse distance methods described above, ordinary kriging (OK) is based on a weighted average of the data:

$$\hat{Z}_{OK}(s_o) = \sum_{i=1}^{N} \lambda_i Z(s_i)$$

The weights are based on the data using the semivariogram two statistical criteria. The first is lack of bias, which is that the predicted value (s_o) should on average be consistent with the value of the unknown value. In statistical terms:

$$E\left[\hat{Z}_{OK}(s_o)\right] = \mu = E\left[Z(s_o)\right]$$

The second criterion is to minimize the mean-squared prediction error (MSPE) as defined by $E\left[\hat{Z}_{OK}(s_o) - Z(s_o)\right]^2$. This can be achieved with the use of the Lagrange multiplier. This method minimizes the following function:

$$E\left[\left(\sum_{i=1}^{N}\lambda_i Z(s_i) - Z(s_o)\right)^2\right] - 2m\left(\sum_{i=1}^{N}\lambda_i - 1\right)$$

to find values for $\lambda_1,\ldots,\lambda_N$ and the Lagrange multiplier m. It can be shown that this can be simplified to:

$$\sum_{i=1}^{N}\lambda_j\gamma(s_i - s_j) + m = \gamma(s_0 - s_i), \qquad i = 1,\ldots,N$$

$$\sum_{i=1}^{N}\lambda_i = 1$$

.

The predicted value s_o has weights that are dependent on spatial autocorrelation between the predict point and every data point (s_i) and the correlation between all pairs of data points (s_i and s_j). The kriging variance is determined by the equation:

$$\sigma^2(s_o) = 2\sum_{i=1}^{N}\lambda_i\gamma(s_o - s_i) - \sum_{i=1}^{N}\sum_{j=1}^{N}\lambda_i\lambda_j\gamma(s_i - s_j)$$

To summarize the kriging process, a semivariogram is estimated for the data points and this information is then used to solve the kriging equations that allow us to predict point s_o. Similar to inverse distance weighting methods kriging methods can be done locally as points outside the range of the semivariogram would have no weight and not contribute to the estimation of our predicted point.

Several statistical packages are available that can perform kriging. This includes SAS, S-plus and R. ESRI's ArcGIS version 8 (ArcGIS, 2002) or above also have the ability to perform kriging using the Spatial Analyst Extension.

Appendix C: Cluster Detection Methods for Spatially Distributed Health Data

Cluster Detection Methods

The nature of the risk factor will suggest the appropriate scale at which analysis methods should be considered. We are more interested in the clustering of risk factors that may lead to disease.

Several different methods are available for cluster detection. Some methods are designed to primarily detect overdispersion in a series of disease case counts. Overdispersion in data can represent (a) heterogeneity in the data, that is independent counts with a variance greater than what would be expected or (b) spatial dependence, dependence between counts in one area and the next that is dependent on the spatial distance between the two areas.

Other methods assess the spatial dependence in a data set and produce a single summary statistic to describe the dependence. Some methods assume whether the number of cases within an area is in excess of what would be expected by chance alone. The only method that will be described here is the SaTScan statistic, developed by Kulldorf, since it was the only one used in the analysis of this project.

The SaTScan statistic is used to evaluate reported spatial or space-time clusters, to determine if they are statistically significant and to test whether the disease is randomly distributed over space, time and space-time. It is also used to perform geographical surveillance of disease to detect areas of significantly higher or lower rates. Lastly, it is used to perform repeated time period disease surveillance for early detection of disease outbreaks.

How the SaTScan Statistic Works

Purely Spatial Clusters

The purely spatial scan statistic imposes a circular window on the region. The window is centered on several grid points throughout the study region. For each grid point, the radius of the window varies in radius, from zero to a specified upper limit. The window is flexible in both location and size. The user specifies the grid point used, so a coarse or fine grid can be used. Co-ordinates of the data points are used if no grid is specified.

Purely Temporal Clusters

Space-Time Clusters

A cylindrical window with a circular geographical base and a height corresponding to time defines the space-time scan statistic. The base is the same as the spatial scan statistic, while the height reflects the temporal clusters. The window is moved through space and time so that all possible geographical locations and all temporal units are visited.

Testing Clusters for Significance

A likelihood ratio test is used to determine the significance of a purely spatial, purely temporal or space-time disease cluster. The likelihood ratio function is maximized over all window locations and sizes. The one with the highest maximum likelihood estimate constitutes the most likely cluster. The likelihood ratio for this scanning window forms the likelihood ratio test statistic. A p-value for the window is obtained using Monte-Carlo simulations. The rank of the maximum likelihood from the scanning window is compared to maximum likelihood values from the random datasets.

Most spatial clustering statistics test for global clustering of disease. They test for clustering throughout the study region without specifically pinpointing the location of specific clusters. The SaTScan statistic is designed to evaluate whether cases that are close in space and time adjusting for any purely spatial or temporal clustering. Other methods are unable to detect location and size of the cluster and test the cluster's significance.

The SaTScan statistic (Kulldorf, 1997) was used to formally investigate spatial clustering of disease for watersheds and CSD level data for each province. The SaTScan statistic examines the spatial distribution of a factor, in this case disease incidence, for potential disease clusters. The statistic identifies areas that can be classified as either the primary cluster or one more secondary clusters. The centroid of each watershed or CSD was used to represent the spatial location of the geographical area since the SaTScan statistic requires point location to calculate the statistic. The SaTScan statistic was also used to identify clusters that occur in both space and time.

Appendix D: Thin-plate Spline Interpolation Method

The mathematical model for thin-plate splines can be written as

$$z(s_i) = f(s_i) + \epsilon(s_i) \qquad (2.1)$$

where $z(s_i)$ is the value at location s_i as a smoothed function $f(s)$ and with a random error $e(s_i)$. It is generally assumed that the $e(s_i)$ are independent, have mean $\mu = 0$ and variance σ^2 (Luo et al., 1998). The TPS method is problematic when it comes to estimating $f(s_i)$ for use in estimating $z(s)$ at unobserved locations. This requires minimizing

$$\sum_{i=1}^{n} [z(s_i) - f(s_i)]^2 + \lambda J_m(f) \qquad (2.2)$$

for a given choice of f, where λ is a Lagrange multiplier (Shen et al., 2001) used to determine the minimum of this linear system. The parameter λ is known as the Cross Validation Parameter. Further, we have that $J_m(f)$ is defined as

$$J_2(f) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \left[f_{xx}^2 + 2f_{xy}^2 + f_{yy}^2 \right] dxdy. \qquad (2.3)$$

in the case of the two dimensional ($d = 2$), second order ($m = 2$) TPS method. The function $J_m(f)$ is known as the penalty function (Xia et al., 2000) of order m and is used to determine the amount of smoothing to apply to the given data points. For examples of the penalty function in higher dimensions, see Boer et al. (2001) or Hutchinson (1998).

To extend this work to higher dimensions, one simply needs to define f appropriately while adjusting Equation 2.2 accordingly. This would involve use of additional partial derivatives in the penalty function, as well as updating the error term by incorporating the increased dimensionality.

Choosing the smoothing parameter (λ)

The minimization of Equation 2.2 is not dependent solely on the selection of f, but also on choice of the smoothing parameter λ. This parameter controls how close the predicted f is to the observed data and the level of smoothing (Luo et al., 1998).

The smoothing parameter λ is selected based on the data itself and was done by choosing λ that minimizes the Generalized Cross Validation Function (GCV). Model and Interpolation validation were based on the Root Mean Square Error (RMSE) of prediction.

Simulations

Typically, TPS methodology is applied to spatially correlated data. In this study, there exists not only a spatial relationship of climate between locations, but also a temporal one. To account for the temporal correlation, attempts are made to extend basic spatial TPS methods by incorporating temporal information. These attempts are tested via simulation. Simulations are used to determine the most effective method of prediction that reduces the Root Mean Square Error, while accounting for space-time correlation structures.

Several models are tested as described below. The first model is a function of latitude and longitude (x and y variables) only. Model 2 extends the first model with the inclusion of elevation (Hutchinson, 1998). Model 3 adds a temporal day of study variable, while Model 4 also includes an autoregressive lag. The models can be written as,

$$
\begin{aligned}
z^i_{1|t} &= s(x_i, y_i) \\
z^i_{2|t} &= s(x_i, y_i, e_i) \\
z^i_{3|t} &= \frac{1}{N} \sum_{\substack{|t-j|\le 3 \\ 0\le j\le n}} s(x_i, y_i, e_i, t_{j,|t-j|\le 5}) \\
z^i_{4|t} &= \frac{1}{N} \sum_{\substack{|t-j|\le 3 \\ 0\le j\le n}} s(x_i, y_i, e_i, t_{j,|t-j|\le 5}, z^i_{4|t_j-1})
\end{aligned}
$$

where i represents the i^{th} location, and t the time. Additionally $i = 1...l$ and $t = 1...n$, where l and n are the number of locations and total length of the study respectively. Latitude, longitude and elevation are denoted by x, y and e respectively.

Due to computational limitations, models 3 and 4 were averaged over a set of predictions based on interpolation using a temporal window. The method involves selecting observations for given space-time events within a certain time span of said event. In this simulation study, a window of ±5 days was used. To reduce edge effects, only predictions within ±3 days were saved (thus producing up to 7 predictions for each space-time event). Once prediction for a space-time event was complete, the window shifted to the next space-time event (Figure 40). In this way, multiple predictions would be observed for each space-time event. Resulting predictions were then averaged, to obtain a final prediction value.

current time													
4	1	2	3	4	5	6	7						
5		2	3	4	5	6	7	8					
6			3	4	5	6	7	8	9				
7				4	5	6	7	8	9	10			
8					5	6	7	8	9	10	11		
9						6	7	8	9	10	11	12	
10							7	8	9	10	11	12	13

Figure 40. Each Line Represents a Temporal Window Created Over the Identified Current Time. The Box of Sevens Illustrates How 7 Interpolated Values Could be Produced for Each Space-time Event.

The predictions were tested using the following climate models, where x represents the latitude, y the longitude, t the time and z the elevation. A snapshot in time of each of the climate models can be found in the figures below.

$$
\begin{aligned}
P_1 &= \sin(x+y+z+t) \\
P_2 &= z\frac{\sin\left((x-y)t\right)+\cos\left((x+y)t\right)}{\sqrt{2}} \\
P_3 &= z\frac{\sin\left(\frac{x}{y}\right)\cos\left(\frac{t}{y}\right)+\cos\left(\frac{y}{x}\right)\sin\left(\frac{t}{x}\right)}{\sqrt{2}}
\end{aligned}
$$

To test the predictability of models, various configurations regarding distribution of stations are considered. The first three assume a lattice structure of 100, 25 or 16 stations in a square grid configuration. Yet another configuration includes stations distributed such that both latitude and longitude values are the absolute value of randomly generated standard normal variables. The final configuration is one where spatial coordinates are obtained from a standard uniform distribution. Two final configurations use 30 stations each.

Simulation Results

When comparing models across model-grid combinations (akin to finding the smallest RMSE in each row for each table), it was evident that climate P_1 always generates the smallest RMSE regardless of which TPS model was used.

If we compare the RMSE across climate-grid combinations (now searching for the smallest RMSE in each column for each table), the resulting best model should indicate the most appropriate for interpolation of climate data. The pattern here was not as obvious. Instead, we see that for the simple climate (P_1) and non-lattice structures, Model 2 provided the smallest RMSE. Lattice grid structures seemed to indicate Model 3 as the best choice. Moving to the other two more complicated climates (P_2 and P_3), Model 4 was the obvious choice for all grid structures, save one exception.

Based on these results, Model 4 might be selected as the best TPS model as it consistently produced the smallest RMSE across all grid structures and for the more complicated climate models. However, the model provided very specific challenges during implementation. The most obvious

was the need to have unobserved lag climate information to predict current unobserved climate data. Another issue was that of computational limitations. It should be noted that as the thin-plate model incorporates more and more covariates, the amount of time to produce a model increases. This is a function of the higher dimensionality needed in the penalty function, as well as that required to determine λ. Thus, we disregard Model 4 from consideration until further research can be done.

Noting that RMSE values under the P_2 and P_3 columns are of the same magnitude within each grid structure, the choice for the best thin-plate model was based on observations under P_1. Model 3 was selected as the best thin-plate model. This was done, since the incorporation of temporal covariates was deemed significant. Additionally, it produced adequate results for all climate-grid combinations.

Appendix E: Python Data Extraction for Climate Data Retrieval and Programming Code

Due to the amount of climate data required for the TPS and IDW interpolation techniques, programming was designed to quickly extract raw data from the Environment Canada Climate CD's. This was done for simulation purposes, but also to expedite the interpolation process. Code available on the Internet provided a starting point for this purpose, but needed to be updated to accommodate the requirements of this research.

For the purpose of extraction and use of the data the following requirements and instructions follow. The following files are required:

- StationList.txt (Generated by program)
- DataList.txt (Generated by program)
- ExtractionList.txt
- ExtractClimate3.exe
- W9xpopen.exe
- Python24.dll

StationList.txt contains a list of stations populated from the Climate compact disks. It will contain either the Eastern or Western stations, depending on the CD. The file contains a counter, the station number, latitude, longitude and elevation of the station. Note that latitude and longitude should be converted to degrees and minutes as follows - 12342 would represent 123 degrees and 42 minutes.

DataList.txt contains sample output from the programs. It lists the data in the following way: Station Number, Year, DAY OF YEAR, max temp, flag, min temp, flag, rain, flag, snow, flag, precip, flag, snow depth, flag.

There are 366 days listed for each year. Day 60 is the one to watch. If it is a leap year, there will be data provided. If it is not a leap year, day 60 will have -9999 listed, as well as a flag of 14.

If something is listed as NA - it means that the information was not recorded (that is, the weather station may not have had the functionality to do so).

The flags are as follows

0. no flag
1. estimated
2. trace
3. precipitation occurred, but it's unknown
4. may have been precipitation
5. accumulated
6. accumulated and estimated

7-13. not used

14. leap year flag (ie - not a leap year if you see this)
15. missing data

ExtractionList.txt contains a list of weather station numbers. This is what the program uses to pull the data from the CD. If you need to extract data for different stations, simply create an Extraction list that follows this format - one station number per line.

Note they can be run from the DOS prompt, or within the python module. The python code can be found below

To run, open the command prompt (START -> RUN -> CMD)
Change the directory in the DOS prompt to the one in which the files are stored.
At the DOS prompt, type ExtractClimate3 and hit enter.

The program will prompt you for a number of things. First, it will ask the directory location of the climate CD's. Next it asks for the name of the Station list file.
For the next question, enter an appropriate file name to store the extracted data. The final question regards the location of the file with the list of stations you wish to extract. The program will also ask which climate variables you wish to extract.

Once all relevant information has been obtained, the program will begin processing the request. When it is finished, the raw data file will be populated with the relevant extracted data.

Python Code:

Canadian_Data2

```
# 24.8.1999 Bernhard Reiter
#         Original Author of code
#
# 03.01.2005 Daniel Gillis
#         Second Author
#         Corrected the record search engine.  The engine was extracting data incorrectly if
#         gaps were included in the observed years, or if the first variable recorded was not
#         a temperature variable.  This has been corrected.  Other functionality has been
#         deactivated or updated as required by the HPRP project.

import sys
import os.path     # portable path manipulations

import array       # Efficient arrays of uniformly typed numeric values.
import struct      # Interpret strings as packed binary data

# from the Library Reference documentation for struct:
#  Format
#         C Type              Python
#
#   x pad byte      no value
#   c char                    string of length 1
#   b signed char integer
#   B unsigned char           integer
#   h short                   integer
#   H unsigned short          integer
#   i int             integer
#   I unsigned int            integer
#   l long                    integer
```

```
#   L unsigned long         integer
#   f float                 float
#   d double                float
#   s char[]                string
#   p char[]                string
#   P void *                integer

###############################################################################
# Format strings for the struct pack and unpack functions
# corresponding to the binary format within the data and index files
#
Index_File_header_fmt= ( "<" + # indicates little-endian data
            "4s" +          # ID
            "HH" +          # MaxLat, MinLat
            "HH" +          # MaxLong, MinLong
            "hh" +          # MaxElev, MinElev
            "HH" +          # EarliestYear, LatestYear
            "H"  +          # Number of Stations in the district
            "3s" +          # District ID
            "42s"           # District Name
            )

Index_File_data_fmt=  ( "<" + # indicates little endian data
            "4s" +          # CSN, the last four characters of the 7-char statHon ID
            "24s" +         # StationName
            "3s" +          # Airport
            "HH" +          # Lat, Long
            "h"  +          # Elevation
            "7H" +          # First Year
            "7H" +          # Last Year
            "H"             # [20] Starting Record Number
            )


Data_File_header_fmt= ( "<" +
            "4s" +          # Data file version id (should be "WWWW")
            "7s" +          # CSN = station ID number
            "24s" +         # Station Name
            "3s" +          # Airport
            "HH" +          # Lat, Long
            "H"  +          # Elevation
            "HH" +          # First Year, Last Year    for station
            "300H" +        # Record Num for each year's 1st element starting w 1801
            "300B" +        # Available indicator, left to right 6 bit of each byte
            "123x" ) #

Data_File_data_fmt= (  "<" +
            "732s" +# contains array of short ints: one day's value
            "183s" +# contains array of nybbles: one day's flag
            "156s" ) # contains 12 month summaries a 13 bytes

Record_size=struct.calcsize(Data_File_data_fmt)
if Record_size != struct.calcsize(Data_File_header_fmt) or Record_size != 1071:
   sys.stderr("Something wrong with the internal record structure formats!\n")
   sys.exit(5)
```

```
Maximum_Temperature_fmt = (  "<" +
      "12h"  +      #  Mean Max for Month
      "12B"  +      #  # Days Missing
      "12B"  +      #  # Days with Max above 0
      "12h"  +      #  Maximum Max for Month
      "12B"  +      #  Date of Maximum Max
      "12h"  +      #  Minimum Max for Month
      "12B"  +      #  Date of Minimum Max
      "12B"  +      #  Max # Days in a Row with Missing Data
      "12B"  +      #  # Days with Misg Mean Temperature
      "12B"  )      #  Maximum # Days in a row with Misg Mean Temperature

Minimum_Temperature_fmt = ( "<" +
      "12h"  +      # Mean Minimum for Month
      "12B"  +      # # Days Missing
      "12B"  +      # # Days with Min above 0
      "12h"  +      # Maximum Min for Month
      "12B"  +      # Date of Maximum Min
      "12h"  +      # Minimum Min for Month
      "12B"  +      # Date of Minimum Min
      "12B"  +      # Max # Days in a Row with Missing Data
      "12h"  )      # Mean Temperature

Precipitation_fmt = ( "<" +
      "12H"  +      # Total for Month
      "12B"  +      # # Days Missing
      "12B"  +      # # Days with > 0 cm/mm
      "12H"  +      # Max one-day total for Month
      "12B"  +      # Date of Max
      "12B"  +      # # Days with > Trace
      "12B"  +      # # Days with > 1 cm
      "12B"  +      # # Days with Uncrtn/accum pcpn
      "12B"  +      # Maximum # Days in a row with Uncrtn/accum Pcpn
      "24x" )

Snow_on_the_Ground_fmt = ( "<" +
      "12H"  +      # Median for Month
      "12B"  +      # # Days Missing
      "12B"  +      # Days with >0 cm
      "12H"  +      # Max for Month
      "12B"  +      # Date of Max
      "12H"  +      # Min for Month
      "12B"  +      # Date of Min
      "12B"  +      # Days with > Trace
      "12B"  +      # Days with > 1 cm
      "12x" )

################################################################################
#
#

def read_all_records(file,fmt):
   """Return list containing all records read from the monotoniously build file.

         Parameter:
               file      an open file object (seeked to the right place)
               fmt       a struct module format string
```

```
        This routine will read till end of the file and
        give a message if the last read count was not 0.
    """
    list=[]
    size=struct.calcsize(fmt)

    while 1:
       s=file.read(size)
            if len(s) == size:
                    list.append(struct.unpack(fmt,s))
                    continue

            if len(s)!=0:
                    sys.stderr.write("Only got %d bytes on last read!" % len(s))
            return list



def build_file_index(topdirectory):
    """ Returns list of (index filename, data filename, district) tuples.

    Reads the "index.all" file in the topdirectory and calculates all other
    index filenames.
    """
    file=open(os.path.join(topdirectory,"index.all"),"rb")
    list=read_all_records(file,Index_File_header_fmt)
    file.close()

    # Okay, using a lambda construct and map is a bit complicated, but elegant
    def create_index_name(topdir):
            return lambda x,td=topdir: \
               ( os.path.join(td,x[10][0],"Index."+x[10]),
               os.path.join(td,x[10][0],"Data."+x[10]),
               x[10])

    return map(create_index_name(topdirectory),list)


################################################################################
#
class weather_station:
    """Manages data for one station.


    To creat it, you need to give it the
    filetuple with (Indexfilename,datafilename,districtnumber) and
    the index record. A function to do this is get_station_list().
    The datafile is not open, when the object is instanciated.

    Call    get_data(year,what)  what being among avail.keys()
                                 to get a tuple with two lists: values, flags, both raw

                    write_temperature_for_mark(.... )

                    deactivate() to close the open datafile, if open.
```

```
                AvailFor(year)    get the start_record and the avail_flags
                                  for the year

                decode_avail_flags(avail_flags) to get text representation

    Variables (see __init__()), most visible:
            stationnumber
            district
            dataindex         if activate() was called contains the tuple
                              with all the data of the data file header.

    Internal:

    Class constant:
            avail     dictionary        maps string representation to
                                        a tuple with
                                        (avail_flag, denominator, summary binary format)
    """

    avail= {
    "MAX_TEMP":(1,10.0,Maximum_Temperature_fmt),
    "MIN_TEMP":(1<<1,10.0,Minimum_Temperature_fmt),
    "ONE_DAY_RAIN":(1<<2,10.0,Precipitation_fmt),
    "ONE_DAY_SNOW":(1<<3,10.0,Precipitation_fmt),
    "ONE_DAY_PRECIPITATION":(1<<4,10.0,Precipitation_fmt),
    "SNOW_ON_THE_GROUND":(1<<5,10.0,Snow_on_the_Ground_fmt)
    }
# flags explanation out of cdcd.doc, values out of format description
#  0   (no flag)
#  7-13 unused
# 14   29th of February in non leap years
#  5 A Amount accumulated over more than one day; Previous value's flag was
#    C or L
#  3 C Precipitation occurred; amount is uncertain; recorded value is 0;
#     value displayed is the word "Yes"
#  1 E Estimated
#  6 F Amount accumulated over more than one day and estimated
#  4 L Precipitation may or may not have occurred; amount is unknown;
#     recorded value is 0; value displayed is the word "Maybe"
# 15 M Missing
#  2 T A trace occurred; recorded value is zero



    def __init__(self,filetuple,index_record):
        """Initialise instance variables."""
            self.index_record=index_record
            self.indexfilename=filetuple[0]
            self.datafilename=filetuple[1]
            self.district=filetuple[2]
            self.startrecord=self.index_record[20]
            self.stationnumber=self.district+self.index_record[0]
            self.datafileopen=0
            self.dataindex=[]

    def activate(self):
        """Make sure the datafile is open and we have the dataindex."""
```

```
        if not self.datafileopen:
                self.datafile=open(self.datafilename,"rb")
                self.datafileopen=1
        if not self.dataindex:
                self.datafile.seek((self.startrecord-1)*Record_size)
                string=self.datafile.read(Record_size)
                self.dataindex=struct.unpack(Data_File_header_fmt,string)


def deactivate(self):
   """Close the datafile if necessary."""
        if self.datafileopen:
                self.datafile.close()
                self.datafileopen=0

def AvailFor(self,year):
   """Return tuple with recordindex and availabilty flags or null."""
        self.activate()

        recnumb_index=year-1801+9
        dataavail_index=year-1801+309

        firstrec= self.dataindex[recnumb_index]
        if firstrec:
                return(firstrec, self.dataindex[dataavail_index])
        else:
                return 0


def get_data(self,year,what):
   """Returns list w [values,flags,summaries] for wanted year and item.

        All non-missing values have been turned into normal representation.
        The missing values are undefined.
        """

        tuple=self.AvailFor(year)

        if (not tuple) or (not self.avail[what][0] & tuple[1]):
                return 0
      # get flag code list
        curFlagCodes=[]
        curFlags=decode_avail_flags(tuple[1])
        for m in range(0,len(curFlags)):
          curFlagCodes=curFlagCodes+[self.avail[curFlags[m]][0]]
      # sort flag code list.  find desired variable location in the list.  call this 'place'
        curFlagCodes.sort()
        for j in range(0,len(curFlagCodes)):
          if self.avail[what][0]==curFlagCodes[j]:
             place=j
      # use place to find the desired variable data
        self.datafile.seek((self.startrecord+tuple[0]-1+place)*Record_size)
        string=self.datafile.read(Record_size)
        r=struct.unpack(Data_File_data_fmt,string)

        raw_values=array.array("h")
        raw_values.fromstring(r[0])
```

```
        flags=array.array("B")
        for i in range(183):
                flags.append(ord(r[1][i])>>4&15)
                flags.append(ord(r[1][i])&15)

        # sanity check:
        if len(raw_values)!=len(flags):
                sys.stderr.write("Arg! Something is very wrong! :-( \n")
                sys.exit(10)

        # transform values into normal representation
        def trans_into_value(denominator):
                return lambda v, d=denominator: v/d

        values=array.array("f")
        values.fromlist(map(trans_into_value(self.avail[what][1]),raw_values))

        # unpack summaries
        summaries=struct.unpack(self.avail[what][2],r[2])

        return [values,flags,summaries]


def write_temperature_for_mark(self, file, year):
   """Appends daily max and min temperatures to file in Mark S's format.

        This is a special format used by another older program.
        It uses Fahrenheit (yuck) and non-leap years have a missing value
        at the end.
        """

        def fix_leap_year(raw):
           """ pay attention to leap year at position 31+29=60. """
           if raw[1][59]==14:
              #shift leap year to end ->written out like missing value later
                raw[0].append(raw[0][59])
                raw[0]=raw[0][:59]+raw[0][60:]
                raw[1].append(raw[1][59])
                raw[1]=raw[1][:59]+raw[1][60:]

        def trans_into_fahrenheit_or_missing(celsius,flag):
                if flag in [0,1]:
                        return celsius # (9.0/5.0)*celsius+32
                else:
                        return 99.0

        def write_in_marks_format(list,file=file,self=self,year=year):
        file.write("%7s %4d " % (self.stationnumber, year) )
        for i in range(0,366,20):
                   # writing one line
                   if not i==0:
                      file.write(" ")
           for t in list[i:i+20]:
                        #we have to be sure to write only three characters
                        if t<-99:
                           t=-99
                           sys.stderr.write(
```

```
                                "Temperature below -99 detected and cut!\n")
                        if t>999:
                            t=99
                            sys.stderr.write(
                                "Temperature value >999 detected and cut!\n")
                    file.write("%5.1f" % t)
                file.write("\n")


        rawmax=self.get_data(year,"MAX_TEMP")
        rawmin=self.get_data(year,"MIN_TEMP")
        if not (rawmax and rawmin):
                sys.stderr.write("%s's Temp not available for s %s\n" %
                        (year, self.stationnumber) )
                return 0
        fix_leap_year(rawmax)
        fix_leap_year(rawmin)

        max=map(trans_into_fahrenheit_or_missing,rawmax[0],rawmax[1])
        min=map(trans_into_fahrenheit_or_missing,rawmin[0],rawmin[1])

        del(rawmax)
        del(rawmin)

        write_in_marks_format(max)
        write_in_marks_format(min)
#
# END of class
################################################################################


def decode_avail_flags(avail_flags):
    """ Returns unordered list of text representations of avail flags.

    Needs the avail_flags integer value as argument.
    """
    items=[]
    for repr in weather_station.avail.keys():
        if weather_station.avail[repr][0] & avail_flags:
            items.append(repr)
    return items


def get_station_list(topdirectory):
    """ Return list of weather_station objects."""

    files=build_file_index(topdirectory)
    wlist=[]

    for filetuple in files:
            # read index file
        file=open(filetuple[0],"rb")
            string=file.read(struct.calcsize(Index_File_header_fmt))
            Index_File_header=struct.unpack(Index_File_header_fmt,string)

            Index_File_data_list=read_all_records(file,Index_File_data_fmt)
            if len(Index_File_data_list) != Index_File_header[9]:
```

```
                    sys.stderr.write("Found %d out of %d!\n" %
                                (len(Index_File_data_list), Index_File_header[9]) )
        file.close()

            for record in Index_File_data_list:
           wlist.append(weather_station(filetuple,record))

    return wlist
```

ExtractClimate3

```
# Initial 25.8.1999 Bernhard Reiter
# Current 24.2.2005 Daniel Gillis
# The following Code will extract data from the Environment Canada CD's for
# a given list of stations.  The extracted data will be stored in two text files
# The first will contain a station reference list, the second the extracted data
# Data is extracted for all available dates for each station selected

import sys
import time
import fileinput
import string
import canadian_data2

print '\n'
print '************************************************************'
print '*                                          *'
print '*          Climate Data Extraction Script              *'
print '*                                          *'
print '*             Written By Daniel Gillis                *'
print '*                  March 2005                    *'
print '*                                          *'
print '*        The program extracts a set of data from         *'
print '*     Environment Canada Climate Database using a list    *'
print '*       of user supplied stations.  The program can       *'
print '*       generate a list of available stations with        *'
print '*   station location information (lat, long, elevation).  *'
print '*    Additionally allows the user to select the climate   *'
print '*    variables extracted.  Data is extracted to a user    *'
print '*                provided text file.               *'
print '*                                          *'
print '************************************************************'
print '\n'

StationCount = 1
VarList=['MAX_TEMP', 'MIN_TEMP', 'ONE_DAY_RAIN', 'ONE_DAY_SNOW',
'ONE_DAY_PRECIPITATION', 'SNOW_ON_THE_GROUND']
Source1 = raw_input('\nWhat directory is the data stored in? ')
GetStations = raw_input('Would you like to generate a list of available stations (Y or N)? ')
stations = canadian_data2.get_station_list(Source1)

#############################################################################################
def waitforkey_on_windows():
      """on windows, wait for a keypress (good for console programs)"""
      if sys.platform=="win32":
            import msvcrt
            sys.stderr.write("*** press any key ***\n")
```

```
            msvcrt.getch()
##############################################################################
if GetStations=='Y' or GetStations=='y':
   output1 = raw_input('Name of file to output station list to? ')
   print "\nLooking for climate data at \"%s\" ..." % Source1
   print "\nFound %s stations" % len(stations)
   print "\nWriting Stations to %s" % output1

   StatFile = open(output1, 'w')

   # set up quickindex for station numbers
   stationindex={}
   for station in stations:
      station.activate()
      stationindex[station.stationnumber]=station
      print '%5d of %s: %s' % (StationCount, len(stations), station.stationnumber)
      StatFile.write('%5d ' % StationCount)
      StatFile.write(station.stationnumber)
      StatFile.write('%6.0f %6.0f %6.0f \n' %(station.dataindex[4], station.dataindex[5], station.dataindex[6]))
      StationCount +=1
      station.deactivate()

   StatFile.close()

varsToOutList=[]
output2 = raw_input('Name of file to output extracted data to? ')
input1 = raw_input('Name of the input station list file? ')

for curVar in range(0,len(VarList)):
   varsToOutList=varsToOutList+[raw_input('Would you like to extract %s? (Y or N)' % VarList[curVar])]

print "Getting station list from %s:" % input1

InputFile=fileinput.input(input1)
stationList=[]

for line in InputFile:
      stationList=stationList + [string.strip(line)]

stationList.sort()

DataFile=open(output2,'w')

print "Writing results to %s:" % output2
currentStation=0

for station in stations:
   if station.stationnumber == stationList[currentStation]:
      print '\nFound station... %s' %stationList[currentStation]

      startYear=station.index_record[6]
      finYear=station.index_record[13]

      if startYear!=9999 and finYear!=55537:
         years=range(startYear,finYear+1)
         print '     Extractable data runs from %4d to %4d...' %(startYear, finYear)
```

```
        s=station
        for year in years:
            print '         Extracting year %4d ' % year
            tempMax=s.get_data(year,"MAX_TEMP")
            tempMin=s.get_data(year,"MIN_TEMP")
            tempRain=s.get_data(year,"ONE_DAY_RAIN")
            tempSnow=s.get_data(year,"ONE_DAY_SNOW")
            tempPre=s.get_data(year,"ONE_DAY_PRECIPITATION")
            tempDep=s.get_data(year,"SNOW_ON_THE_GROUND")

            for i in range(0,366):
                DataFile.write(station.stationnumber)
                DataFile.write('%5d %4d' %(year, i+1))

                if varsToOutList[0]=='Y' or varsToOutList[0]=='y':
                    if tempMax!=0:
                        DataFile.write('%8.2f %3d ' % (tempMax[0][i], tempMax[1][i]))
                    else:
                        DataFile.write('      NA  NA ')

                if varsToOutList[1]=='Y' or varsToOutList[1]=='y':
                    if tempMin!=0:
                        DataFile.write('%8.2f %3d ' % (tempMin[0][i], tempMin[1][i]))
                    else:
                        DataFile.write('      NA  NA ')

                if varsToOutList[2]=='Y' or varsToOutList[2]=='y':
                    if tempRain!=0:
                        DataFile.write('%8.2f %3d ' % (tempRain[0][i], tempRain[1][i]))
                    else:
                        DataFile.write('      NA  NA ')

                if varsToOutList[3]=='Y' or varsToOutList[3]=='y':
                    if tempSnow!=0:
                        DataFile.write('%8.2f %3d ' % (tempSnow[0][i], tempSnow[1][i]))
                    else:
                        DataFile.write('      NA  NA ')

                if varsToOutList[4]=='Y' or varsToOutList[4]=='y':
                    if tempPre!=0:
                        DataFile.write('%8.2f %3d ' % (tempPre[0][i], tempPre[1][i]))
                    else:
                        DataFile.write('      NA  NA ')

                if varsToOutList[5]=='Y' or varsToOutList[5]=='y':
                    if tempDep!=0:
                        DataFile.write('%8.2f %3d ' % (tempDep[0][i], tempDep[1][i]))
                    else:
                        DataFile.write('      NA  NA ')
                DataFile.write('\n')
        currentStation +=1
        if currentStation==len(stationList):
            currentStation=0

DataFile.close()
```

```
        print "\nDone."
waitforkey_on_windows()
```

Appendix F: Inverse Distance Weighing Method for Spatial Interpolation

Let s_i, $i = 1 \ldots n$ represent the d-dimensional location of a given set of n observed data points. Let s_j, $j = 1 \ldots m$ represent the set of unobserved d-dimensional locations.

Define $d_{i,j}$ as the Euclidean distance between locations s_i and s_j. That is

$$d_{i,j} = \sqrt{\sum_d (s_{i_d}^2 - s_{j_d}^2)} \qquad \text{(A.10)}$$

Further, define the weight $w_{i,j}$ as the inverse of $d_{i,j}$. This implies that smaller distances provide larger weights, and vice versa. Let p_i represent a specific observed quantity at s_i. The goal is to determine p_j, the unobserved quantity at location s_j.

Then define p_j as follows

$$p_j = \sum_{s_i \in \aleph(s_j)} \left(\frac{w_{i,j} p_i}{\sum_i w_{i,j}} \right) \qquad \text{(A.11)}$$

where $s_i \in \aleph(s_j)$ represents the observed locations within a given neighbourhood of the unobserved location. Note that the neighbourhood could be defined based on a maximum radial distance from the unobserved location, or by selection of the closest k observed locations.

Appendix G: Hospitalizations for Acute Gastroenteritis in Canada

Table 5. Proportion of hospitalizations with diagnosis of acute gastroenteritis by cause of enteritis, 1993 – 1997, from the Canadian Institutes of Health Information (CIHI) hospitalizations discharge database.

Age Group (years)	Number	Bacterial (%)	Parasitic (%)	Viral (%)	Combination of B, P or V (%)	Non-specific etiology %
< 1	31757	3.2	0.4	23.6	0.1	72.7
1 - 4	56081	3.6	1.0	24.1	0.3	71.0
5 - 9	20574	5.8	0.7	17.1	0.2	75.9
10 - 19	24537	7.5	0.5	11.6	0.1	80.3
20 - 49	102729	8.3	0.6	7.2	0.08	83.8
50 - 69	68926	8.7	0.3	4.4	0.04	86.6
70 - 79	50208	9.8	0.2	4.4	0.04	85.6
>=80	41515	9.7	0.1	4.9	0.01	85.2
Total	396327	7.4	0.5	10.6	0.10	81.3

Appendix H: Links Between Weather And Endemic Gastrointestinal Disease

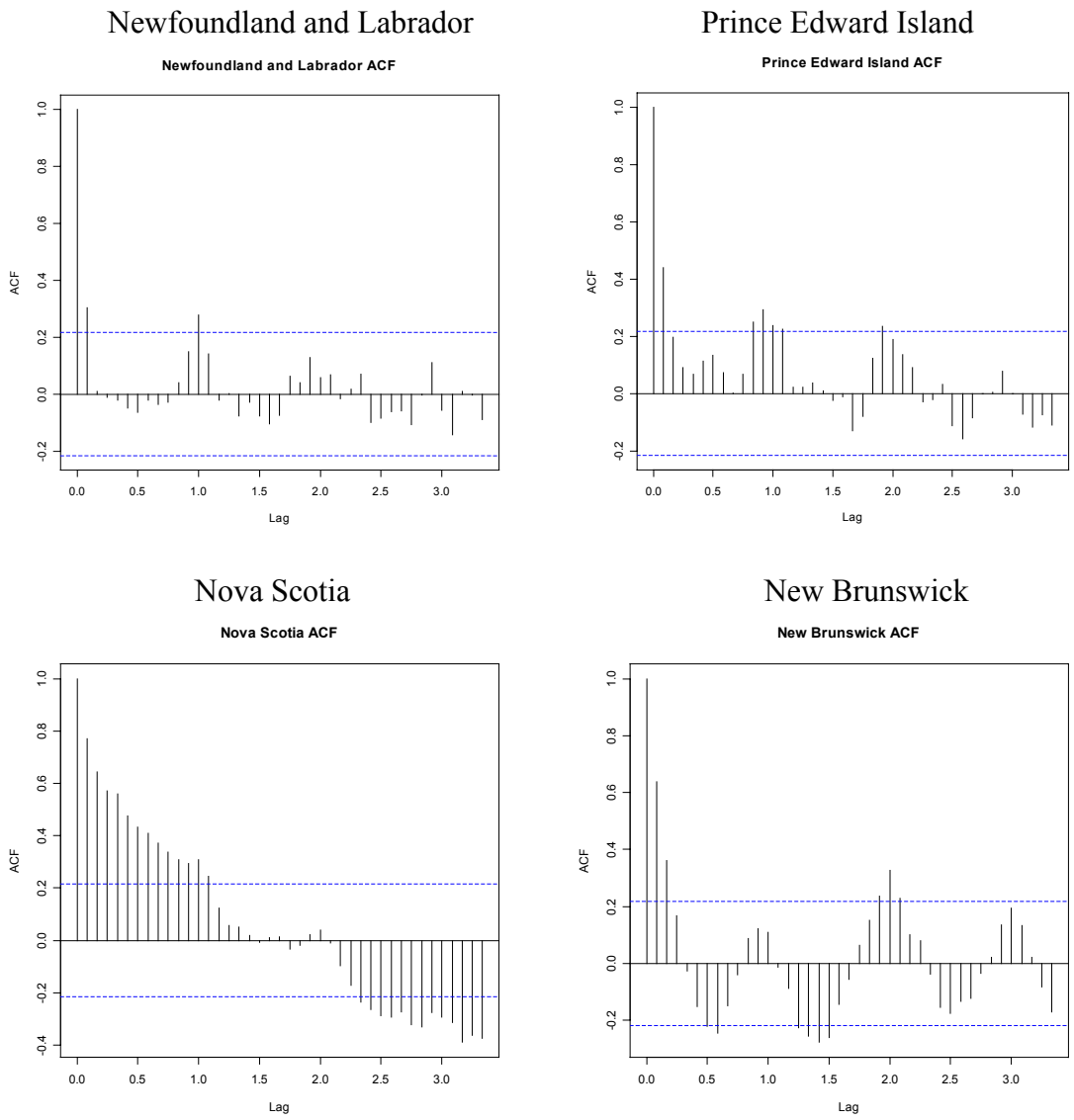


Figure 41. Temporal autocorrelation for the incidence of acute GID (cases per 10,000 person-months) in the Atlantic provinces for the time period 1992-1998. The lag represents a period of 1 year broken in to monthly (1/12) lags.

Table 6. Temporal clusters identified by the SaTScan statistic for the incidence of acute gastro-intestinal illness in Atlantic Canada from 1992-1998.

Province	Time frame of primary cluster
Newfoundland and Labrador	1995/1/30 – 1995/4/30
Prince Edward Island	1994/12/11 – 1995/4/24
Nova Scotia	1995/11/24 – 1996/7/28
New Brunswick	1997/2/17 – 1997/7/1

Table 7. Local consolidated census subdivision (CSD) clusters in the Atlantic province as identified by the SaTScan statistic.

Province	Cluster Type	CSDs Included	P-value	Relative Risk
Newfoundland and Labrador	Primary	1005030,1005028, 1005018, 1005025, 1005017, 1005015, 1005033	0.001	4.413
	Secondary	1006001, 1006017	0.001	2.470
		1006009,1006011, 1006012,1007045,1006008, 1007047, 1008038,1007049	0.001	2.197
		1001352,1001361, 1001365,1001357, 1001321, 1001370	0.001	2.325
		1001169	0.001	6.676
		1001557,1001559, 1001565,1001519, 1001551, 1001542	0.001	1.176
		1001234	0.001	9.104
		1002008	0.006	2.423
Prince Edward Island	Primary	1103025	0.001	3.121
	Secondary	1102075,1102048, 1102065,1102085, 1102070, 1102050, 1102030,1102080, 1102040	0.001	1.902
Nova Scotia	Primary	1217008, 1217030	0.001	1.923
	Secondary	1202006	0.001	5.923
		1211011	0.001	4.207
		1213001,1209038, 1209034,1214002	0.001	1.191
		1201008	0.001	3.364
		1204015, 1206004	0.013	1.603
New Brunswick	Primary	1309038,1309036,1309044,1309047, 1309001, 315001,1315003, 1309006,1315021,1315022,1315006,1309031,1309004,1309050, 1315019, 1308026, 315024,1315020,1315016,1309035,1315036, 1315010, 1315017,1315028, 1308021, 1315030,1315011	0.001	2.220
	Secondary	1311026,1311028,1311011,1311024,1311029,1311030,1311023, 1311012		2.573
		1302052,1302001	0.001	3.682
		1307001,1307002, 1307008,1307009	0.001	1.860
		1302037	0.001	2.140
		1302039	0.001	3.717
		1303014,1304021,1303016,1304022,1304011,1303013,1304005,1303011,1303012,1304004,1304013, 1310031, 1310034	0.001	1.348
		1307022	0.001	1.181

Appendix I: The Impact Of High Impact Weather Events On Waterborne Disease Outbreaks

Table 8. Model of weather and risk of waterborne disease outbreaks, Canada, 1971-2000. Variable names, derivations and reasons for inclusion

	Variable Name	Variable Derivation	Reason for Inclusion
Rainfall	Accumulated rainfall (AR) (mm)	The rolling five-day cumulative average amount was calculated for all years during the 27-year study period for each station. The maximum value achieved during the six-week hazard period prior the onset date was selected for analysis.	To determine if the absolute amount of rain differed between case and control times and to determine if there was a certain threshold amount of rain that was of particular significance.
Rainfall	Accumulated rainfall percentile (AR percentile)	The annual distribution of the five-day rolling cumulative average rainfall amounts was calculated for the entire 27-year study period for each station. The maximum value of the five-day rolling cumulative average amount achieved during the six-week hazard period was assigned a percentile based on comparison with this average annual distribution.	To standardise the rainfall to the station location and thus determine if there was a relationship with extreme rainfall percentiles and the occurrence of a waterborne disease outbreak.
Rainfall	Accumulated rainfall days (AR days)	The number of days prior to the outbreak when the percentile of the maximum five-day rolling cumulative average amount was achieved during the six-week hazard period.	To determine what temporal relationship exists between a peak rainfall weather event and a waterborne disease outbreak.
Temperature	Degree-days	The sum of the maximum daily temperature for all days with a minimum temperature greater than 0^{o}C in the six-week hazard period preceding the onset date. This resulted in one accumulated total value of temperature for the entire hazard period.	To capture the accumulated heat over the six-week hazard period that would contribute to pathogen growth and survival. In addition, water would not be frozen at temperatures greater than 0 ^{o}C.
Temperature	Maximum temperature (max. temp.) (^{o}C)	The rolling five-day cumulative average temperature was calculated for all years during the 27-year study period for each station. The maximum value achieved during the six-week period prior the onset date was selected for analysis.	As a measure of surges in temperature that might affect pathogen growth.
Temperature	Max. temp. days	The number of days prior to the outbreak when the maximum five-day rolling cumulative average temperature was achieved during the six-week hazard period.	To determine what temporal relationship may exist between increases in temperature and the occurrence of a waterborne disease outbreak.
Stream flow	Peak stream flow (SF peak) (m^3/s)	For cases and controls occurring between January and May, the three largest peaks per year for the entire 27-year study period for each station were identified. The value of the largest peak occurring within the six-week hazard time frame prior the onset date was included.	As a surrogate for spring thaw conditions for those outbreaks occurring between January and May.

	Variable Name	Variable Derivation	Reason for Inclusion
Stream flow	Percentile of peak stream flow (SF peak percentile)	For each station, the distribution of the 3 largest stream flow peaks occurring prior to the onset date of all outbreaks happening between January and May for the entire 27-year study period was generated. The maximum peak stream flow was assigned a percentile based on this distribution.	To standardise the stream flow peaks by station and to determine if there was a relationship between extreme stream flow peak percentiles and the occurrence of a waterborne disease outbreak.
Stream flow	SF peak percentile days	The number of days between onset date and peak stream flow within the six-week hazard period.	To determine what temporal relationship may exist between peaks in stream flow and the occurrence of a waterborne disease outbreak.
Stream flow	Stream flow (SF) (m^3/s)	The rolling five-day cumulative average stream flow was calculated for all years during the 27-year study period for each station. The maximum value achieved during the six-week period prior the onset date was selected for analysis.	To capture increases in water flow that may not have been peaks but could still be indicative of other weather-related contributing factors to a waterborne disease outbreak.
Stream flow	Maximum percentile of stream flow (SF percentile)	The annual distribution of the five-day rolling cumulative average stream flow was calculated for the entire 27-year study period for each station. The maximum value of the five-day rolling cumulative average achieved during the six-week hazard period was assigned a percentile based on comparison with this annual average distribution.	To standardise the stream flow to the station location and determine if there was a relationship between an extreme stream flow percentile and the occurrence of a waterborne disease outbreak.
Stream flow	SF days	The number of days between the onset date and the maximum stream flow within the six-week hazard period.	To determine what temporal relationship may exist between increases in stream flow and the occurrence of a waterborne disease outbreak

The form of the final model, for the relative odds of an outbreak (RO), is described as follows:

$$RO = \exp\left[\beta_1 (degree\text{–}days) + \beta_2 (AR\ 93^{rd}\ percentile) + \sum \gamma_j I_j\right] \text{ (equation 1)}$$

where I_j are indicator variables for the year effects and the γ_j are the corresponding parameters.

Appendix J: Outbreaks and Climate Thresholds

Results

Table 9. Number of outbreaks exceeding extreme rainfall and temperature thresholds (Percentiles) occurring prior to selected waterborne disease outbreaks in Canada 1971-2001 (percentiles are calculated from the period of record for each station)

Meteorological Variable	# outbreaks > 90th percentile	# outbreaks > 85th percentile
Max 1 day Rainfall (1-2 weeks prior)	16	19
Max 1 day Precip (1-2 weeks prior)	15	17
Max Daily Tmax (1-2 weeks prior)	13	15
Max 1 day Rainfall (5-6 weeks prior)	18	20
Max 1 day Precip (5-6weeks prior)	18	20
Max Daily Tmax (5-6 weeks prior)	13	14
Max 1 day Rainfall (6-8 weeks prior)	21*	23
Max 1 day Precip (6-8 weeks prior)	21	23
Max Daily Tmax (6-8 weeks prior)	18	20
	<10th	<25th
Min daily Tmin (1-2 weeks prior)	17	23
Min daily Tmin (5-6 weeks prior)	13	21
Min daily Tmin (6-8 weeks prior)	18	22

* 13 outbreaks were above the 95th percentile

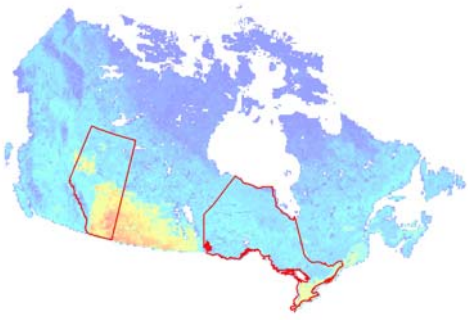
Appendix K: Model of Hospitalization for Gastrointestinal Disease Risk in Southern Alberta

The final list and explanations of variables and interactions for the Southern Alberta study are listed below. Included with each variable is the Wald Type III chi-square p-value. Following the list is a full description of the variables (excluding interactions) included in the model, as well as a brief outline of others that were not included due to non-significance or failing to improve the fit of the model.

Va	P-value
Land Use	<0.0001
Daily Lag Case Count	<0.0001
Age Group	<0.0001
Daily Case and Control Count (CCCount)	<0.0001
CCS	<0.0001
Elevation	<0.0001
Sex	0.0004
Watershed	<0.0001
Latitude	<0.0001
Water Treatment Score	<0.0001
Longitude	<0.0001
Special Degree Days (Max15Min5)	<0.0001
42 Day Count of Precipitation Exceeding 50mm (nPD50)	0.9308
42 Day Count of Rain Exceeding 0mm (nRD)	<0.0001
95th Percentile for Rain Days	0.0085
Elevation * Latitude	<0.0001
Age Group * Land Use	<0.0001
Age Group * Sex	<0.0001
Sex * Watershed	<0.0001
Water Treatment Score * 42 Day Count of Precipitation Exceeding 50mm	<0.0001

Land Use

The land use variable represents data obtained from SPOT4 Satellite imagery that has been cross referenced with the Canadian Agricultural Land Use survey (1996). It is a classification variable representing the specific type of land use for a given parcel of land. It has a resolution of 1km by 1km grid. The classification list can be found below:



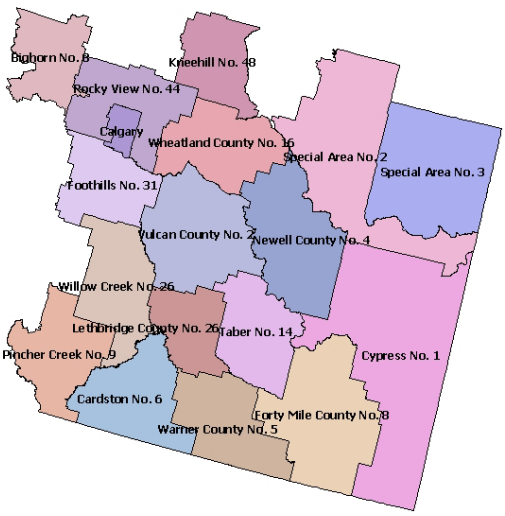
1. Grassland (very low density grazing)
2. Rangeland in central plains – very low moisture
3. Pasture – predominantly fescue rangeland near Rockies
4. V. low vegetation cover, relatively wild lands, low density pasture

5. Grain/pasture mix
6. Grain – low moisture
7. Grain – better moisture/soil
8. Grain/natural vegetation mix with water/indeterminate water mix
9. Grain/canola or other high biomass crops
10. Canola
11. Corn/soybean
12. Corn Soybean mix with pasture
13. Woodland-agriculture
14. Other high biomass
15. Urban
16. Urban-bare
17. Unclassified
18. Unclassified
19. Unclassified
20. Coniferous, coniferous low density
21. Southern coniferous, conifer with broadleaf
22. Northern conifers, often lower density
23. Very low density with various understory or barren
24. Deciduous, mixed or open
25. Post-burn of various descriptions
26. Wetlands (treed or otherwise)
27. Treed barren land
28. Treeless barrens
29. Treeless rocky and/or snow
30. Water

Daily Lag Case Count — Represents the total number of cases the day prior to the case or control event.

Age Group — An age classification variable. Classification is as follows

1. Infants and Toddlers (0-4)
2. Children (5 – 12)
3. Teenagers (13-19)
4. Young Adults (20-29)
5. Thirties (30-39)
6. Forties (40-49)
7. Fifties and above (50-64)
8. Post Retirement (65+)



Daily Case Control Total — This represents the 'at risk' population within the study. It is a sum of all the cases and

controls for the given case or control date.

CCS — A variable identifying the Consolidated Census Subdivision. Those considered in the study are as follows

4801003	Cypress No. 1
4801008	Forty Mile County
4802001	Warner County
4802011	Lethbridge County
4802021	Taber No. 14
4802031	Newell County
4803001	Cardston No. 6
4803011	Pincher Creek
4803018	Willow Creek No. 26
4804004	Special Area No. 2
4804012	Special Area No. 3
4805001	Vulcan County No. 2
4805012	Wheatland County
4805041	Kneehill No. 48
4806001	Foothills No. 31
4806014	Rocky View No. 44
4806016	Calgary
4815015	Bighorn No. 8

Elevation — The average elevation based on the postal code centroid of the case or control event. The Elevation was obtained from the Canadian Digital Elevation Model using ArcGIS software.

Sex — An indicator variable representing Male or Female

Watershed — A classification identifying the secondary watershed in which the case or control event falls. For the study region, these are

9	Battle River
12	Red Deer River
13	Bow River
14	Oldman River
15	Seven Persons Creek, Bigstick Lake, Swift Current
16	South Saskatchewan River
30	Milk River

Latitude/Longitude — The latitude and longitude of the centroid of each postal code region. The postal code was that of the case or control event.

Water Treatment Score — A score based on the number of water treatments applied by a water treatment plant. If a plant had two specific treatments, a score of 2

	was applied. Treatments scored include filtration, chlorination, ozonation, etc.
Special degree-day	The special degree-days (SDD) represents a total of the maximum temperature for each day (in the 42 days prior to case or control event) where the maximum temperature was smaller than 15 degrees, and the minimum temperature was above 5 degrees Celsius.
nRD	A count of the number of days in the 42 prior to case or control event in which the rainfall exceeded 0mm.
nPD50	A count of the number of days in the 42 prior to case or control event in which the precipitation exceeded 50mm.
95th percentile RD	An indicator variable identifying whether or not the 42 days prior to case or control event were subject to an nRD value that exceeded the 95th percentile for that variable, based on the CCS and season in which the case or control occurred.

Other variables considered in the model included other forms of the SDD. These variables would sum up the maximum temperature using a similar minimum threshold value, but with a different maximum limit. For example, the maximum temperature could not exceed 20 or 25 Celsius.

Additional variables considered were lag case counts by week and month, as well as lags for each of the 42 days prior to a case or control for each of the climate variables considered (Maximum and Minimum Temperature, rainfall, snowfall, total precipitation and snow depth).

Various temporal variables such as Day of Week, Month of Year, Season and Holiday indicators were considered.

Agricultural treatments (Total Manure Spread by CCS, etc) were considered. This included livestock density variables.

Significant Variables

The final southern Alberta study model contained 15 main effect variables plus 5 interaction terms. The tables below outline the parameter estimates, standard errors and p-values associated with each. Note that since some of the variables included in the model represent classification variables, there are more than 20 'variables' listed.

Parameter	Estimate	Standard Error	p-value
Intercept	257.4000	24.0115	<.0001

Parameter	Estimate	Standard Error	p-value
Longitude	-0.8847	0.0979	<.0001
Latitude	-7.1492	0.5065	<.0001
Elevation	-0.3625	0.0238	<.0001
Elevation*Latitude	0.00725	0.000466	<.0001

Parameter		Estimate	Standard Error	p-value
SEX	F	0.1031	0.0293	0.0004
CCCount		-0.0300	0.000978	<.0001
Dcount1		0.1259	0.00233	<.0001
Max15Min5 (SDD)		0.0030	0.000912	0.001
nPD50		-0.00081	0.00929	0.9308
nRD		0.00447	0.00113	<.0001
highRD	0	-0.0590	0.0224	0.0085

Parameter		Estimate	Standard Error	p-value
CONTOUR	4	0.3744	0.096	<.0001
CONTOUR	5	0.3845	0.0974	<.0001
CONTOUR	6	0.3591	0.0814	<.0001
CONTOUR	7	0.2095	0.0617	0.0007
CONTOUR	8	0.2199	0.0541	<.0001
CONTOUR	9	0.0834	0.0463	0.0716
CONTOUR	10	0.1436	0.0503	0.0043
CONTOUR	11	0.0872	0.0433	0.0439
CONTOUR	12	0.2128	0.0473	<.0001
CONTOUR	13	0.0596	0.0647	0.3567
CONTOUR	14	0.4495	0.0648	<.0001
CONTOUR	15	0.1323	0.0553	0.0166
CONTOUR	16	-0.1425	0.0561	0.0111
CONTOUR	17	-0.3702	0.0541	<.0001
CONTOUR	18	-0.2227	0.0544	<.0001
CONTOUR	19	-0.2399	0.0545	<.0001
CONTOUR	20	-0.2200	0.0557	<.0001
CONTOUR	21	-0.2250	0.056	<.0001
CONTOUR	22	-0.2512	0.0605	<.0001
CONTOUR	23	-0.3111	0.0769	<.0001
CONTOUR	24	-0.2302	0.0834	0.0058
CONTOUR	25	-0.1841	0.0932	0.0482

Parameter		Estimate	Standard Error	p-value
agegrp	1	0.3130	0.0246	<.0001
agegrp	2	0.1962	0.0368	<.0001
agegrp	3	0.1987	0.0484	<.0001
agegrp	4	0.4429	0.0331	<.0001
agegrp	5	0.1980	0.0297	<.0001
agegrp	6	-0.1998	0.031	<.0001
agegrp	7	-0.5201	0.0239	<.0001

Parameter		Estimate	Standard Error	p-value
prcdccs	4801003	1.7930	0.2135	<.0001
prcdccs	4801008	1.4398	0.1904	<.0001
prcdccs	4802001	0.7786	0.208	0.0002
prcdccs	4802011	-0.5917	0.1117	<.0001
prcdccs	4802021	0.5084	0.1196	<.0001
prcdccs	4802031	1.3433	0.1628	<.0001
prcdccs	4803001	0.3015	0.1793	0.0927

prcdccs	4803011	-0.3925	0.2003	0.05
prcdccs	4803018	-0.8763	0.128	<.0001
prcdccs	4804004	2.5658	0.2325	<.0001
prcdccs	4804012	3.0939	0.3097	<.0001
prcdccs	4805001	-0.3745	0.1035	0.0003
prcdccs	4805012	0.1843	0.105	0.0792
prcdccs	4805041	-0.0196	0.1679	0.9069
prcdccs	4806001	-1.0610	0.1125	<.0001
prcdccs	4806014	-2.3954	0.1416	<.0001
prcdccs	4806016	-2.2516	0.1214	<.0001

Parameter		Estimate	Standard Error	p-value
WS	9	0.6970	0.2514	0.0056
WS	12	0.1944	0.1611	0.2274
WS	13	-0.4563	0.1122	<.0001
WS	14	-0.0104	0.1124	0.9259
WS	15	-0.5120	0.1477	0.0005
WS	16	-0.2464	0.1406	0.0797

Parameter		Estimate	Standard Error	p-value
Treated	0	0.0219	0.1058	0.8359
Treated	1	-0.1540	0.0905	0.089
Treated	2	0.6906	0.1287	<.0001
Treated	3	-0.1482	0.0637	0.0199

Parameter		Estimate	Standard Error	p-value
SEX*agegrp	F*1	-0.0212	0.0207	0.3057
SEX*agegrp	F*2	-0.0493	0.0301	0.1017
SEX*agegrp	F*3	-0.1474	0.036	<.0001
SEX*agegrp	F*4	-0.066	0.0303	0.0294
SEX*agegrp	F*5	0.00414	0.0268	0.8773
SEX*agegrp	F*6	0.1688	0.0269	<.0001
SEX*agegrp	F*7	0.0619	0.0207	0.0028

Parameter		Estimate	Standard Error	p-value
SEX*WS	F*9	0.00573	0.1476	0.969
SEX*WS	F*12	-0.0493	0.0362	0.1729
SEX*WS	F*13	0.0936	0.0301	0.0019
SEX*WS	F*14	-0.0344	0.032	0.2821
SEX*WS	F*15	-0.017	0.0374	0.649
SEX*WS	F*16	-0.00219	0.0373	0.9532

Parameter		Estimate	Standard Error	p-value
nPD50*Treated	0	0.0255	0.0228	0.2628
nPD50*Treated	1	-0.0163	0.0178	0.3604
nPD50*Treated	2	0.0028	0.0224	0.9005
nPD50*Treated	3	-0.0257	0.00903	0.0044

Parameter	Estimate	Standard Error	p-value
agegrp*CONTOUR 1*4	-0.1756	0.0906	0.0527

agegrp*CONTOUR 1*5	-0.2677	0.1418	0.059
agegrp*CONTOUR 1*6	-0.1928	0.0747	0.0098
agegrp*CONTOUR 1*7	-0.3386	0.0904	0.0002
agegrp*CONTOUR 1*8	-0.275	0.0845	0.0011
agegrp*CONTOUR 1*9	-0.1345	0.0575	0.0193
agegrp*CONTOUR 1*10	-0.1589	0.0935	0.0892
agegrp*CONTOUR 1*11	0.1025	0.0644	0.1111
agegrp*CONTOUR 1*12	0.0349	0.0855	0.6828
agegrp*CONTOUR 1*13	-0.0255	0.1226	0.8354
agegrp*CONTOUR 1*14	-0.0653	0.1437	0.6496
agegrp*CONTOUR 1*15	-0.00639	0.1097	0.9536
agegrp*CONTOUR 1*16	0.0175	0.1126	0.8766
agegrp*CONTOUR 1*17	-0.0113	0.1076	0.9165
agegrp*CONTOUR 1*18	-0.0264	0.1075	0.8063
agegrp*CONTOUR 1*19	0.228	0.1046	0.0293
agegrp*CONTOUR 1*20	0.2771	0.1071	0.0097
agegrp*CONTOUR 1*21	0.218	0.1118	0.0512
agegrp*CONTOUR 1*22	0.2329	0.1107	0.0355
agegrp*CONTOUR 1*23	-0.1648	0.1622	0.3095
agegrp*CONTOUR 1*24	0.4964	0.1516	0.0011
agegrp*CONTOUR 1*25	0.1895	0.1577	0.2294
agegrp*CONTOUR 2*4	-0.0743	0.1249	0.552
agegrp*CONTOUR 2*5	-0.0874	0.2015	0.6644
agegrp*CONTOUR 2*6	-0.1645	0.1144	0.1507
agegrp*CONTOUR 2*7	-0.1767	0.1231	0.1513
agegrp*CONTOUR 2*8	0.00238	0.1293	0.9853
agegrp*CONTOUR 2*9	-0.1552	0.0848	0.0673
agegrp*CONTOUR 2*10	0.00367	0.1315	0.9777
agegrp*CONTOUR 2*11	-0.1228	0.0968	0.2043
agegrp*CONTOUR 2*12	0.0523	0.1169	0.6544
agegrp*CONTOUR 2*13	-0.1296	0.1785	0.4678
agegrp*CONTOUR 2*14	-0.3093	0.1926	0.1084
agegrp*CONTOUR 2*15	-0.1098	0.157	0.4845
agegrp*CONTOUR 2*16	0.0675	0.1479	0.648
agegrp*CONTOUR 2*17	-0.0268	0.1576	0.8649
agegrp*CONTOUR 2*18	0.1684	0.1443	0.2432
agegrp*CONTOUR 2*19	0.1908	0.1477	0.1964
agegrp*CONTOUR 2*20	0.012	0.1565	0.939
agegrp*CONTOUR 2*21	0.0986	0.162	0.543
agegrp*CONTOUR 2*22	0.0397	0.1727	0.8183
agegrp*CONTOUR 2*23	0.0994	0.2463	0.6864
agegrp*CONTOUR 2*24	0.1435	0.2591	0.5796
agegrp*CONTOUR 2*25	0.5932	0.2765	0.0319
agegrp*CONTOUR 3*4	-0.2571	0.1429	0.072
agegrp*CONTOUR 3*5	0.2231	0.243	0.3585
agegrp*CONTOUR 3*6	0.0368	0.1239	0.7666
agegrp*CONTOUR 3*7	0.1659	0.1455	0.254
agegrp*CONTOUR 3*8	0.2105	0.1366	0.1233
agegrp*CONTOUR 3*9	-0.2202	0.1047	0.0354
agegrp*CONTOUR 3*10	0.1458	0.1674	0.384
agegrp*CONTOUR 3*11	0.05	0.1171	0.6694

agegrp*CONTOUR 3*12	-0.1542	0.158	0.329
agegrp*CONTOUR 3*13	-0.0355	0.1849	0.8477
agegrp*CONTOUR 3*14	0.0766	0.2354	0.7449
agegrp*CONTOUR 3*15	-0.2368	0.2001	0.2366
agegrp*CONTOUR 3*16	0.1656	0.1811	0.3604
agegrp*CONTOUR 3*17	0.1218	0.1806	0.4998
agegrp*CONTOUR 3*18	0.141	0.1997	0.4801
agegrp*CONTOUR 3*19	-0.0209	0.1978	0.9159
agegrp*CONTOUR 3*20	-0.0503	0.1965	0.798
agegrp*CONTOUR 3*21	0.2399	0.1898	0.2062
agegrp*CONTOUR 3*22	-0.0738	0.2497	0.7676
agegrp*CONTOUR 3*23	0.3388	0.2854	0.2351
agegrp*CONTOUR 3*24	-0.4973	0.3851	0.1966
agegrp*CONTOUR 3*25	-0.3939	0.4961	0.4272
agegrp*CONTOUR 4*4	-0.1121	0.1363	0.4109
agegrp*CONTOUR 4*5	0.0523	0.2373	0.8255
agegrp*CONTOUR 4*6	-0.1264	0.1171	0.2805
agegrp*CONTOUR 4*7	-0.0832	0.1361	0.5409
agegrp*CONTOUR 4*8	-0.2294	0.1157	0.0475
agegrp*CONTOUR 4*9	-0.0588	0.091	0.5179
agegrp*CONTOUR 4*10	-0.2074	0.14	0.1386
agegrp*CONTOUR 4*11	-0.044	0.1026	0.668
agegrp*CONTOUR 4*12	0.0892	0.1394	0.5224
agegrp*CONTOUR 4*13	-0.0867	0.1605	0.589
agegrp*CONTOUR 4*14	0.2391	0.1953	0.221
agegrp*CONTOUR 4*15	0.00995	0.1499	0.9471
agegrp*CONTOUR 4*16	-0.1426	0.1599	0.3724
agegrp*CONTOUR 4*17	-0.1023	0.144	0.4774
agegrp*CONTOUR 4*18	-0.00703	0.1376	0.9593
agegrp*CONTOUR 4*19	-0.00082	0.1521	0.9957
agegrp*CONTOUR 4*20	0.2459	0.1468	0.0941
agegrp*CONTOUR 4*21	-0.0918	0.1487	0.5372
agegrp*CONTOUR 4*22	0.0767	0.1336	0.5659
agegrp*CONTOUR 4*23	0.2264	0.1734	0.1916
agegrp*CONTOUR 4*24	0.2088	0.1733	0.2282
agegrp*CONTOUR 4*25	0.0539	0.1693	0.7502
agegrp*CONTOUR 5*4	-0.0983	0.1188	0.4082
agegrp*CONTOUR 5*5	-0.2869	0.1985	0.1483
agegrp*CONTOUR 5*6	-0.1245	0.0987	0.2075
agegrp*CONTOUR 5*7	-0.1262	0.1162	0.2775
agegrp*CONTOUR 5*8	-0.1462	0.1132	0.1965
agegrp*CONTOUR 5*9	-0.12	0.0807	0.1369
agegrp*CONTOUR 5*10	-0.0406	0.111	0.7146
agegrp*CONTOUR 5*11	-0.0724	0.0965	0.4529
agegrp*CONTOUR 5*12	0.0131	0.1182	0.9118
agegrp*CONTOUR 5*13	-0.1025	0.1523	0.501
agegrp*CONTOUR 5*14	-0.2581	0.1632	0.1138
agegrp*CONTOUR 5*15	0.0399	0.1367	0.7704
agegrp*CONTOUR 5*16	0.1588	0.1383	0.2508
agegrp*CONTOUR 5*17	-0.0127	0.1336	0.9245
agegrp*CONTOUR 5*18	0.1538	0.1357	0.2569

agegrp*CONTOUR 5*19	0.1114	0.1315	0.3968
agegrp*CONTOUR 5*20	0.0976	0.136	0.4728
agegrp*CONTOUR 5*21	0.1755	0.1344	0.1915
agegrp*CONTOUR 5*22	0.0139	0.1503	0.9261
agegrp*CONTOUR 5*23	-0.1434	0.1955	0.4632
agegrp*CONTOUR 5*24	0.2395	0.1624	0.1404
agegrp*CONTOUR 5*25	0.1725	0.1679	0.3041
agegrp*CONTOUR 6*4	0.2869	0.1145	0.0122
agegrp*CONTOUR 6*5	-0.0871	0.2202	0.6924
agegrp*CONTOUR 6*6	0.0631	0.1021	0.5369
agegrp*CONTOUR 6*7	0.0411	0.1136	0.7178
agegrp*CONTOUR 6*8	-0.0295	0.1089	0.7863
agegrp*CONTOUR 6*9	0.091	0.0771	0.2379
agegrp*CONTOUR 6*10	0.0985	0.1175	0.402
agegrp*CONTOUR 6*11	0.0874	0.0895	0.3283
agegrp*CONTOUR 6*12	0.00382	0.116	0.9737
agegrp*CONTOUR 6*13	-0.0978	0.1465	0.5044
agegrp*CONTOUR 6*14	-0.2843	0.144	0.0484
agegrp*CONTOUR 6*15	-0.1781	0.1398	0.2027
agegrp*CONTOUR 6*16	-0.0368	0.1524	0.8095
agegrp*CONTOUR 6*17	0.0446	0.1399	0.7497
agegrp*CONTOUR 6*18	-0.1722	0.1472	0.2422
agegrp*CONTOUR 6*19	-0.1019	0.1427	0.4753
agegrp*CONTOUR 6*20	-0.2051	0.1596	0.1988
agegrp*CONTOUR 6*21	-0.1357	0.1519	0.3717
agegrp*CONTOUR 6*22	0.326	0.1434	0.023
agegrp*CONTOUR 6*23	-0.0903	0.2001	0.652
agegrp*CONTOUR 6*24	0.0926	0.1975	0.6391
agegrp*CONTOUR 6*25	0.1388	0.1702	0.4148
agegrp*CONTOUR 7*4	0.1538	0.0874	0.0784
agegrp*CONTOUR 7*5	0.3198	0.1418	0.0241
agegrp*CONTOUR 7*6	0.294	0.0779	0.0002
agegrp*CONTOUR 7*7	0.2388	0.0845	0.0047
agegrp*CONTOUR 7*8	0.1976	0.0815	0.0153
agegrp*CONTOUR 7*9	0.2631	0.0576	<.0001
agegrp*CONTOUR 7*10	-0.0205	0.0937	0.8268
agegrp*CONTOUR 7*11	-0.0108	0.0702	0.8779
agegrp*CONTOUR 7*12	-0.177	0.0968	0.0674
agegrp*CONTOUR 7*13	0.163	0.1148	0.1558
agegrp*CONTOUR 7*14	0.2805	0.109	0.0101
agegrp*CONTOUR 7*15	0.2055	0.1051	0.0506
agegrp*CONTOUR 7*16	-0.1616	0.1185	0.1725
agegrp*CONTOUR 7*17	0.0888	0.1123	0.429
agegrp*CONTOUR 7*18	-0.1485	0.1093	0.1743
agegrp*CONTOUR 7*19	-0.1772	0.1074	0.0991
agegrp*CONTOUR 7*20	-0.2163	0.1082	0.0456
agegrp*CONTOUR 7*21	-0.2576	0.1146	0.0246
agegrp*CONTOUR 7*22	-0.1114	0.1176	0.3433
agegrp*CONTOUR 7*23	0.0737	0.1452	0.6119
agegrp*CONTOUR 7*24	-0.3211	0.1596	0.0442
agegrp*CONTOUR 7*25	-0.4839	0.1529	0.0016

Appendix L: Model of Hospitalization for Gastrointestinal Disease Risk in Ontario

Variable	P-value
Age Group	<0.0001
Sex	<0.0001
Admission Category	<0.0001
Daily Case and Control Count (AtRisk)	0.0007
Monthly Lag Case Count	<0.0001
Daily Lag Case Count	<0.0001
Distance to Nearest Water Treatment Facility	0.00039
Latitude	0.06740
Elevation	0.05890
Land Use	<0.0001
Water Treatment Score	<0.0001
Watershed	<0.0001
Month of the Year	<0.0001
42 Day Count of Precipitation Exceeding 0mm	0.14720
42 Day Count of Precipitation Exceeding 50mm	0.40490
42 Day Average Minimum Temperature	0.00300
special degree-days (SDD)	0.14030
42 Day Average Maximum Temperature	0.00490
Age Group * Sex	<0.0001

Admission Category — A classification variable indicating how an individual presented themselves to a medical professional. The options include Elective, Emergency Admission and Urgent Admission.

Monthly Lag Case Count — Total count of all cases in the month prior to the current case or control event.

Distance — A measure (as obtained from ArcGIS) representing the distance from the postal code centroid of a case or control event to the nearest water treatment facility. Water treatment facilities were located based on the centroid of the postal code region in which they fell.

Watershed — A similar classification as that described in Alberta, but specific to the watersheds of Ontario. They are described below.

2A
2B
2C
2D
2E
2F

2G
2H
2J
2K
2L
2M
4J
4K
4L
4M
5P
5Q

Month of Year — A variable used to identify the month of the current case or control event. January is assigned a value of 1, up to December which is assigned a value of 12.

Average Max/Min Temp — The average maximum or minimum temperature for the 42 days prior to case or control event.

Special degree-days — The special degree-days (SDD) represents a total of the maximum temperature for each day (in the 42 days prior to case or control event) where the maximum temperature was smaller than 20 degrees, and the minimum temperature was above 5 degrees Celsius.

Significant Variables

As outlined in the preceding table, 18 main effect variables plus 1 interaction term were included in the final Ontario study model. The tables below outline the parameter estimates, standard errors and p-values associated with each. Note that since some of the variables included in the model represent classification variables, there are more than 19 'variables' listed.

Parameter	Estimate	Standard Error	p-value
Intercept	-1.21530	1.601100	0.4478

Parameter	Estimate	Standard Error	p-value
nPD	-0.00240	0.001650	0.1472
nPD50	0.02500	0.030000	0.4049
avgMin	-0.01560	0.005250	0.003
Max20Min5	-0.00015	0.000105	0.1403
avgMax	0.01590	0.005650	0.0049

Parameter	Estimate	Standard Error	p-value
SEX F	0.25240	0.008440	<.0001
ADMTCATY E	-0.14610	0.007460	<.0001
atRisk	-0.00033	0.000098	0.0007
MCount1	0.00023	0.000033	<.0001
DCount1	0.00407	0.000641	<.0001

Distance	0.19560	0.067800	0.0039
LATITUDE	-0.03370	0.018400	0.0674
Elevation	0.00027	0.000145	0.0589

Parameter		Estimate	Standard Error	p-value
agegrp	1	0.78740	0.014300	<.0001
agegrp	2	0.74920	0.021300	<.0001
agegrp	3	0.37400	0.032200	<.0001
agegrp	4	0.52680	0.024600	<.0001
agegrp	5	0.18220	0.022800	<.0001
agegrp	6	-0.41910	0.024100	<.0001
agegrp	7	-0.98410	0.020100	<.0001

Parameter		Estimate	Standard Error	p-value
treated	0	-0.08600	0.013300	<.0001
treated	1	0.03790	0.012400	0.0021

Parameter		Estimate	Standard Error	p-value
CONTOUR	4	0.18020	1.355900	0.8943
CONTOUR	5	0.23440	1.354800	0.8626
CONTOUR	6	0.30590	1.351800	0.821
CONTOUR	7	0.16190	1.350300	0.9046
CONTOUR	8	0.18300	1.349200	0.8921
CONTOUR	9	0.21440	1.348700	0.8737
CONTOUR	10	0.23120	1.348200	0.8639
CONTOUR	11	0.33980	1.348100	0.801
CONTOUR	12	0.26900	1.348100	0.8419
CONTOUR	13	0.21350	1.348100	0.8742
CONTOUR	14	0.15430	1.348200	0.9089
CONTOUR	15	0.16500	1.348200	0.9026
CONTOUR	16	0.15880	1.348300	0.9062
CONTOUR	17	0.19620	1.348200	0.8843
CONTOUR	18	0.22890	1.348200	0.8652
CONTOUR	19	0.22680	1.348200	0.8664
CONTOUR	20	0.18600	1.348200	0.8903
CONTOUR	21	0.25700	1.348200	0.8488
CONTOUR	22	0.26320	1.348200	0.8452
CONTOUR	23	0.26330	1.348200	0.8452
CONTOUR	24	0.18750	1.348000	0.8894
CONTOUR	25	0.12140	1.348100	0.9282
CONTOUR	26	0.10980	1.348100	0.9351
CONTOUR	27	0.16350	1.348400	0.9035
CONTOUR	28	0.22950	1.349400	0.865
CONTOUR	29	1.13640	1.370000	0.4068

Parameter		Estimate	Standard Error	p-value
WS	2A	0.07290	0.089000	0.4128
WS	2B	-0.08180	0.115900	0.4804
WS	2C	0.05180	0.069000	0.4529
WS	2D	0.35600	0.069700	<.0001
WS	2E	0.02710	0.068900	0.6944

WS	2F	0.08920	0.078300	0.2546
WS	2G	0.01690	0.088800	0.8493
WS	2H	0.07880	0.074000	0.2869
WS	2J	0.03860	0.096800	0.6896
WS	2K	-0.00890	0.062100	0.886
WS	2L	-0.27750	0.063400	<.0001
WS	2M	0.03890	0.069500	0.5759
WS	4J	0.08020	0.129100	0.5344
WS	4K	-0.98330	0.727900	0.1767
WS	4L	0.25400	0.083900	0.0025
WS	4M	0.14790	0.154800	0.3393
WS	5P	0.29380	0.104800	0.0051

Parameter		Estimate	Standard Error	p-value
MOY	1	-0.03470	0.042300	0.4115
MOY	2	-0.13930	0.045700	0.0023
MOY	3	0.02540	0.039800	0.523
MOY	4	0.07990	0.028800	0.0055
MOY	5	0.01730	0.031200	0.5807
MOY	6	0.04770	0.036700	0.1935
MOY	7	0.14000	0.041600	0.0008
MOY	8	0.22300	0.043600	<.0001
MOY	9	-0.18630	0.039400	<.0001
MOY	10	-0.23450	0.033800	<.0001
MOY	11	-0.02820	0.028100	0.3169

Parameter		Estimate	Standard Error	p-value
SEX*agegrp F	1	-0.08340	0.014100	<.0001
SEX*agegrp F	2	-0.11760	0.021200	<.0001
SEX*agegrp F	3	-0.23300	0.032100	<.0001
SEX*agegrp F	4	-0.11940	0.024600	<.0001
SEX*agegrp F	5	0.00134	0.022800	0.9533
SEX*agegrp F	6	0.20930	0.024100	<.0001
SEX*agegrp F	7	0.25170	0.020000	<.0001

Appendix M: Downscaled Climate Data from Global Climate Models

Table 10. 30-year return period of single day maximum precipitation (mm). Current values and projected increase by 2099 listed, as obtained from downscaled data from two Global Climate Models: CGCM2 and HadCM3, using the A2 IPCCscenario. N represents the number of years in the historical record used to calculate the current values.

Location	n (no. of years)	Current maximum precipitation in 1 day, occurring on average once in 30 years(mm)	Future scenario, 2010-2099 (mm)	
			CGCM2	HadCM3
Victoria, BC	40	87	89	84
Cranbrook, BC	39	48	47	45
Lethbridge, AB	40	79	80	77
Northbattleford, SK	63	66	57	57
Deerwood, MB	43	125	100	121
Walkerton, ON	89	96	97	97
Orangeville, ON	40	75	75	77
Montreal, QC	63	81	86	107
Val D'Or, QC	40	114	95	104
Fredericton, NB	40	96	89	86
Yarmouth, NS	40	118	110	112
Charlottetown, PE	62	85	92	93
St. John's, NF	63	100	87	88

Table 11. 30-year return period of 5-Day maximum precipitation (mm). Current values and projected increase by 2099 obtained from downscaled data from two Global Climate Models: CGCM2 and HadCM3, using the A2 IPCC scenario. N represents the number of years in the historical record used to calculate the current values

Location	n (no. of years)	Current maximum precipitation in 5 days, occurring on average once in 30 years (mm)	Future scenario, 2010-2099 (mm)	
			CGCM2	HadCM3
Victoria, BC	40	166	141	132
Cranbrook, BC	39	85	66	66
Lethbridge, AB	40	112	116	100
Northbattleford, SK	63	110	84	107
Deerwood, MB	43	130	130	149
Walkerton, ON	89	135	117	130
Orangeville, ON	40	109	117	130
Montreal, QC	63	105	134	140
Val D'Or, QC	40	155	125	125
Fredericton, NB	40	142	131	136
Yarmouth, NS	40	137	137	164
Charlottetown, PE	62	122	133	132
St. John's, NF	63	152	137	149

Table 12. 30-year return period of maximum monthly precipitation (mm). Current value and projected increase by 2099 obtained from downscaled data from two Global Climate Models: CGCM2 and HadCM3, using the A2 scenario. N represents the number of years in the historical record used to calculate the current values.

Location	n (no. of years)	Current maximum precipitation in 1 month occurring on average once in 30 years (mm)	Future scenario, 2010-2099 (mm)	
			CGCM2	HadCM3
Victoria, BC	40	286	300	302
Cranbrook, BC	39	154	108	125
Lethbridge, AB	40	164	159	189
Northbattleford, SK	63	156	138	170
Deerwood, MB	43	270	264	271
Walkerton, ON	89	223	238	263
Orangeville, ON	40	219	227	244
Montreal, QC	63	210	238	240
Val D'Or, QC	40	235	223	214
Fredericton, NB	40	230	282	256
Yarmouth, NS	40	310	275	288
Charlottetown, PE	62	248	284	278
St. John's, NF	63	322	316	331

Table 13. 30-year return period of warmest maximum daily temperature (°C). Current values and projected increase by 2099 obtained from downscaled data from two Global Climate Models: CGCM2 and HadCM3, using the A2 scenario. N represents the number of years in the historical record used to calculate the current values.

Location	n (no. of years)	Current maximum daily temperature occurring on average once in 30 years °C)	Future scenario, 2010-2099 (°C)	
			CGCM2	HadCM3
Victoria, BC	40	34	34	37
Cranbrook, BC	39	37	42	47
Lethbridge, AB	40	39	44	46
Northbattleford, SK	63	38	45	44
Deerwood, MB	43	39	48	46
Walkerton, ON	89	37	42	41
Orangeville, ON	40	35	41	42
Montreal, QC	63	36	40	42
Val D'Or, QC	40	36	41	42
Fredericton, NB	40	37	40	41
Yarmouth, NS	40	30	30	35
Charlottetown, PE	62	34	37	37
St. John's, NF	63	31	37	37

Table 14. 30-year return period for warmest average minimum daily temperature (°C). Current values and projected increase by 2099 obtained from downscaled data from two Global Climate Models: CGCM2 and HadCM3, using the A2 scenario. N represents the number of years in the historical record used to calculate the current values.

Location	Obs. record (no. of years)	Currentminimum daily temperature occurring on average once in 30 years (°C)	Future scenario, 2010-2099 (°C)	
			CGCM2	HadCM3
Victoria, BC	40	16	19	21
Cranbrook, BC	39	21	23	27
Lethbridge, AB	40	23	27	27
Northbattleford, SK	63	21	25	26
Deerwood, MB	43	24	31	31
Walkerton, ON	89	24	30	30
Orangeville, ON	40	24	30	32
Montreal, QC	63	25	29	32
Val D'Or, QC	40	21	27	28
Fredericton, NB	40	23	26	29
Yarmouth, NS	40	20	21	25
Charlottetown, PE	62	21	27	26
St. John's, NF	63	20	23	25

Table 15. Number of days with precipitation > 50 mm (30-year Normals) based on IPCC Scenario A2 downscaled data from GCMs

Location	**Present-day climate***	**2020's**		**2050's**		**2080's**	
		CGCM2	HadCM3	CGCM2	HadCM3	CGCM2	HadCM3
Victoria, BC	11	23	11	17	13	19	18
Cranbrook, BC	1	0	0	0	0	0	0
Lethbridge, AB	8	12	13	7	7	11	10
Northbattleford, SK	1	0	5	1	2	3	1
Deerwood, MB	14	12	25	8	16	19	18
Walkerton, ON	15	17	10	9	11	23	16
Orangeville, ON	14	17	15	13	18	17	13
Montreal, QC	10	23	18	16	28	19	17
Val D'Or, QC	5	11	9	12	6	16	18
Fredericton, NB	26	31	34	40	45	39	31
Yarmouth, NS	49	57	51	45	46	46	64
Charlottetown, PE	25	33	20	36	29	28	30
St. John's, NF	43	41	63	45	54	49	44

* Based on 1961-1990 Climate Normals

Appendix N: Climate Change Scenarios for Alberta

Table 16. Summary of the Climate Change Scenarios for 2010-2039, and projected values for variables used in the gastrointestinal hospitalizations model for southern Alberta: number days with rainfall(nRD); number days with precipitation (rain or snow) in excess of 50 mm (nPD50); number of days with minimum temperature greater than 5 °C and maximum temperature no greater than 15.

Year	Model	Season	nRD days	nPD50 days	Max15Min5 ºC	Comments
2020	CGCM2	Spring	16	2	25	Wetter, More Extreme Precipitation, Increase Moderate Temperatures (Max<15ºC)
2020	HadCM3	Spring	0	0	0	No Change
2020	CGCM2	Summer	-8	-1	-100	Drier, Less Extreme Precipitation, Increase in Higher Temperatures (Max>15ºC)
2020	HadCM3	Summer	0	0	0	No Change
2020	CGCM2	Autumn	8	1	50	Wetter, More Extreme Precipitation, Increase Moderate Temperatures (Max<15ºC)
2020	HadCM3	Autumn	0	0	10	Increase Moderate Temperatures (Max<15ºC)
2020	CGCM2	Winter	16	2	0	Wetter, More Extreme Precipitation,
2020	HadCM3	Winter	0	0	0	No Change

Table 17. Summary of the Climate Change Scenarios for 2040-2069, and projected values for variables used in the gastrointestinal hospitalizations model for southern Alberta: number days with rainfall(nRD); number days with precipitation (rain or snow) in excess of 50 mm (nPD50); number of days with minimum temperature greater than 5 °C and maximum temperature no greater than 15.

Year	Model	Season	nRD days	nPD50 days	Max15Min5 ºC	Comments
2050	CGCM2	Spring	10	2	50	Wetter, More Extreme Precipitation, Increase Moderate Temperatures (Max<15ºC)
2050	HadCM3	Spring	10	1	15	Wetter, More Extreme Precipitation, Increase Moderate Temperatures (Max<15ºC)
2050	CGCM2	Summer	0	0	-140	Increase in Higher Temperatures (Max>15ºC)
2050	HadCM3	Summer	-40	-1	-180	Drier, Less Extreme Precipitation, Increase in Higher Temperatures (Max>15ºC)
2050	CGCM2	Autumn	10	2	250	Wetter, More Extreme Precipitation, Increase Moderate Temperatures (Max<15ºC)
2050	HadCM3	Autumn	0	0	15	Increase Moderate Temperatures (Max<15ºC)
2050	CGCM2	Winter	5	1	0	Wetter, More Extreme Precipitation,
2050	HadCM3	Winter	10	1	0	Wetter, More Extreme Precipitation,

Table 18. Summary of the Climate Change Scenarios for 2070-2099, and projected values for variables used in the gastrointestinal hospitalizations model for southern Alberta: number days with rainfall(nRD); number days with precipitation (rain or snow) in excess of 50 mm (nPD50); number of days with minimum temperature greater than 5 °C and maximum temperature no greater than 15.

Year	Model	Season	nRD days	nPD50 days	Max15Min5 ºC	Comments
2080	CGCM2	Spring	21	4	80	Wetter, More Extreme Precipitation, Increase Moderate Temperatures (Max<15ºC)
2080	HadCM3	Spring	10	2	40	Wetter, More Extreme Precipitation, Increase Moderate Temperatures (Max<15ºC)
2080	CGCM2	Summer	-6	-1	-200	Drier, Less Extreme Precipitation, Increase in Higher Temperatures (Max>15ºC)
2080	HadCM3	Summer	-55	-1	-400	Drier, Less Extreme Precipitation, Increase in Higher Temperatures (Max>15ºC)
2080	CGCM2	Autumn	21	4	400	Wetter, More Extreme Precipitation, Increase Moderate Temperatures (Max<15ºC)
2080	HadCM3	Autumn	5	2	-150	Wetter, More Extreme Precipitation, Increase in Higher Temperatures (Max>15ºC)

Table 19. Logistic model (spatial variables only) of hospitalization risk for gastrointestinal disease in Lethbridge, Alberta, using Spatial Analyst in ArcGIS. In the case (such as with Land Use) that more than one classification is applicable to Lethbridge and area, the class levels causing the smallest and largest (significant) change to the overall log-odds were used.

Variable	Value/Class	Estimate	Log-odds
Land Use class	8	0.2199	0.2199
Land Use class	11	0.0872	0.0872
Consolidated Census Subdivision	4802011	-0.5917	-0.5917
Elevation (m)	900	-0.3625	-326.2500
Latitude (degrees converted to decimal)	49.70	-7.1492	-355.3152
Longitude (degrees converted to decimal)	-112.83	-0.8847	99.82070
Watershed	14	-0.0104	-0.0104
Elevation * Latitude (900*49.70)	44730	0.0073	324.2925
Total Spatial Effect + Intercept (257.4000)			-0.3470

Table 20. Observed seasonal meteorological information for southern Alberta 1992-1997

Variable	Spring	Summer	Autumn	Winter
Number rain days (nRD)	5.77	11.25	12.52	0.37
Number days with precipitation >50mm (nPD50)	0	0	0	0
Average Maximum Temperature (°C)	7.45	22.17	22.34	0.27
Average Minimum Temperature (°C)	-5.77	7.49	5.96	-11.59
Number days with temperature between a minimum of 5°C and a maximum of 15 °C (Max15Min5)	6.65	52.70	44.95	6.75

Table 21. Projected average seasonal maximum temperature (Tmax), minimum temperature (Tmin) and precipitation using downscaled data from the Canadian Climate Model for Lethbridge.

	Winter	**Spring**	**Summer**	**Autumn**
Tmax (1961-1990) (°C)	-0.8	11.8	24.6	12.8
Tmax (2010-2039) (°C)	2.2	14.4	25.6	14.2
Tmax (2040-2069) (°C)	3.2	16.8	26.7	14.7
Tmax (2070-2099) (°C)	6.2	19.5	28.2	16.6
Tmin (1961-1990) (°C)	-12.5	-1.2	10.0	-0.4
Tmin (2010-2039) (°C)	-10.2	1.0	10.9	0.5
Tmin (2040-2069) (°C)	-9.1	3.3	11.9	1.1
Tmin (2070-2099) (°C)	-6.3	6.3	13.5	2.8
Precip (1961-1990) (mm)	54.86	114.69	155.58	77.36
Precip (2010-2039) (mm)	49.16	127.03	172.95	78.48
Precip (2040-2069) (mm)	55.74	124.45	145.05	82.32
Precip (2070-2099) (mm)	55.20	143.17	149.55	95.83