Investigation of the association between meteorological variables and the rate of reported Salmonellosis and Campylobacteriosis in Oregon: 2000-2010

By

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A Thesis

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Abstract

Background: The climate of Oregon is highly variable and ranges from a temperature rainforest to the high desert. The average annual temperature in the Pacific Northwest has increased 1.5ºF since 2003. There has been a 14% increase in precipitation during this time as well. As the climate of Oregon changes, meteorological variability may have a significant impact on the incidence of foodborne disease and can affect food safety for the population through pathways of temperature and precipitation, extreme weather events, ocean warming and acidification, and changes in transport pathways.

Methods: Temperature, precipitation, and ENSO data were obtained from the National Oceanic Atmospheric Administration. *Campylobacter* and *Salmonella* case data were obtained from a database managed by the Oregon State Public Health Division. Multiple exclusion criteria were applied to ensure that the cases included in this study were sporadic cases without travel outside of Oregon during their exposure period. Poisson regression with the log population as the offset was used to determine if there were associations between monthly meteorological variables (mean monthly maximum and minimum temperature, highest recorded monthly maximum and minimum temperature, lowest recorded monthly maximum and minimum temperature, precipitation and snow depth) and reported *Salmonella* and *Campylobacter* infections. Case data and meteorological data were merged on the regional and county level so generalized estimating equations were used to control for geographic correlation.

Results: We found that increased temperature was associated with higher rates of both reported *Campylobacter* and *Salmonella* infections in Oregon. The mean monthly minimum temperature was associated with the highest increase in the rate of reported *Campylobacter* (rate ratio: 2.9%, 95% CI: 2.5%, 3.4%) and *Salmonella* (rate ratio: 3.0%, 95%CI: 2.1%, 3.4%) infections. We also found that precipitation was inversely associated with the rate of reported *Campylobacter* and *Salmonella* in Oregon. However, these associations between temperature and precipitation did not remain after adjusting for seasonal trends. An opposing effect was seen between El Niño and La Niña events. El Niño events were associated with higher rates of reported *Campylobacter* and *Salmonella* infections, while La Niña events were associated with lower rates of reported

Campylobacter and *Salmonella* infections. We found that the opposing effect of El Niño and La Niña persisted even after adjusting for seasonal trends.

Conclusion: As reported in analysis of data for other regions, temperature and precipitation in Oregon were associated with incidence of enteric infections from *Campylobacter* and *Salmonella.* The associations of these meteorological factors were strongly correlated to season. On a longer temporal cycle, El Niño and La Niña events demonstrated opposing effects on the rates of reported *Campylobacter* and *Salmonella* illness in Oregon. El Niño events were associated with higher rates of reported illness and La Niña events were associated with lower rates of reported illness. These findings suggest that the incidence of enteric illness attributable to *Campylobacter* and *Salmonella* in Oregon are influenced by temperature and precipitation. Because these meteorological factors are expected to change with climate trends, public health planning should incorporate food safety interventions into climate change adaptation efforts.

Definitions

ENSO: El Niño/Southern Oscillation, which includes both El Niño and La Niño events

ONI: Oceanic Nino Index is the de-facto standard used by the National Oceanic Atmospheric Administration to identify El Niño and La Niño events. It is the running 3-month mean sea surface temperature anomaly for the Niño 3.4 region.

El Niño event: Oceanic Nino Index readings that are 5 consecutive overlapping 3-month periods at or above the $+0.5^{o}$ anomaly. Also known as a warm episode.

La Niña event: Oceanic Nino Index readings that are 5 consecutive overlapping 3-month periods at or above the -0.5^{o} anomaly. Also known as a cold episode.

Weak ENSO event: 0.5 to 0.9 sea surface temperature anomaly

Moderate ENSO event: 1.0 to 1.4 sea surface temperature anomaly

Strong ENSO event: Above 1.5 sea surface temperature anomaly

ORPHEUS: Oregon Public Health Epidemiologist User System is a database of all reportable diseases in Oregon. This database is managed by the Oregon State Public Health Division

OSPHL: Oregon State Public Health Laboratory is the state's laboratory. All positive *Salmonella* and *Campylobacter* samples from independent labs are sent to the OSPHL for a confirmatory culture.

Confirmed case: *Campylobacter* or *Salmonella* case that has had a confirmatory culture performed at the Oregon State Public Health Laboratory

Specimen collection date: Date the case first gave a specimen sample. This date is captured in ORPHEUS and is reported by the initial testing lab.

Region: One of the four climate regions of Oregon. The four regions include Coastal, Eastern, Southwestern Valley, and Willamette Valley/Cascades

Mean monthly maximum temperature: Monthly average of the daily maximum temperature (^{o}F)

Mean monthly minimum temperature: Monthly average of the daily minimum temperature (^{o}F)

Highest recorded monthly maximum temperature: Absolute highest daily maximum temperature in one month (^{o}F)

Highest recorded monthly minimum temperature: Absolute highest daily minimum temperature in one month (^{o}F)

Lowest recorded monthly maximum temperature: Absolute lowest daily maximum temperature in one month (^{o}F)

Lowest recorded monthly minimum temperature: Absolute highest daily minimum temperature in one month (^{o}F)

Mean precipitation: The monthly average of daily rainfall (mm)

Mean snow depth: The monthly average of daily snowfall (mm)

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CHAPTER 1 – INTRODUCTION

Preface

Climate change affects public health through a multitude of pathways, from droughts and monsoons to increased incidence of infectious diseases like malaria. As the concentration of greenhouse gases continue to increase in the Earth's atmosphere, we will see devastating changes to Earth's climate. Prediction models postulate that the mean global surface temperatures will continue to increase, extreme temperature events will increase, and glaciers and ice caps will continue to melt (CIG, 2013). All of these climate changes will adversely affect the health of humans. The climate zones in Oregon are diverse and range from temperate rainforest to the high desert. Oregon has already seen the effects of climate change as the average annual temperature has risen 1.5^{o}F between 1920 and 2003 (Mote, 2003). Predictions for Oregon show that temperature and precipitation will continue to change over the next 100 years (OCCRI, 2014).

Salmonellosis and Campylobacteriosis are two foodborne illnesses that are prevalent in all areas of the world. Both are common bacterial illnesses in the United States and the specific exposures causing most cases remain unsolved. In Oregon, there are 400-500 reported cases of *Salmonella* infection per year and even more reported cases of *Campylobacter* infection. The relationship between *Salmonella* and *Campylobacter* and human infections is complex. There are multiple factors, from the environment, biological properties, and even human behavior that can play a role in the incidence of disease. Biological properties of the bacteria itself can also vary the incidence of disease. Lastly, human behaviors, such as seasonality of foods, preparation and storage of foods, community events, and exposure (e.g., swimming) are thought to contribute to variation in the incidence of disease. Thus, the occurrence of disease is not solely based on temperature, but a myriad of other complex pathways. The number and types of outbreaks vary strongly by season, and it is hypothesized that temperature and precipitation are major environmental determinants.

Kovats et al. (2004) found that there was a 5-10% increase in *Salmonella* infections per one degree ^{o}C increase in average weekly temperatures in the European Union. Tam et al. (2006) found a linear relationship between mean ambient temperature in the previous 6-week period and reported *Campylobacter* infections. The researchers also found that there is a 5% increase of the number of reports of *Campylobacter* infections associated with each 1°C increase in temperature. The relationship between meteorological events and the incidence of *Salmonella* and *Campylobacter* in Oregon is not yet elucidated. Additionally, no studies have documented associations between macro scale climate conditions, specifically El Niño and La Niña events, and the incidence of foodborne disease. This study aims to evaluate the putative association between various meteorological variables as well as El Niño/La Niña events and the incidence of reported *Salmonella* and *Campylobacter* infections in Oregon between 2000 and 2010. The knowledge gained from this study can be used when developing public health plans and climate change adaptation policies. Public health officials can also use these data to prevent disease in Oregon by warning citizens of potential increases in foodborne illnesses related to weather events, and prevent disease.

Background

Climate Change

The Earth's climate is a controlled by the balance of the output of energy from the Earth's surface, and the energy from the sun. There has been an increase in the Earth's energy output via burning of fossil fuels, which increases gases in the Earth's atmosphere. These gases are commonly referred to as greenhouse gases and include carbon dioxide, methane and nitrous oxide. The atmospheric concentrations of greenhouse gases are far greater now than at anytime during the last 650,000 years (CIG, 2013). There have been indications that Earth's climate, ecological systems, and physical systems are changing on a global scale due to increased greenhouse gases (IPCC, 2007). Overall, the mean global surface temperature has increased by 1.3°F since 1906 (CIG, 2013). In addition to increased mean global surface temperatures, extreme temperature events have also increased. Hot days and hot nights have become more frequent, while cold days and cold nights have become less frequent since 1950 (CIG, 2013). It is also thought that there has been an increase in the number and duration of heat waves since the 1950s (CIG, 2013). Global warming has also caused a decrease in snow-covered areas and a decrease in snow pack in most regions (CIG, 2013). Glaciers and ice caps have had widespread mass loss and the sea ice has decreased in the Arctic (CIG, 2013).

Climate change in the Pacific Northwest

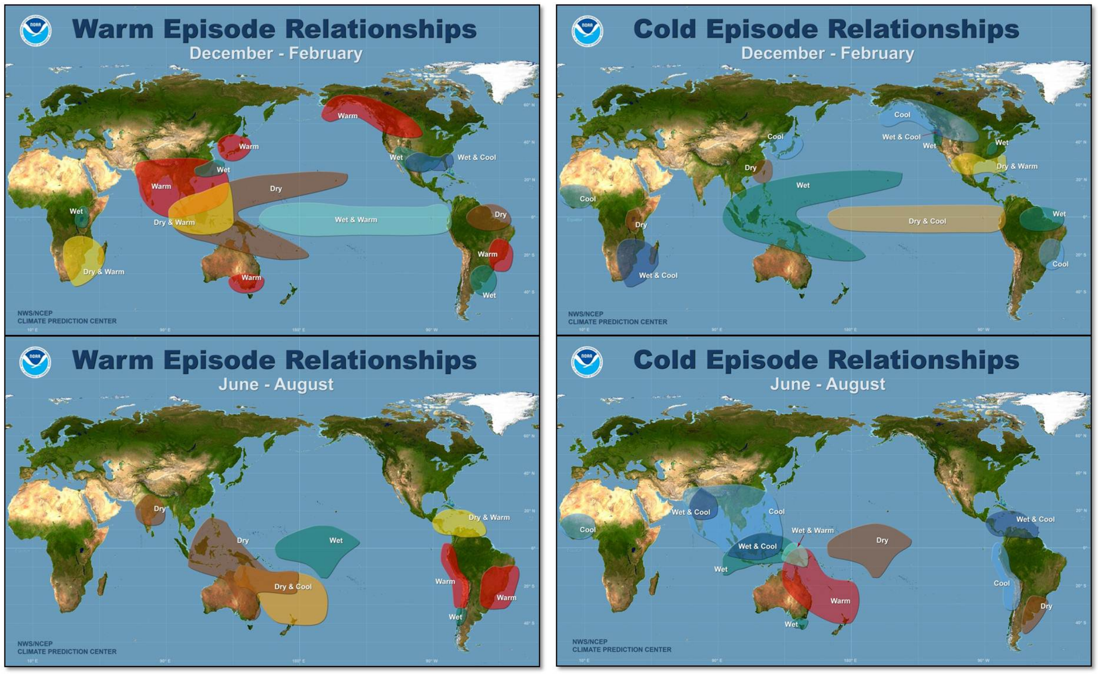
The climate of the Pacific Northwest (PNW) is highly variable. In Oregon, the climate zones range from the high desert to a temperate rainforest. Two major geographic features, the Pacific Ocean and the Cascade Range, dominate the climate in Oregon. The Cascade Range divides the Eastern and the Western portions of the state. The climate of Eastern Oregon is drier than Western Oregon due to the rain shadow cast by the Cascade Range. The climate of Western Oregon is generally dry in the summer and wet and mild in the winter. Climate in the areas along the coastline is heavily mediated by the Pacific Ocean and can receive up to 200 inches of rain in a year.

In the PNW, the average annual temperature has increased 1.5°F between 1920 and 2003 with the warmest decade in the 1990s (Mote, 2003). The minimum daily temperature rose faster than the maximum daily temperature through the middle of the 20th century, with minimum and maximum temperatures rising about the same rate in the latter half of the century (Mote, 2003). In recent decades, substantial changes in precipitation patterns in the PNW have also been observed. Annual precipitation increased 14% between 1930 and 1995 and sub-regional trends of precipitation showed an increase ranging from 13% to 38% (Mote, 2003). Hamlet and Lettenmaier (2007) found that precipitation during the cool season is more variable from year to year. An increase of temperature and a decrease in precipitation over the same period of record is correlated with a decline of snow water equivalent at nearly all sites in the PNW between 1950 and 2000 (Mote et al, 2003, Hamlet et al, 2005). Snow water equivalent levels at individual stations in the Washington and Oregon Cascades are decreased at 40% or more (Mote et al, 2003). It is clear that the climate of the PNW has been changing.

El Niño/Southern Oscillation

Climate in the Pacific Northwest is influenced by oscillations in the surface temperature of the Pacific Ocean. One of these oscillations is known as the El Niño/Southern Oscillation (ENSO) and causes year-to-year variations in sea surface temperatures, convective rainfall, surface air pressure and atmospheric circulation across the equatorial Pacific Ocean (NOAA, 2012). ENSO is comprised of two opposing climate phenomenon called El Niño and La Niña, as well as a neutral phase. El Niño (the Christ Child) refers to a periodic warming in the equatorial Pacific Ocean between the International Date Line and 120 ^{o}W longitude that leads to above average sea surface temperatures (NOAA, 2012). This warming of ocean surface waters disrupts normal patterns of tropical precipitation and atmospheric circulation. The warm waters increase the cloudiness and rainfall in that region (NOAA, 2012b). The increased heating of the tropical atmosphere during El Niño events also affects jet streams in the subtropics. El Niño diverts the jet stream into California, which directly affects the climate in Oregon. La Niña (the Little Girl) refers to periodic cooling of the equatorial Pacific Ocean, and is thought to have the opposite effect of El Niño. La Niña directs the jet stream directly across the PNW from the north Pacific. The neutral phase of ENSO refers to the transition between El Niño and La Niña events. During the neutral phase, ocean surface temperatures, tropical rainfall patterns, and atmospheric winds over the equatorial Pacific Ocean are near the long term average (NOAA, 2012). El Niño and La Niña episodes typically occur every 3-5 years. El Niño events typically last 9-12 months and La Niña events typically last 1-3 years. Both develop between March-June with peak intensity during December-April due to equatorial Pacific sea surface temperature being the warmest during this time (NOAA, 2012).

Research conducted by the Climate Impacts Group (CIG) found that ENSO is one of the two oscillations that strongly shape the climate of the PNW. The CIG examined monthly averaged temperature and precipitation values for El Niño versus La Niña years between 1931 and 1999 in the PNW. The CIG found that El Niño winters tend to be warmer and drier than average and La Niña winters tend to be cooler and wetter than average (Fig. 1). Specifically, the temperature between December through June is 0.7 to 2.7 ^{o}F higher during El Niño events compared to La Niña events. They also found that the precipitation is, on average, 14% less between October and March during El Niño events when compared to La Niña events. The climate variability due to ENSO can cause flooding and droughts, reduce forest productivity, increase forest fire risk, and affect salmon abundances and the quality of coastal and near shore habitat (CSES, 2014).



High Resolution Images can be found at:
http://www.cpc.ncep.noaa.gov/products/precip/CWlink/ENSO/ENSO-Global-Impacts/

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Figure 1. (Left) The changes in global climate caused by El Niño. (Right) The change in global climate caused by La Niña

Infectious Disease and Climate Change

Climate change and climate variability are frequently framed as only an environmental issue. However, climate change and climate variability may affect human health directly from extreme heat-related illnesses to catastrophic weather events (Tirado et al, 2010). Microbial pathogens are also affected by climate change, which in turn can and will affect humans. More frequent and intense heavy rainfall and floods will cause higher pathogen concentrations in water (Funari et al, 2012). This causes a worse quality of drinking and bathing water, as well as crops and shellfish. Heavy rainfall can also cause flooding of sewage plants, runoff of animal waste, and remobilization and redistribution of contaminated sediments (Funari et al, 2012). All of these events can lead to increased infections in humans. Curriero et al (2001) found a significant association between excess rainfall and waterborne disease outbreaks on a national scale in United States. The researchers found that 51% of waterborne disease outbreaks were preceded by rainfall events above the 90th percentile of historic trends.

Climate change and variability are hypothesized to affect food safety through various pathways such as: changes in temperature and precipitation patterns, extreme weather events, ocean warming and acidification, and changes in transport pathways. Increased temperature and changes in precipitation patterns have an effect on the patterns of occurrence and persistence of foodborne bacteria, parasites, and fungi (Tirado et al, 2010). These changes also have an impact on microbial ecology and growth, plant and animal physiology, and host susceptibility all of which could result in the emergence, redistribution, and changes in incidence of foodborne diseases (Tirado et al, 2010). All foodborne pathogens and their associated diseases are potentially affected by climate change.

Since ENSO is known to affect the climate of the PNW, and the climate can affect the incidence of foodborne illness, it could be that ENSO is also associated with the incidence of foodborne illnesses. Previous research has shown that ENSO is associated with vector borne diseases such as Dengue fever and malaria, as well as waterborne diseases, such as cholera (Hall et al, 2002). Previous research has shown that El Niño events were associated with a 2-fold increase in the number of daily admissions due to diarrheal disease in Peruvian children (Checkley et al, 2000). The study also found that admissions for diarrhea increased by 8% per 1 ^{o}C increase in mean ambient temperature caused by the El Niño event. However, no prior studies have been conducted to determine if there are any associations between El Niño events and *Salmonella* and *Campylobacter* infections. Since El Niño events have been linked to increased incidence of water and vector borne disease, one could hypothesize that El Niño events could also be associated with increased foodborne illnesses.

I.Salmonella

Salmonellosis is one of the most common foodborne illnesses in the United States. An estimated 1.2 million cases occur annually in the United States (CDC, 2013). Additionally, there is an estimated 400 fatal cases each year. A wide range of domestic and wild animals is a carrier of *Salmonella.* The most common source of human infection is thought to come through fecal-contaminated food or water. Raw or undercooked produce and products (e.g.., milk) have also been implicated as sources. In Oregon, there are between 400 and 500 cases of reported *Salmonella* infections per year and this figure underestimates the true incidence of disease (OR Communicable Disease Report, 2012).

The effect of temperature on the growth of *Salmonella* on food is well understood, however, the effect of ambient air temperature on the transmission of sporadic *Salmonella* infections is yet to be fully elucidated. Several studies have shown that temperature is associated with *Salmonella* infections. Kovats et al (2004) found that there was a 2.5-18.3% increase in *Salmonella* infections per one degree increase in average weekly temperatures above a temperature threshold. The researchers found that the greatest effect of temperature is one week before the onset of illness but there were effects up to five weeks prior. D'Souza et al (2004) also reported a positive association between monthly *Salmonella* infection notifications and mean monthly temperature of the previous month. Zhang et al (2010) found that *Salmonella* infections may double by 2050 in South Australia due to climate change factors alone.

Although the effect of ambient temperature on *Salmonella* has been researched, investigations of the potential relationship of temperature and precipitation associated with ENSO events and *Salmonella* incidence have not been conducted. The combined effect of above average precipitation and above average temperature associated with ENSO events may be synergistic and cause a higher incidence of disease.

II. Campylobacter

Campylobacter is one of the most common causes of diarrheal illness in the United States (CDC, 2013). *Campylobacter* is estimated to affect over 1.3 million people in the US every year. In Oregon, the incidence of *Campylobacter* infections has been increasing since 2000, from 400 cases per year to about 1000 cases per year in 2013. Most of the human illnesses are caused by the species *C. jejuni,* but other species of *Campylobacter* have also been known to cause illness. *Campylobacter* grows best at 37 °C to 42 °C (CDC, 2013). This is the body temperature of birds, and birds can carry *Campylobacter* without becoming ill.

Campylobacter illness usually occurs in sporadic cases. Most cases are associated with eating raw or undercooked poultry or by cross contamination with these products. Outbreaks of *Campylobacter* have been attributed to unpasteurized dairy products, contaminated water, poultry or produce (CDC, 2013). Very few *Campylobacter* organisms (fewer than 500) are needed to make someone sick (CDC, 2013). In Oregon, the rate of *Campylobacter* infection is 23.4 cases per 100,000, which is 2.8 times the 2020 Healthy People national objective.

There is a known effect of seasonality on *Campylobacter* infections. An international study, involving Europe, Australia, Canada, and New Zealand showed that most countries have a peak in *Campylobacter* in April or May (Kovats et al, 2005). Some countries, like Denmark, Switzerland and the Netherlands, had late summer peaks (Kovats et al, 2005). Although a seasonality effect has been demonstrated, short-term temperature fluctuations have not been found to be strongly associated with *Campylobacter* illnesses. Tam et al (2006) found a linear relationship between mean ambient temperature in the previous 6-week period and reported *Campylobacter* infections. The researchers also demonstrated a 5% increase of the number of reports of *Campylobacter* infection associated with a 1°C increase in mean 6-week temperature. While a few published studies have examined the association of the temperature on the incidence of *Campylobacter* illness, no research has been conducted to evaluate the potential effect of precipitation on incidence of illness from this foodborne pathogen.

CHAPTER 2 – METHODS

This study utilizes data aggregated by the Environmental Public Health Tracking Division (EPHT) of the Oregon Public Health Division, and data from Oregon Public Health Epidemiologist User System (ORPHEUS), an Oregon Public Health Division database that tracks individual cases. The primary goal of this research project was to test the association between meteorological factors (precipitation, temperature, and ENSO events) and the incidence of reported cases of *Salmonella* and *Campylobacter* infections in Oregon between 2000 and 2010.

Surveillance data of cases

A search was performed in the ORPHEUS database for all reported *Salmonella* and *Campylobacter* illnesses from 2000 to 2010. Only cases that had a positive stool culture by the Oregon State Public Health Laboratory (OSPHL) were considered confirmed cases and were entered into the analysis database. Cultures that only had a positive result at a private lab were considered "Presumptive" cases and excluded from our study. Household members that also became ill were also excluded from the study. Each case in ORPHEUS is dated according to "earliest specimen date" and documents the date when the stool specimen was received and processed at the first lab. Only those cases that have OSPHL positive stool samples were used in this study because isolates that are cultured from urine, blood, or other specimens do not have specific onset dates and the period of food exposure is unknown. Restriction to cases with positive stool samples provides more accurate determination of the time of infection and exposure, because the stool specimen was likely obtained when the case was experiencing diarrhea. To ensure that all cases are independent from each other, only the first reported case that is part of a cluster was included in the analysis database. We also excluded cases that contracted the infections from a known source (e.g., reptile associated *Salmonella* serotype with reptile contact) and cases that reported foreign travel or travel outside of Oregon during their exposure period, which is seven days prior to onset date. *Salmonella* cases are routinely interviewed by the Local Health Departments (LHD) to obtain self-reported information about onset date, clinical symptoms, exposure to high-risk foods and foreign travel. No cases were excluded because of missing interviews by local or the state health departments. However, interview data may not be complete prior to 2005, and LHDs do not routinely interview *Campylobacter* cases.

Table 1. Inclusion and exclusion criteria

Inclusion criteria	Exclusion Criteria
Confirmed stool culture at the Oregon Public Health Lab	non-stool sample culture
	secondary cases or household case (person-to-person transmission_
	part of a cluster
	known source (i.e., food tested positive, reptile associated salmonellas with reptile contact)
	typhodial *Salmonellas* (*S. Typhi*)
	travel outside of Oregon during exposure period
	no reported postal code

Meteorological data

Meteorological data were provided by the Environmental Public Health Tracking (EPHT) Division of the Oregon Public Health Division. EPHT aggregated meteorological data by zip codes and zip code source boundary for Oregon was selected from ESRI's 2000 data disk for the base geography and assigned demographic information from the 2000 US census. Zip codes from ESRI's 2010 data were used to identify new or obsolete zip codes. Zip code centroids were located based on the population weighted mean center, and population concentrations were derived from the 2000 Census Block centroids. Mean elevations for the zip codes were added to these data as well.

Weather stations managed by the National Oceanic Atmospheric Administration (NOAA) were used for meteorological data. Weather station locations were coded to the longitude and latitude coordinates provided by NOAA. Maximum and minimum temperature readings from the weather stations were used to estimate temperatures near the weighted zip code centroids. Geographic Information Systems (GIS) data were used to determine the two nearest weather stations within 25 miles of the weighted centroid of each zip code. If there was only one reported temperature reading for either the nearest or second nearest weather station, the single recording was used. If the nearest weather station was located within 2 miles of the zip code centroid, then the nearest weather station reading was used. If the two nearest weather stations were within a 15-degree area of the zip code centroid, then the meteorological data from the nearest weather station was used. When both weather stations were available, an average of the temperatures was used. Precipitation data were not included in the dataset provided by EPHT. Precipitation data [*precipitation* (mm) and *snow depth* (mm)] were obtained from the National Oceanic atmospheric Administration and merged by the weather station ID with the existing temperature dataset.

Population data

The EPHT data also included population data between 2000 and 2010. Census block data was used to identify population changes within each zip code between 2000 and 2010. Population data from Census block was used for the 2000 and 2010 population data. Population data for the years between 2000 and 2010 were estimated by assuming a linear change in population between 2000 and 2010.

El Niño/Southern Oscillation data

ENSO data were retrieved from the National Oceanic Atmospheric Administration. ENSO forecasts are derived from prediction models that use data collected from more than 400 deep ocean monitoring buoys. These buoys provide information on the temperature, currents, and winds (NOAA, 2012). ENSO is characterized by a five consecutive 3-month running mean of sea surface temperature anomalies in the Nino 3.4 region that is either above or below the threshold of +0.5 °C (-0.5 °C). Since there has been a significant warming trend in the Nino 3.4 region, the threshold is based on centered 30-year base periods that are updated every five years to remove the warming trend. This standard of measure is called the Oceanic Nino Index (ONI). Since ONI is based upon a three month moving average, each month has three separate readings. These three readings were averaged to produce one mean ONI for each month. El Niño and La Niña events were indicated by 0=neutral, 1=El Niño, and 2=La Niña. NOAA categorized each El Niño and La Niña even at weak, moderate, or strong. In our analysis, the *ENSO* categorical variable was created by using a combination of the pattern and strength (Table 2).

Table 2. Categorical coding of the ENSO variable to take into account both pattern and strength

ENSO code	**Pattern-Strength**
0	Neutral-Neutral
1	El Niño-Weak
2	El Niño-Moderate
3	El Niño-Strong
4	La Niña-Weak
5	La Niña-Moderate
6	La Niña-Strong

Statistical Analysis

Regional analysis

There are four distinct climate regions of Oregon: Eastern Oregon, Coastal, Willamette Valley and Southwestern Oregon (Fig.2). A dataset provided by the EPHT matched each Oregon postal code to one of the four regions and county. This dataset was used to match case to region and county. Cases were matched to each region and county by reported zip code. Meteorological data were also matched to region and county by zip code.

The primary analysis used region as the level of aggregation, and in secondary analysis, the ten counties with the highest number of reported cases were used. Counties (especially those in in Eastern Oregon) consistently have only one or two cases of reported *Salmonella* and *Campylobacter* infections per year. We relied upon the regional level as the primary analysis because it included all (non-excluded) reported cases and completely covers all four climate regions of the state.

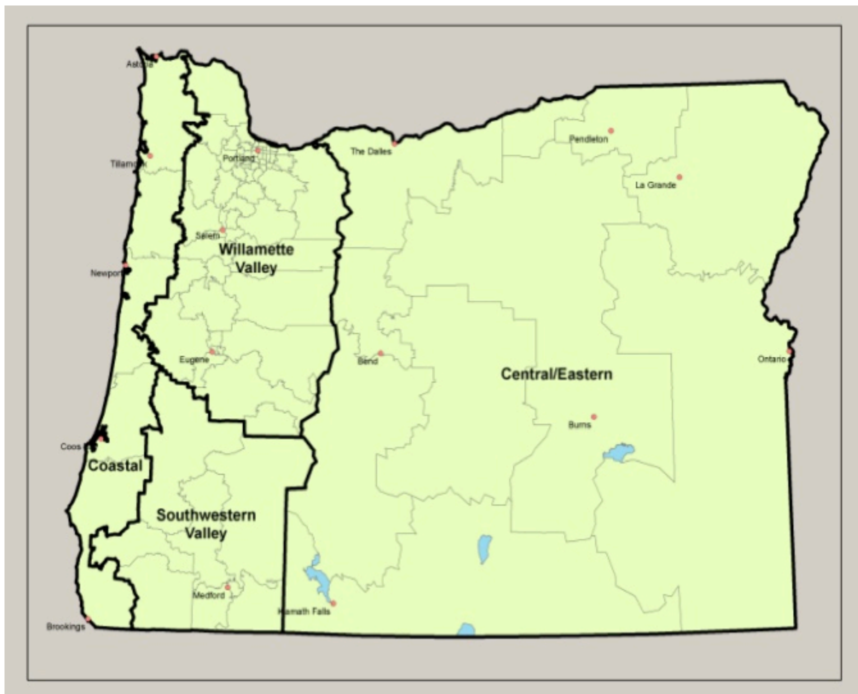

Figure 2. Four climate zones of Oregon

Descriptive statistics:

Cases were aggregated on a weekly, monthly, and seasonal basis to determine the number of reported *Salmonella* and *Campylobacter* cases by region and county. *Season* was coded as a binary variable with 1=peak 6 months of *Salmonella* (May-October) or *Campylobacter* (April-September) activity and 0= off peak 6 months of *Salmonella* or *Campylobacter* infections. Descriptive statistics for meteorological data were performed by week, month, and season on the county and region level. Seasonal meteorological data were aggregated by the same peak and off peak months used for the case aggregation. The most appropriate temporal and spatial aggregation was determined to be at the monthly level for both county and region. The month level aggregation was used to ensure that there were enough cases to estimate the incidence rate of *Salmonella* and *Campylobacter* infections while capturing the temporal variability in meteorological data.

A repeated model with fixed effects, using a exchangeable correlation matrix to account for within region and within county variation, was used to determine if the mean age, mean monthly maximum temperature (^{o}F), mean monthly minimum temperature(^{o}F), mean monthly precipitation (mm), and mean monthly snow depth (mm) was significantly different between region and county. Tukey's post hoc test was used to determine if the mean age and mean monthly meteorological variables were significantly different between each region and each county. A repeated model with fixed effects using an exchangeable correlation matrix to account for variation within each ENSO category was also used to determine if the mean monthly maximum temperature (^{o}F), mean monthly minimum temperature (^{o}F), and mean precipitation (mm) was significantly different among ENSO categories. Tukey's post-hoc test was used to determine if the mean meteorological variables was significantly different between each ENSO category.

Poisson Regression analysis

Prior to regression analysis, variable inflation factor were estimated to determine the level of collinearity between meteorological variables. Poisson regression was performed with the count of monthly aggregated reported *Salmonella* and *Campylobacter* cases as the dependent variable and meteorological variables averaged on a monthly level. The generalizing estimating equation (GEE) approach was used to control for clustering within region and within county. An exchangeable or autoregressive correlation matrix was used depending on which correlation matrix contributed to a higher QIC. The incidence rate of reported cases was estimated by using the log population of the region and the log population of the county as the offset variable. The negative binomial model was used in the final model, but not in univariate models, to control for overdispersion. There were six temperature variables: mean monthly maximum temperature (*Tmax*), mean monthly minimum temperature (*Tmin*), the highest recorded monthly maximum temperature (*Tmax_max*) the lowest recorded monthly maximum temperature (*Tmax_min*), the highest recorded monthly minimum temperature (*Tmin_max*), the lowest recorded monthly minimum temperature (*Tmin_min*), two precipitation variables (*precipitation*, and *snow depth*), and one categorical *ENSO* variable used in the analysis. Univariate Poisson analysis was conducted between the monthly aggregated count of *Salmonella* and *Campylobacter* cases and all of the meteorological variables. Continuous variables were assessed for linearity by generating a categorical variable by quintiles and running the model with the categorical variable and the count of cases. The ß coefficients were then plotted to assess the linearity. The categorical variable with levels defined as quintiles was then used in lieu of the continuous variable for those that did not show a linear association. Both continuous and categorical variables that had a significance level $p<0.25$ were considered for variable selection.

Multivariate Poisson regression modeling was then used to characterize the association between incidence of reported *Salmonella* and *Campylobacter* illness and the meteorological factors. Since the variable inflation factor (VIF) showed that all temperature variables were highly collinear, only one temperature variable and one precipitation variable was chosen to enter the full model. The variable selection process consisted of entering the maximum and minimum variable counterparts (e.g., mean monthly maximum/mean monthly minimum, highest recorded monthly maximum temperature/highest recorded monthly minimum temperature, lowest recorded monthly maximum temperature/lowest recorded monthly minimum temperature) into the same model to choose one variable from each pair. Then the three variables, which were significant or had a higher ß coefficient from each pair, were entered into the same model. The variable that was significant or had the highest ß coefficient out of the three was used in the full model. Likewise, the two precipitation variables (precipitation and snow depth) were entered into the same model. The precipitation variable that was significant or had a higher ß coefficient was entered into the full model. Thus, the full model always started with one temperature variable, one precipitation variable, and the ENSO variable. To control for confounding the temperature effects with seasonal trends, we included terms in the full model to adjust for these. Annual cycles were modeled through sine and cosine terms of $\sin(2\pi m/12)$ and $\cos(2\pi m/12)$ where m=the month from January=1 to December=12 (Cohen et al, 2012). Variables tat were not significant in this model were dropped. The final model was then assessed for outliers by using Cook's distance. Outliers were removed and the model was run without the outliers. The model without the outliers was used if the model without the outliers had a large change (>10%) in ß coefficient. SAS 9.3 (Cary NC, USA) was used for all statistical analysis

Chapter 3—Results

Descriptive Statistics

Campylobacter and *Salmonella* Cases

The highest frequency of reported *Campylobacter* cases from 2000 to 2010 occurred in Multnomah County (n=1367, Fig. 3). This was equal to 29.31% of the total reported *Campylobacter* cases in these ten counties. Washington County had the next highest reported *Campylobacter cases* (n=795, 17.05%) followed by Lane County (n=589, 12.63%). Although Multnomah County had the highest count of reported *Campylobacter* cases, Linn County had the highest incidence of 21.6 cases per 100,000 (Fig. 3). The lowest incidence of reported *Campylobacter* cases occurred in Marion County (4.67 cases per 100,000). A similar trend can be seen for reported *Salmonella* cases. The highest frequency of reported *Salmonella* cases between 2000 and 2010 occurred in Multnomah County (n=400, Fig 3). This accounts for 27.10% of the reported *Salmonella* cases in these ten counties. The second highest frequency of reported *Salmonella* cases occurred in Washington County (n=256, 17.34%), followed by Clackamas County (n=179, 12.13%). Jackson County had the highest incidence of reported *Salmonella* cases (6.96 per 100,000). Interestingly, Marion County had the lowest incidence of reported *Salmonella* cases again (1.61 per 100,000).

The highest frequency of reported *Campylobacter* cases from 2000 to 2010 occurred in the Willamette Valley/ Cascades region (n=3801, Fig 4). This accounts for 81.50% of the reported *Campylobacter* cases in the four regions. The Willamette Valley had the highest incidence (92.26 cases per 100,000) of *Campylobacter.* There was a much smaller difference in the incidence per 100,000 in reported *Campylobacter* cases between the regions (Fig. 4). A similar trend was seen for reported *Salmonella* cases. The highest frequency of reported *Salmonella* cases was seen in the Willamette Valley/Cascades region (n=1034, Fig. 4). This accounts for 70.05% of the reported *Salmonella* cases. Although the Willamette Valley by far had the greatest number of reported *Salmonella* cases compared to the other three counties, the incidence between the four regions were relatively similar. The Southwestern Valley had the greatest incidence of 29.92 cases per 100,000, followed by the Eastern Valley (29.5 cases per 100,000). The Coastal Valley had the smallest incidence of 19.97 cases per 100,000.

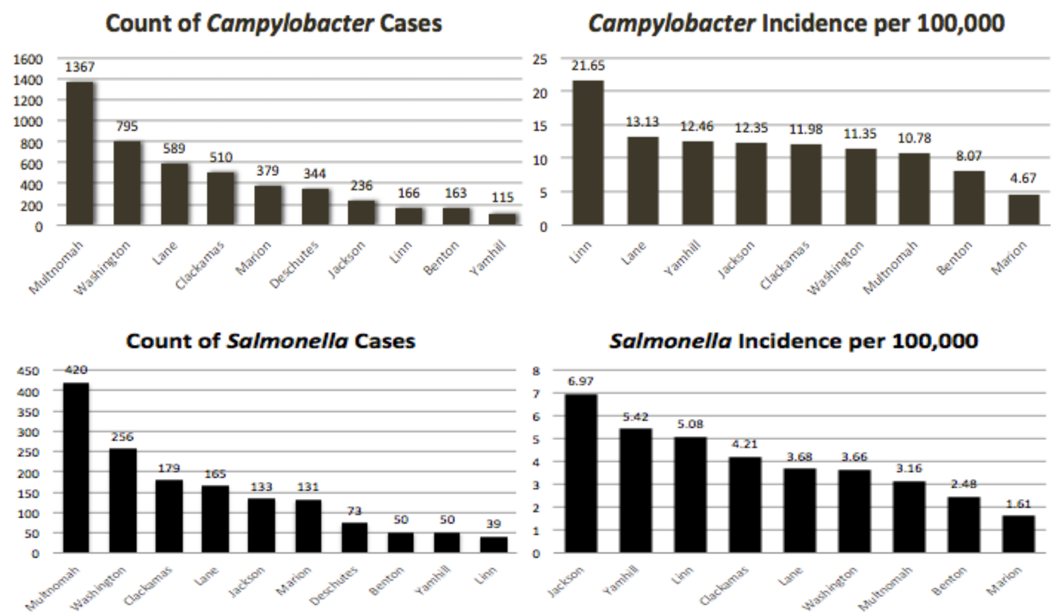

Fig 3 (Top) The count (right) and incidence (right) of total reported *Campylobacter* cases by county. The 2005 population of each county was used to determine incidence. (Bottom) The count (left) and incidence (right) of total reported *Salmonella* cases by county. The 2005 population of each county was used to determine incidence.

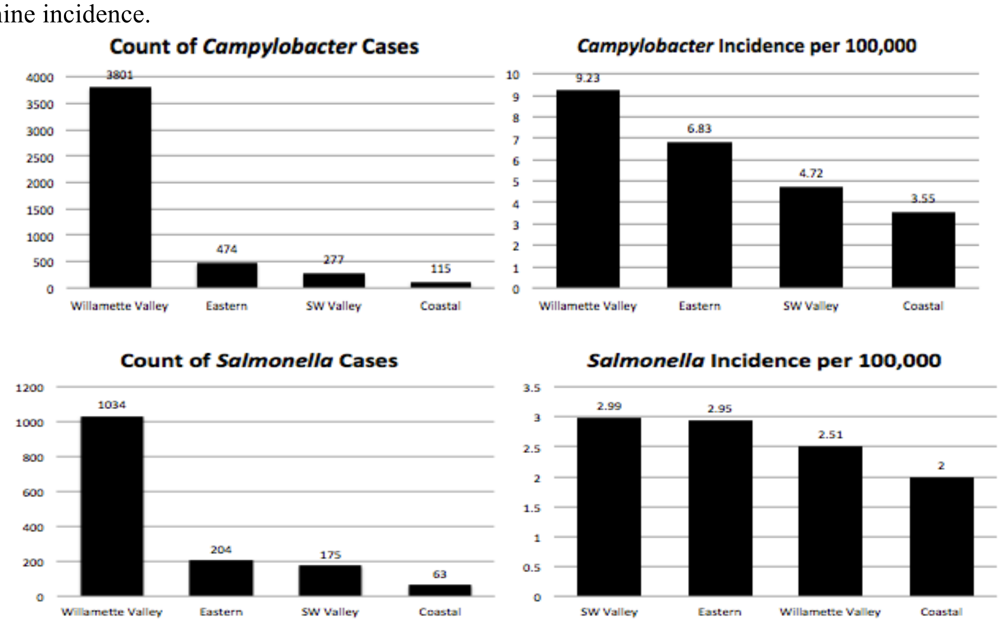

Figure 4. (Top) Count (left) and reported incidence (right) of reported *Campylobacter* cases by region. The 2005 population of each region was used to determine incidence. (Bottom) Count (left) and reported incidence (right) of reported *Salmonella* cases by region. The 2005 population of each region was used to determine incidence.

The frequency of reported *Campylobacter* cases by month and the top five counties are shown (Fig. 5). The peak of reported *Campylobacter* cases for these five counties occurred between June and September. The peak activity for Clackamas County occurred in June, the peak activity for Clackamas and Lane counties occurred in July. The peak activity for Marion County did not occur until September. Interestingly, Multnomah County seemed to have a dual peak in reported *Campylobacter* infection activity. There as a small peak in reported *Campylobacter* cases in March and April, followed by a decrease in reported cases in May, and a drastic increase in cases in June.

The frequency of reported *Salmonella* cases by month and top five counties are shown (Fig. 6). There was a more pronounced annual peak in reported *Salmonella* cases compared to reported *Campylobacter* cases. Multnomah County had two peaks in reported *Salmonella* infection activity. The first peak occurred in June, followed by a slight decrease in July, and then a higher peak in August. Washington County had three peaks in activity. Lane County also had two peaks in activity, once in June and once in August. Clackamas County had a peak that occurred in September and in November. For reported *Salmonella* cases, it seems as though reported cases started to increase in May and did not decrease until November.

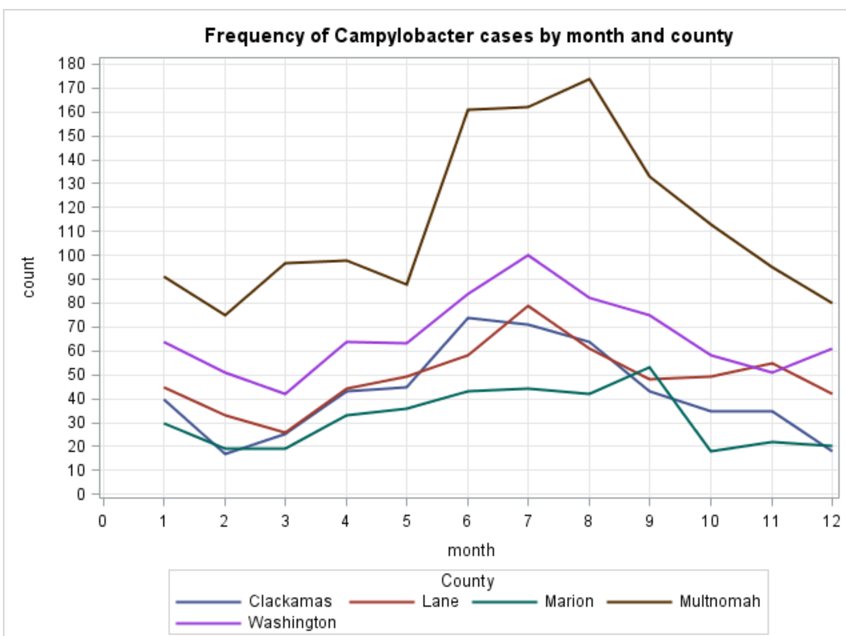

Figure 5. The frequency of reported *Campylobacter* cases by month and top five counties

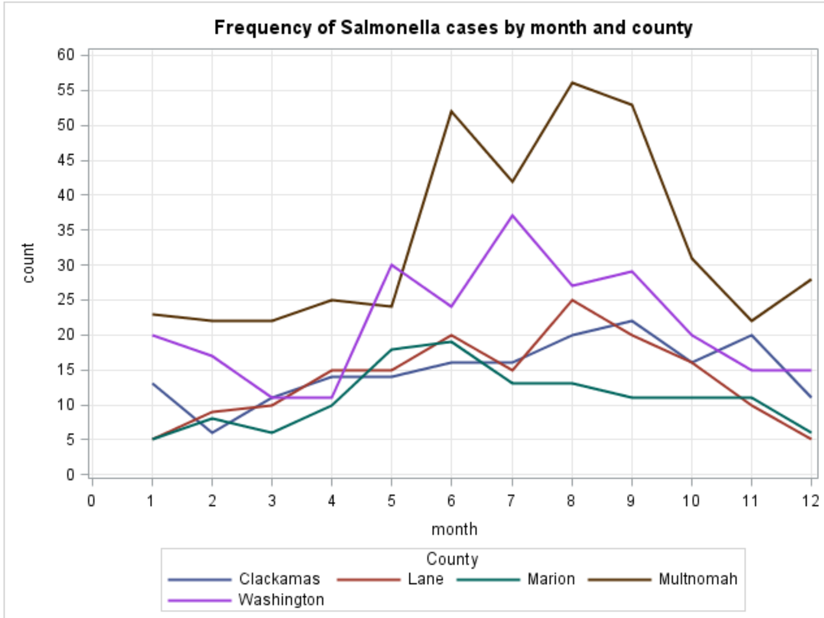

Figure 6. The frequency of reported *Campylobacter* cases by month and top five counties

The frequency of reported *Campylobacter* cases were plotted with the mean monthly maximum temperature (^{o}F), mean monthly minimum temperature (^{o}F), and mean precipitation (mm) by region (Fig. 7). As expected, the mean maximum temperature and mean minimum temperature increased from January until July, and then decreased from July to December. Precipitation (mm) was highest in the winter and fall months, and fell close to zero in the summer months. The peak of reported *Campylobacter* cases in all of the regions occurred between June and August. The peak of reported *Campylobacter* cases corresponded with the peak in monthly maximum and monthly minimum temperatures. The peak of reported *Campylobacter* cases also corresponded with the months with the lowest amount of rainfall.

The frequency of reported *Salmonella* cases was plotted with the mean monthly maximum temperature (^{o}F), mean monthly minimum temperature (^{o}F), and mean precipitation (mm) by region (Fig. 8). As expected, the mean maximum temperature and mean minimum temperature increased from January until July, and then decreased from July to December. Precipitation (mm) was highest in the winter and fall months, and fell close to zero in the summer months. The monthly reported *Salmonella* cases in the Coastal, Eastern, and Southwestern Valley regions remain relatively similar throughout the year. However, in the Willamette Valley/Cascades region, there was a peak in reported *Salmonella* cases in June and August. This peak corresponded with the peak of the mean monthly maximum and mean monthly minimum temperatures in the Willamette Valley/Cascades region.

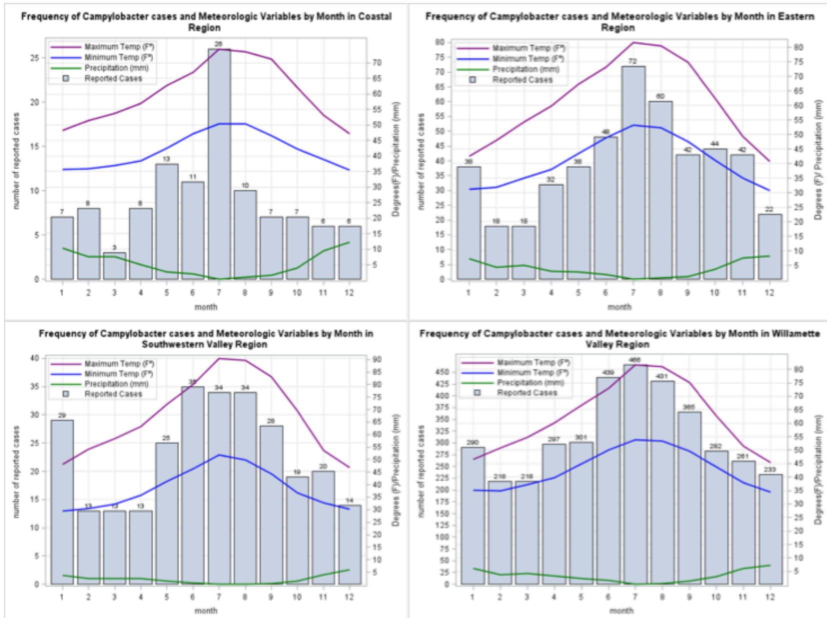

Figure 7. The frequency of *Campylobacter* cases by region (Coastal, Eastern, SW Valley, Willamette Valley) and the mean maximum temperature (F, purple line), mean minimum temperature (F, blue line) and precipitation (mm, green line). Left axis scale changes with respect to number of reported cases. Right axis scale remains constant.

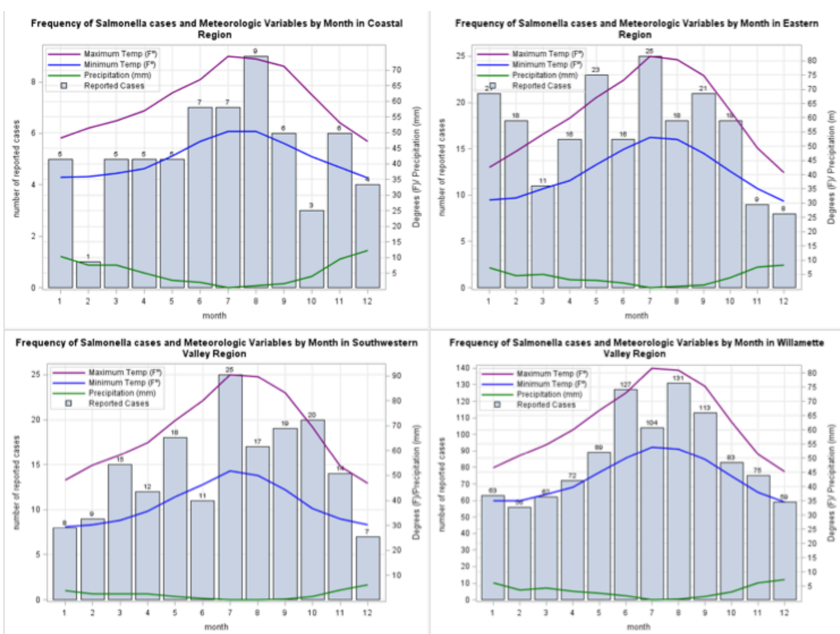

Figure 8. The frequency of *Salmonella* cases by region (Coastal, Eastern, SW Valley, Willamette Valley) and the mean maximum temperature (F, purple line), mean minimum temperature (F, blue line) and precipitation (mm, green line). Left axis scale changes with respect to number of reported cases. Right axis scale remains constant.

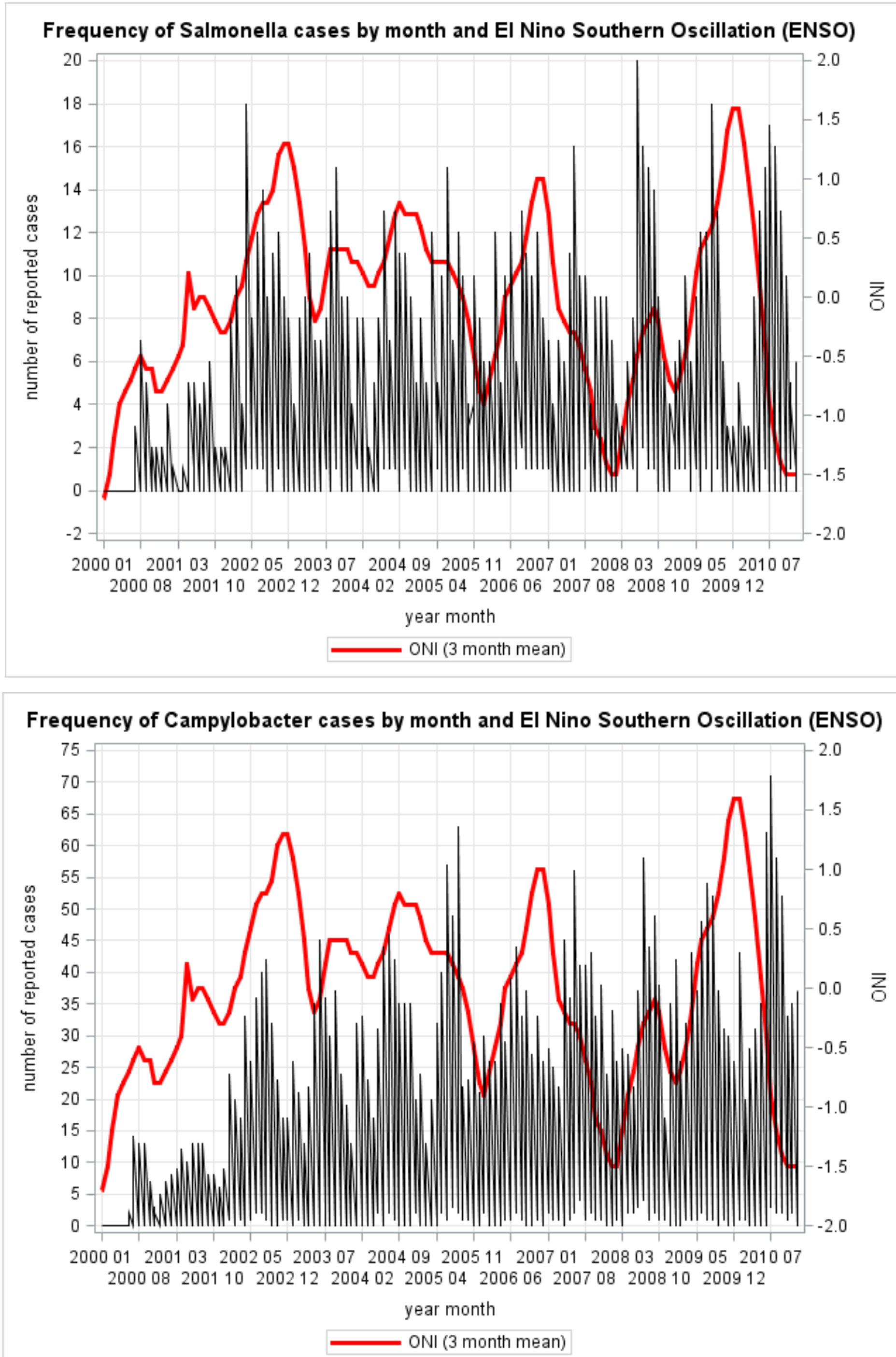

Figure 9. Frequency of reported *Salmonella* (top) and *Campylobacter* (bottom) infection and continuous Oceanic Nino Index (ONI) between 2000-2010. Left Y-axis is the number of reported cases and right Y-axis is the Oceanic Nino Index with a range from -2 to 2.

The frequency of reported *Salmonella* and *Campylobacter* cases by month was plotted with the Oceanic Nino Index (ONI) (Fig. 9). We observe numerous El Niño and

La Niña conditions during this 10-year period. Visually inspecting the graphs showed that the frequencies of both *Salmonella* and *Campylobacter* decreased when La Niña conditions occurred. We see that there were more conditions of moderate and strong La Niña (ONI <-1.0) than conditions of moderate and strong El Niño (ONI >1.0). Additionally, the periodicity of reported *Salmonella* and *Campylobacter* cases can be seen. The number of reported cases of each type of infection followed a sine wave pattern, with a peak number of reported cases in the summer months and the lowest number of reported cases in the winter months.

The mean age by county and region were compared using a repeated model with fixed effects using an exchangeable correlation matrix to account for variation within region and county (Table 3). The mean age of reported *Campylobacter* cases was significantly different between counties ($F_{df=9}$=2.5, p=0.0075) and by region ($F_{df=3}$=6.75, p=0.0002). Tukey's post hoc test demonstrated a significant difference between the mean age of reported *Campylobacter* illness in the Coastal region and the reported *Campylobacter* illness in the Eastern, Southwestern Valley and Willamette Valley/Cascades regions (all p<0.05). There was not a significant difference in the mean age of reported *Salmonella* cases by county ($F_{df=9}$=1.00, p=0.438) or region ($F_{df=3}$=0.54, p=0.657).

Table 3. Mean age and standard deviation of reported Campylobacter and Salmonella infection by county and region. **$p<0.05$, ^ $ --significantly different ($p<0.05$) based from Tukey's post hoc test.

County	**Campylobacter**	**Salmonella**
	Age (mean±SD)**	Age (mean±SD)
Benton	38.41 ± 20.92 (n=163)	27.56 ± 19.51 (n=50)
Clackamas	39.91 ± 22.01 (n=510)**	31.54 ± 23.19 (n=179)
Deschutes	37.26 ± 22.64 (n=344)	29.83 ± 22.75 (n=73)
Jackson	39.21 ± 22.67 (n=236)	30.29 ± 25.33 (n=133)
Lane	37.89 ± 23.51 (n=589)	26.14 ± 23.74 (n=165)
Linn	38.01 ± 23.19 (n=166)	33.25 ± 23.70 (n=39)
Marion	34.35 ± 24.22 (n=379)^	27.90 ± 26.13 (n=131)
Multnomah	37.98 ± 19.87 (n=1366)	30.91 ± 22.18 (n=400)
Washington	32.48 ± 24.06 (n=1115)	28.44 ± 22.24 (n=256)
Yamhill	32.48 ± 24.06 (n=795)**^	29.96 ± 24.70 (n=50)
Region	**	
Coastal	46.4 5± 23.66 (n=112)*^$	32.99 ± 25.03 (n=63)
Eastern	36.74 ± 22.45 (n=474)*	28.86 ± 22.37 (n=204)
Southwestern Valley	38.83 ± 22.62 (n=277)^	29.87 ± 24.46 (n=175)
Willamette Valley/Cascades	37.42 ± 21.63 (n=3800)$	29.44 ± 23.09 (n=1034)

Meteorological Variables

The means for monthly maximum (^oF), monthly minimum (^oF), precipitation (mm) and snow depth (mm) by county and region were compared using a repeated model with fixed effects using an exchangeable correlation matrix to account for variation within region and county (Table 4). There was a significant difference in the mean monthly maximum temperature by county ($F_{df=8}$=290.65, p<0.001), the minimum temperature by county ($F_{df=9}$=1675.13, p<0.0001), the mean precipitation (mm) by county ($F_{df=8}$=227.41, p<0.0001), and the mean snow depth by county ($F_{df=8}$=447.75, p<0.0001). There was a significant difference in the mean monthly maximum temperature ($F_{df=3}$=369.85, p<0.0001), the mean minimum temperature ($F_{df=3}$=570.94, p<0.0001) by region. Tukey's post hoc test indicated that the mean minimum and maximum temperature was significantly different between all regions (p<0.05). The mean amount of precipitation (mm) was also significantly different by region ($F_{df=3}$=409.52, p<0.0001) and Tukey's post hoc test showed that the mean amount of precipitation (mm) was significantly different for all combinations of region (p<0.05). There was also a significant difference in the mean amount of snow depth by region ($F_{df=3}$=32.17, p<0.0001). Tukey's post hoc test indicated that there was a significant difference in the mean snow depth for all region combinations (p<0.05) except for Southwestern Valley/Willamette Valley.

Table 4. Mean maximum temperature, minimum temperature, precipitation and snow depth by county and by region. **p<0.05

County	Mean Max Temp (F)**	Mean Min Temp (F)**	Precipitation (mm) **	Snow (mm) **
Benton	63.15 ± 14.68	41.17 ± 8.60	37.61 ± 81.65	0.33 ± 5.02
Clackamas	60.54 ± 14.99	42.21 ± 9.54	38.25 ± 74.41	3.02 ± 17.67
Deschutes				
Jackson	67.58 ± 17.24	38.50 ± 9.53	20.72 ± 52.47	1.08 ± 7.77
Lane	62.79 ± 14.41	41.65 ± 8.12	41.03 ± 81.89	0.26 ± 4.02
Linn	62.85 ± 14.75	40.83 ± 8.34	37.98 ± 71.12	0.23 ± 3.08
Marion	62.07 ± 14.66	42.13 ± 8.98	33.97 ± 71.23	1.36 ± 12.37
Multnomah	62.90 ± 14.28	45.28 ± 9.01	29.18 ± 59.48	0.244 ± 3.61
Washington	62.28 ± 13.92	41.76 ± 41.76	28.79 ± 58.71	0.03 ± 1.29
Yamhill	64.31 ± 14.70	43.18 ± 8.74	.	.
Region	**Mean Max Temp (F)****	**Mean Min Temp****	**Precipitation (mm)****	**Snow (mm)****
Coastal	59.31±11.60	41.39±7.71	55.74±106.06	0.244±4.24
Eastern	61.19±15.76	40.72±9.46	38.67±79.60	1.97±10.39
Southwestern Valley	67.58±17.24	38.5±9.53	20.722±52.47	1.08±7.77
Willamette Valley	62.56±14.62	42.98±9.02	33.26±67.86	1.14±10.78

There were neutral ENSO pattern months for 43.62% of the months (Table 5). 31.92% of the months between 2000-2010 were La Niña months, and 24.47% of the months were El Niño months. The distribution between weak (10.53%), moderate (12.12%), and strong (9.27%) La Niña months was similar. Interestingly, we find that there were no reports of strong El Niño between 2000-2010 and that there were more months classified as moderate El Niño (15.40%) than months of weak El Niño (9.07%).

Table 5. Frequency of ENSO pattern-strength between 2000-2010

ENSO-ONI strength	Frequency (%) over 10 years
Neutral-Neutral	43.62%
El Nino-Weak	9.07%
El Nino-Moderate	15.40%
El Nino-Strong	0
La Nina-Weak	10.53%
La Nina-Moderate	12.12%
La Nina-Strong	9.27%

Temperature and precipitation was significantly affected by each combination of the pattern-strength (*ENSO* variable). A repeated model with fixed effects using an exchangeable correlation matrix to account for variation within ENSO categories showed that the mean monthly maximum temperature (^{o}F) was significantly different by ENSO pattern-strength ($F_{df=6}$=5970.48, p<0.0001, Table 6). Tukey's post hoc test showed that all combinations of ENSO patterns-strength were significantly different from each other (p<0.05). All mean monthly maximum temperatures (^{o}F) for all ENSO pattern-strength combination were less than the mean monthly maximum temperature (^{o}F) for a neutral-neutral month. The mean monthly maximum temperature was lowest during moderate La Niña months. A repeated model with fixed effects using an exchangeable correlation matrix to account for variation within ENSO categories demonstrated that the mean monthly minimum temperature (^{o}F) was significantly different by ENSO pattern- strength (F=5224.28, p<0.0001). Tukey's post hoc test showed that all combinations of ENSO pattern-strength were significantly different from each other except between El Niño-Weak/El Niño-moderate. Like the mean monthly temperature, all levels of ENSO pattern- strength have a lower mean monthly minimum temperature when compared to the neutral-neutral months. Precipitation was also significantly different by ENSO pattern-strength (F=490.55, p<0.0001). Tukey's post hoc test shows that all combinations of ENSO pattern-strength are significantly different from each other. Interestingly, all combinations of ENSO pattern-strength have higher monthly mean precipitation (mm) when compared to a neutral-neutral months (Table 6).

Table 6. Mean maximum temperature, minimum temperature, precipitation and snow depth by ENSO pattern -ONI strength. ** p<0.05

	Max Temp (^{o}F) Mean ± SD**	Min Temp (^{o}F) Mean ± SD**	Precipitation (mm) Mean ± SD**
Neutral-Neutral	66.15±13.73	44.74±8.30	27.87±59.62
El Nino-Weak	61.39±16.05	42.85±10.02	37.77±81.51
El Nino-Mod	62.33±14.61	42.74±9.05	33.63±68.52
La Nina-Weak	56.45±13.37	39.20±8.96	38.37±75.52
La Nina-Mod	55.10±13.31	38.15±8.62	44.43±81.70
La Nina-Strong	61.88±14.04	43.31±8.57	39.42±73.59

Association between meteorological variables and reported *Salmonella* and *Campylobacter*

Campylobacter by region

Univariate analysis was carried out using Poisson regression with the log population as the offset variable and an autoregressive correlation matrix for both categorical and continuous variables. We found that the continuous highest recorded minimum temperature (*Min Tmax*, ^{o}F) and continuous precipitation were not linear and the quintile categorical variable was used instead. All other continuous variables had a linear association and were entered into the model as continuous variables. In univariate analysis, the mean monthly maximum temperature, the mean monthly minimum temperature, the highest recorded monthly maximum temperature (*Max Tmax*, ^{o}F), the lowest recorded maximum temperature (*Min Tmax*, ^{o}F), and the lowest recorded monthly minimum temperature (*Min Tmin*, ^{o}F) were all significantly associated with higher rate ratios (Table 7, *p*<0.05). These rate ratios ranged between 1.012 and 1.029. The highest recorded monthly minimum temperature (*max Tmin*, ^{o}F) variable was overall significant (*p*<0.0001). However when this variable was entered as a categorical variable, only the highest temperature quintile (> 59 ^{o}F) was significantly associated with a 37% higher rate ratio (95% CI: 1.07, 1.76). These data, aggregated by region, suggests that increased temperature was associated with increased rates of reported *Campylobacter* infections. Interestingly, increased precipitation (mm) as inversely associated with incidence. All quintiles of the categorical precipitation variable were significant at the 0.05 level. We found a stepwise effect and showed that each additional quintile of precipitation was associated with progressively lower rates. Relative to less than 6.88 mm of precipitation, 6.88-19.43 mm level was associated with a 14.6% lower rate in reported *Campylobacter* cases (95%CI: 0.808, 0.903). Precipitation that was greater than 59.16 mm was associated with a 27.2% lower rate in reported *Campylobacter* infections (95%CI: 0.663, 0.799).

The association between reported *Campylobacter* infection and months with El Niño events and months with La Niña events showed an opposing pattern. El Niño months were associated with significantly higher rates of reported *Campylobacter* infections. During weak El Niño months, the rate of reported *Campylobacter* infections was 23% (95%CI: 1.00, 1.51) higher in incidence rate. Periods of moderate El Niño events were associated with a smaller increased rate ratio than weak El Niño events (1.08 vs 1.23). La Niña events were associated with lower incidence rates. During weak La Niña events, the rate ratio in reported *Campylobacter* infections was 16.2% lower (95% CI: 0.723, 0.976) relative to months classified as neutral. Strong La Niña events were associated with 14.6% lower rate in reported *Campylobacter* infections. Moderate La Niña events were associated with the lowest monthly incidence, and we found that there was a 32.4% lower rate ratio in reported *Campylobacter* infections (95% CI: 0.644, 0.913).

Table 7. Poisson regression of the count of reported *Campylobacter* cases by month and one meteorological variable. Rate ratios, 95% confidence limits, and *p*-values are shown.

Variable	Rate ratio (95% CI)	*p*-value
Tmax (^oF)	1.017(1.015,1.019)	<0.0001
Tmin (^oF)	1.029(1.025,1.034)	<0.0001
Max Tmax (^oF)	1.012(1.011,1.14)	<0.0001
Min Tmax (^oF)	1.014 (1.01, 1.019)	<0.001
Max Tmin (^oF)		
1-<44.5	reference	
2-44.5-49.5	0.951 (0.747, 1.21)	0.414
3 49.5-54.5	1.28 (0.845, 1.50)	0.8963
4 54.5-59.0	1.02 (0.796, 1.30)	0.0126
5 >59.0	1.37 (1.07, 1.76)	<0.0001
Min Tmin (^oF)	1.016(1.010,1.022)	<0.0001
Snow depth (mm)	0.986(0.969,1.00)	0.103
Precipitation (mm)		
1-<6.88	reference	
2-6.88-19.43	0.854 (0.808, 0.903)	<0.0001
3-19.43-36.74	0.839 (0.787, 0.894)	<0.0001
4-36.74-59.14	0.737 (0.707, 0.676)	<0.0001
5->59.16	0.728 (0.663, 0.799)	<0.0001
ENSO		
0-Neutral-Neutral	Reference	
1-El Nino-Weak	1.23 (1.00. 1.51)	0.050
2-El Nino-Mod	1.08 (1.01, 1.15)	0.024
3-El Nino-Strong		
4-La Nina-Weak	0.838 (0.723, 0.976)	0.0192
5 La Nina-Mod	0.676 (0.644, 0.913)	0.0029
6 La Nina-Strong	0.854 (0.763, 0.957)	0.0067

The results from the univariate analysis showed that all temperature variables, the categorical *precipitation* (mm) variable, and the *ENSO* variable were significant at the 0.250 level, the criterion for inclusion as a candidate variable for multivariate model building. All temperature variables had a variable inflation factor (VIF) that was greater than 10 (highest VIF=26.95); the temperature variable with the best ß estimate and the lowest *p*-values was first entered into the model. Mean monthly maximum temperature was the best temperature variable with the best ß estimate and lowest *p*-value; therefore this variable was entered into the full model with the categorical precipitation variable, the categorical ENSO variable, and the two sin and cosine terms to adjust for seasonal trends. All variables were significant except for the highest quintile of precipitation (p=0.7138). We then used the negative binomial distribution to account for overdispersion. Additionally, one outlier was removed and we discovered a large difference (up to 47.8%) in the ß coefficients for the ENSO variables and so the model without the outlier was used as the final model.

Mean monthly maximum temperature was associated with lower rates of reported *Campylobacter* infections (RR=0.986; 95% CI 0.974, 0.998) when taking into account the categorical quintile variable, the ENSO variable and the two sin and cosine terms to adjust for seasonal trends. Precipitation was also significantly associated with the rate of reported *Campylobacter* infections when taking into account the mean monthly maximum temperature, ENSO events, and seasonal trends. We saw a stepwise association and found that each additional quintile was associated with lower incidence rates of *Campylobacter* infections (Table 8). When taking into account the monthly maximum temperature and precipitation, weak and moderate El Niño months were associated with large and significantly higher rates of reported *Campylobacter* infection (Table 8). Weak El Niño events were associated with a over a two-fold higher rate of reported *Campylobacter* infection (RR=2.64, 95%CI: 2.53, 2.76) and moderate El Niño events were associated with a 37% higher rate of reported *Campylobacter* infections (95%CI: 1.31, 1.44) relative to months classified as neutral. Strong and weak La Niña events were inversely associated with the rate of reported *Campylobacter* infection when accounting for the mean monthly maximum temperature, precipitation, and seasonal trends. Weak La Niña events were associated with a 57% lower rate (95%CI: 0.397, 0.466) of reported *Campylobacter* infections and strong La Niña events were associated with a 29.8% lower rate (95% CI: 0.608, 0.808) of reported *Campylobacter* infections.

Table 8: Poisson regression using negative binomial of the count of reported *Campylobacter* cases by month the mean monthly maximum temperature, quintile precipitation, and categorical ENSO. Rates and 95% confidence limits are shown. Reported rates take into account all other meteorological variables and have been adjusted for seasonal trends (RR not shown).

Variable	Rate ratio (95% CI)	*p*-value
Tmax (^{o}F)	0.986 (0.974,0.998)	0.0198
Precipitation (mm)		
1-<6.88	reference	
2-6.88-19.43	0.742 (0.725, 0.759)	<0.0001
3-19.43-36.74	0.822 (0.772, 0.874)	<0.0001
4-36.74-59.14	1.07 (1.00, 1.15)	0.0438
5->59.16	0.977 (0.862, 1.11)	0.7138
ENSO		
0-Neutral-Neutral	Reference	
1-El Nino-Weak	2.64 (2.53, 2.76)	<0.0001
2-El Nino-Mod	1.37 (1.31, 1.44)	<0.0001
3-El Nino-Strong		
4-La Nina-Weak	0.430 (0.397, 0.466)	<0.0001
5 La Nina-Mod	1.01 (0.997, 1.03)	0.1112
6 La Nina-Strong	0.702 (0.608, 0.808)	<0.0001

Salmonella by region

Univariate analysis was carried out using Poisson regression with the log population as the offset variable and an exchangeable correlation matrix for both categorical and continuous variables. We found that the continuous precipitation was not linear and the quintile categorical variable was used instead. In univariate analysis, the mean monthly maximum temperature, the mean monthly minimum temperature, the highest recorded monthly maximum temperature (*Max Tmax*, ^{o}F), the lowest recorded monthly maximum temperature (*Min Tmax*, ^{o}F) the highest recorded minimum temperature (*Max Tmin*, ^{o}F), and the lowest recorded monthly minimum temperature (*Min Tmin*, ^{o}F) were all associated with significantly increased rate ratios (Table 9, p<0.05). These rate ratios ranged between 1.016 and 1.030. These data suggest that higher temperatures were associated with higher rates of *Salmonella* infections aggregated by region. Increased precipitation (mm) and increased snow depth (mm) were inversely associated with incidence. All quintiles of the categorical precipitation variable were significant at there 0.05 level. Each additional quintile of precipitation is associated with a lower incidence. Compared to *Campylobacter* infections, increased precipitation is more strongly associated with reductions in monthly reported *Salmonella* infections. Similarly, increased snow depth is inversely associated with *Salmonella* infections, showing a small but significant decrease in the rate ratio (Table 9).

Again, we found an opposing effect between the association between reported *Salmonella* infections and months with El Niño events and months with La Niña events. El Niño months were associated with significantly higher rates of reported *Salmonella* infections. During weak El Niño months, there was a 13.8% higher rate of reported *Salmonella* infections (95% CI: 1.05,1.23). La Niña events were significantly associated with a months of lower incidence rates. During weak La Niña events, the rate of reported *Salmonella* infections was 44.8% (95%CI: 0.456, 0.668) lower, relative to neutral months. Strong La Niña events were associated with a 35.1% lower incidence in reported *Salmonella* infections (95%CI: 0.582, 0.724).

Table 9. Poisson Regression of the count of reported *Salmonella* cases by month and one meteorological variable. Rate rations, 95% confidence limits, and *p*-values are shown.

Variable	Rate Ratio (95% CI)	*p*-value
Tmax (^oF)	1.018(1.015, 1.02)	<0.0001
Tmin (^oF)	1.030 (1.021, 1.039)	<0.0001
Max Tmax (^oF)	1.016(1.013, 1.018)	<0.0001
Min Tmax (^oF)	1.019(1.017, 1.021)	<0.0001
Max Tmin (^oF)	1.029 (1.019, 1.038)	<0.0001
Min Tmin (^oF)	1.022(1.017, 1.027)	<0.0001
Snow depth (mm)	0.972(0.941,1.00)	
Precipitation (mm)		<0.0001
0-<6.88	reference	
2-6.88-19.43	0.907(0.829, 0.992)	0.0327
3-19.43-36.74	0.717(0.658, 0.783)	<0.0001
4-36.74-59.14	0.723 (0.656, 0.797)	<0.0001
5->59.16	0.626 (0.558, 0.701)	<0.0001
ENSO		
0-Neutral-Neutral	reference	
1-El Nino-Weak	1.138 (1.05,1.23)	0.0015
2-El Nino-Mod	1.02(0.907, 1.14)	0.7593
3-El Nino-Strong		
4-La Nina-Weak	0.552 (0.456, 0.668)	<0.0001
5 La Nina-Mod	0.947 (0.833,1.08)	0.4068
6 La Nina-Strong	0.649 (0.582, 0.724)	<0.0001

The results from the univariate analysis show that all temperature variables, the categorical precipitation (mm) variable, snow depth (mm) and the ENSO variable are all significant at the 0.250 level. All temperature VIF were greater than 10 (highest VIF=35.03) and we determine that the highest recorded monthly maximum temperature (^oF) was the best temperature predictor. The highest recorded monthly temperature, the categorical precipitation variable, the categorical ENSO variable, and the two variables that adjust for seasonal trends were entered into a model to determine if all variables were significant. The overall categorical precipitation variable was not significant in the full model (p=0.1495) and was dropped. Next, we ran the model with only the temperature variable, the categorical ENSO variable and the two variables that adjust for seasonal trends. The highest recorded monthly maximum temperature was no longer significant (p=0.1865). Thus, our final model was comprised of the categorical ENSO variable and the two variables that adjust for seasonal trends. We ran this model using the negative binomial distribution to account for overdispersion and found that the overall ENSO variable was significant (p<0.0001).

The categorical ENSO variable showed that weak El Niño, Weak La Niña, and strong La Niña, but not moderate El Niño or La Niña were significant (Table 10) Additionally, one outlier was removed but we found that the model with the outlier was a better fit than the model without the outlier. When taking into account seasonal trends, weak El Niño events were associated with 25% higher incidence rate (95% CI: 1.12, 1.39) of monthly reported *Salmonella* infections. Weak La Niña events were associated with an 18.1% (95% CI: 0.429, 0.859) lower incidence rate of reported *Salmonella* infections. Strong La Niña events were associated with a 32% (95% CI: 0.612, 0.756) lower incidence rate of reported *Salmonella* infections when taking into account seasonal trends (Table 10).

Table 10: Poisson Regression using negative binomial of the count of reported *Salmonella* cases by month the mean monthly maximum temperature, quintile precipitation, and categorical ENSO. Rates and 95% confidence limits are shown. Reported rates take into account all other meteorological variables and have been adjusted for seasonal trends (RR not shown).

Variable	Rate Ratio (95% CI)	*p*-value
ENSO		
0-Neutral-Neutral	reference	
1-El Nino-Weak	1.25 (1.12, 1.39)	<0.0001
2-El Nino-Mod	1.08 (0.961, 1.23)	0.1813
3-El Nino-Strong		
4-La Nina-Weak	0.819 (0.429, 0.859)	0.0049
5 La Nina-Mod	1.11 (0.978, 1.28)	0.1039
6 La Nina-Strong	0.680 (0.612, 0.756)	<0.0001

Campylobacter by county

Univariate analysis was carried out using Poisson regression with the log population as the offset variable and an autoregressive correlation matrix for both categorical and continuous variables. All continuous variables, including precipitation (mm) were linear and were entered into the univariate model as continuous variables. Similar associations were found between the meteorological factors and monthly reported *Campylobacter* cases aggregated at the regional level (Table 11).

For the county level of aggregation, only La Niña events were significantly associated with the rate of reported *Campylobacter* infections. Weak and strong but not moderate La Niña events were significantly associated with lower incidence rates of monthly reported *Campylobacter* infections. Weak La Niña were associated with a 53% (95% CI: 0.294, 0.753) lower rate in reported *Campylobacter* infections, relative to neutral months. Strong La Niña events were associated with a 14.6% lower rate in reported *Campylobacter* infections. Moderate La Niña events were associated with the lowest monthly incidence rate, and we found that there was a 25.3% (95% CI: 0.639, 0.872) lower incidence rate in reported *Campylobacter* infections.

Table 11. Poisson Regression of the count of reported *Campylobacter* cases by month and county and one meteorological variable. Rates and 95% confidence limits are shown. Significant rates at the p<0.05 level is indicated by *

Variable	Rate ratio (95% CI)	*p*-values
Tmax (^oF)	1.019(1.016,1.023)*	<0.0001
Tmin (^oF)	1.036(1.027,1.045)*	<0.0001
Max Tmax (^oF)	1.016(1.0134,1.012*	<0.0001
Min Tmax (^oF)	1.019(1.015,1.023)*	<0.0001
Max Tmin (^oF)	1.04(1.027,1.051)*	<0.0001
Min Tmin (^oF)	1.028(1.021,1.035)*	<0.0001
Precipitation (mm)	0.994(0.992,0.996)*	<0.0001
Snow depth (mm)	0.986(0.957,1.01)	0.4212
ENSO		
0-Neutral-Neutral	reference	
1-El Nino-Weak	1.06 (.887, 1.28)	0.6785
2-El Nino-Mod	0.97(0.841, 1.12)	0.502
3-El Nino-Strong		
4-La Nina-Weak	0.47 (0.294, 0.753)*	0.8913
5 La Nina-Mod	1.01 (0.883, 1.15)	0.0002
6 La Nina-Strong	0.747 (0.639, 0.872)*	0.0017

The results from the univariate analysis show that all temperature variables, the precipitation (mm) variable, and the ENSO variable are all significant at the 0.250 level. All temperature variables had a VIF greater than 10 (highest VIF=35.77). The highest recorded monthly minimum temperature was the best temperature predictor and was used in the full model. The mean monthly maximum temperature was also used to test the same model across regional and county aggregation analyses. The highest recorded monthly minimum temperature, the precipitation variable, the categorical ENSO variable, and the two variables that adjust for seasonal trends were entered into a model to determine if all variables were significant. The precipitation variable was not significant and the model was run again without the categorical precipitation variable, and the highest recorded monthly minimum temperature was no longer significant (p=0.1431).

We also found that the mean monthly maximum temperature was not significant (p=0.9597). Thus, the final model only included the categorical ENSO variable and the two variables that adjust for seasonal trends. We ran this model using the negative binomial distribution to account for overdispersion. Four outliers were removed and the model with outliers was a better fit than the model without outliers.

After adjusting for seasonal trends, strong and weak La Niña events were inversely associated with the rate of reported *Campylobacter* infections (Table 12). Weak La Niña events were associated with a 46.3% (95%CI: 0.391, 0.736) lower incidence rate of reported *Campylobacter* infections after adjusting for seasonal trends. Strong La Niña events were associated with a 29.3% (95%CI: 0.605, 0.825) lower rate of reported *Campylobacter* infections after adjusting for seasonal trends. Interestingly, moderate La Niña events were associated with a 19% (95% CI: 1.03, 1.39) higher incidence rate of reported *Campylobacter* infections after adjusting for seasonal trends. Weak El Niño events were associated with a 27% (95% CI: 1.08, 1.49) higher incidence rate of reported *Campylobacter* infections.

Table 12: Poisson Regression using negative binomial of the count of reported *Campylobacter* cases by month the mean monthly maximum temperature, quintile precipitation, and categorical ENSO. Rates and 95% confidence limits are shown. Reported rates take into account all other meteorological variables and have been adjusted for seasonal trends (RR not shown).

Variable	Rate Ratio (95% CI)	***p*-values**
ENSO		
0-Neutral-Neutral	reference	
1-El Nino-Weak	1.27 (1.08 1.49)	0.0033
2-El Nino-Mod	1.04 (0.897, 1.20)	0.6209
3-El Nino-Strong		
4-La Nina-Weak	0.537 (0.391, 0.736)	0.0001
5 La Nina-Mod	1.19 (1.03, 1.39)	0.0224
6 La Nina-Strong	0.707 (0.605, 0.825)	<0.0001

Salmonella by county

Univariate analysis was carried out using Poisson regression with the log population as the offset variable and an autoregressive correlation matrix for both categorical and continuous variables. The continuous precipitation was not linear and the quintile categorical variable was used instead. All other continuous variables had a linear association and were entered into the model as continuous variables. We found similar associations between the meteorological variables and the rate of reported *Salmonella* infections that were aggregated at the regional level (Table 13).

Again, there was an opposite effect seen between the association between reported *Salmonella* infections and months with El Niño events and months with La Niña events. Weak El Niño events were significantly associated with higher rates of reported *Salmonella* infections. There was a 13.0% (95% CI: 1.05,1.23) higher incidence rate of reported *Salmonella* infections during weak El Niño events. Weak and strong but not moderate La Niña events were inversely associated with the rate of reported *Salmonella* infections. During weak La Niña events, there was a 48.2% (95% CI: 0.374, 0.718) lower rate in reported *Salmonella* infections. Strong La Niña events were associated with a 35.1% (95%CI: 0.582, 0.724) lower rate in reported *Salmonella* infections

Table 13. Poisson regression of the count of reported *Salmonella* cases by month and county and one meteorological variable. Rates and 95% confidence limits are shown. Significant rates at the p<0.05 level is indicated by *

Variable	Rate ratio (95%CI)	***p*-values**
Tmax (^{o}F)	1.018 (1.016, 1.02)	<0.0001
Tmin (^{o}F)	1.03 (1.022, 1.039)	<0.0001
Max Tmax (^{o}F)	1.018 (1.016,1.021)	<0.0001
Min Tmax (^{o}F)	1.03 (1.02,1.04)	<0.0001
Max Tmin (^{o}F)	1.03 (1.02,1.04)	<0.0001
Min Tmin (^{o}F)	1.022 (1.020,1.026)	<0.0001
Snow depth (mm)	0.971 (0.941, 1.00)	0.071
Precipitation (mm)		
0-<7.77	Reference	
2-7.77-19.8	0.906 (0.829, 0.990)	0.0293
3-19.87-35.23	0.718 (0.658, 0.784)	<0.0001
4-35.23-54.57	0.721 (0.656, 0.792)	<0.0001
5->54.57	0.616 (0.557, 0.683)	<0.0001
ENSO		
0-Neutral-Neutral	Reference	
1-El Nino-Weak	1.13 (1.05, 1.23)	0.0016
2-El Nino-Mod	1.02 (0.907, 1.14)	0.7608
3-El Nino-Strong		
4-La Nina-Weak	0.518 (0.374, 0.718)	<0.0001
5 La Nina-Mod	0.947 (0.833, 1.08)	0.4053
6 La Nina-Strong	0.649 (0.581, 0.724)	<0.0001

The results from the univariate analysis show that all variables were significant at the 0.250 level. All temperature variables had high variable inflation factor and the highest recorded monthly maximum temperature was the best temperature predictor. The highest recorded monthly maximum temperature, the categorical precipitation variable, the categorical ENSO variable, and the two variables that adjust for seasonal trends were entered into a model to determine if all variables ere significant. The precipitation variable was not significant (p=0.43) and thus was dropped from the model. The highest recorded monthly maximum temperature was also not significant (*p*=0.7964). Thus, the final model comprised of the categorical ENSO variable and the two variables that adjust for seasonal trends. Then the negative binomial distribution was used to account for overdispersion and three outliers were removed from the model.

After adjusting for seasonal trends, all El Niño events were not significantly associated with rates of reported *Salmonella* infection (Table 14). Weak El Niño events were associated with a 21% (9% CI: 0.968, 1.51) higher incidence rate of reported *Salmonella* infections and this association approaches significance (*p*=0.0947). Weak La Niña events were associated with a 33.4% (95% CI: 0.457, 0.969) lower incidence rate of reported *Salmonella* infections, relative to neutral events and adjusting for seasonal trends. Strong La Niña events were associated with a 41% (95% CI: 0.476, 0.731) lower incidence rate of reported *Salmonella* infections, relative to neutral events and after adjusting for seasonal trends.

Table 14: Poisson Regression using negative binomial of the count of reported *Campylobacter* cases by month the mean monthly maximum temperature, quintile precipitation, and categorical ENSO. Rates and 95% confidence limits are shown. Reported rates take into account all other meteorological variables and have been adjusted for seasonal trends (RR not shown).

Variable	**Rate Ratios (95% CI)**	***p*-values**
ENSO		
0-Neutral-Neutral	reference	
1-El Nino-Weak	1.21 (0.968, 1.51)	0.0947
2-El Nino-Mod	1.08 (0.976, 1.33)	0.4743
3-El Nino-Strong		
4-La Nina-Weak	0.666 (0.457, 0.969)	0.0341
5 La Nina-Mod	1.11 (0.957, 1.29)	0.1657
6 La Nina-Strong	0.59 (0.476, 0.731)	<0.0001

Chapter 4—Discussion

Temperature and precipitation

Our analyses demonstrate that increased temperatures ere associated with higher rates of both reported *Campylobacter* and *Salmonella* infections in Oregon. In univariate (unadjusted) analysis, the strength of association varied by the type of measure, with mean monthly minimum showing the strongest with higher incidence rates of both reported *Campylobacter* and *Salmonella* infections. However, in multivariate analyses, the mean monthly minimum temperature was not the best predictor for any models and was not used in the final model. Rather, we found that the highest recorded monthly maximum, the mean monthly maximum, the highest recorded monthly minimum were the better predictors and therefore were chosen to enter the full models.

When adjusting for seasonal trends, the temperature variable dropped out of the model for all analysis but the reported *Campylobacter* cases aggregated on the regional level. This suggests that the observed association was strongly explained by seasonal trends, and the association with temperature was not significantly stronger than seasonal trends. This is not surprising since the peak activity for both reported *Campylobacter* and *Salmonella* infections consistently occur in July, which was also the highest monthly maximum and minimum temperature (Fig. 6, Fig. 7).

Increased precipitation was inversely associated with the rate of reported *Campylobacter* and *Salmonella* infections in unadjusted models. We found monotonically lower rates of these enteric diseases in all models with the categorical precipitation variable with levels defined by quintiles (Tables 7, 9, 11, 13). The highest quintile of precipitation (> 55mm precipitation per month) was most strongly associated with lower incidence rates, with the strongest association of 39.6% (95% CI: 45.3%, 23.7%) lower incidence observed for reported *Salmonella* infections aggregated at the county level. Precipitation was found to be a better predictor than snow depth (mm).

For all models except for *Campylobacter* aggregated on the regional level, the precipitation variable was not significant when the two variables that adjust for seasonal trends were added. This suggests that the association with precipitation was not stronger than the seasonal trend. Both the inverse association and the seasonality can be explained by the climate of Oregon. For much of the state, the summer is hot and dry, and the winter is wet and mild. The monthly peak incidence for reported *Campylobacter* and *Salmonella* infections occurs in the summer when it almost never rains (Fig. 6, Fig. 7). As the number of cases rise in the late spring, the amount of rainfall drastically decreases. When it rains the most, we see the lowest number of reported *Campylobacter* and *Salmonella* cases. Thus, the association seen between precipitation and reported *Campylobacter* and *Salmonella* cases can be explained by the seasonal climate patterns of Oregon.

Our quantification of the relationship between temperature and the rate of reported *Campylobacter* and *Salmonella* infections are similar to other studies and slightly lower than those of other studies. Kovats et al (2004) reported a 5-10% increase in *Salmonella* infections per one degree increase in average weekly temperatures above a threshold after adjusting for seasonal trends as compared to 3% in our analysis. D'souza et al (2004) also demonstrated a positive association between the mean temperature and the mean *Salmonella* infections in five cities in Australia. They found that a one degree ^{o}C increase in the mean temperature was associated with a 10% increase in the proportion of salmonellosis in Brisbane, 6% in Sydney, 5% in Melbourne and Adelaide, and 4% in Perth. However, the D'souza et al (2004) study was conducted for all reported *Salmonella* infections including all outbreak-related cases while our study considered only sporadic cases. Other studies have also reported an association between temperature and the rate of reported *Campylobacter* infections. Fleury et al (2006) reported that for every degree increase in weekly temperature above the threshold of -10 C, the log relative risk of *Campylobacter* increased by 2.2% after controlling for seasonal trends. Tam et al (2006) also found that a 1°C rise in temperature is associated with a 5% increase in the number of reported *Campylobacter* after adjusting for seasonality, holidays, and relative humidity. This study determined a maximum of 2.9% increase in the rate of reported *Campylobacter* associated with each unit increase in the mean minimum temperature. Similar to our findings, prior studies have shown that precipitation is also associated with *Campylobacter* infections. One Danish study reported that precipitation explained 6% of the variation in the incidence in *Campylobacter* (Patrick et al, 2004). Additionally, a separate study also reported that precipitation explained less than 10% of the variation in the incidence of *Campylobacter* infections in Georgia (Weisant et al, 2012).

The previously published studies examining the weather variables and incidence of *Campylobacter* and *Salmonella* illness have relied upon the mean weekly ambient air temperature as the metric representing temperature, while our analysis included six temperature variables. We demonstrated that the mean monthly minimum temperature was most strongly associated with the rate of reported disease in Oregon, suggesting that increases in temperatures over sustained period of week to weeks increase the risk of these enteric illnesses, possibly due to food handling and storage mechanism.

Temperature strongly affects the growth of both *Campylobacter* and *Salmonella*. *Salmonella* bacteria grow well at a temperature from 20 ^{o}C to 40 ^{o}C (68-104 ^{o}F) on a solid culture media (Stokes & Bayne, 1957). *Campylobacter* is able to grow at temperatures ranging from 30 to 47 ^{o}C (86 to 116.6 ^{o}F) with optimal growth at 42^{o}C (Stintzi, 2003). It is plausible that not only the temperature of the host but also ambient air temperature could play a role in the proliferation of these bacteria. As ambient temperature increases, proliferation of these bacteria is expected to increase. Decreased temperature, especially below the optimal growth range of these two bacteria, would be expected to suppress growth and proliferation. This association between the growth of these bacteria and temperature could explain the seasonal effects observed. As ambient air temperature increases in the late spring, we see higher incidence of reported *Campylobacter* and *Salmonella* infections in Oregon.

We observed a strong association between the rate of reported *Campylobacter* and *Salmonella* infections and the mean monthly minimum temperature. Because the daily minimum temperature is increasing faster than the daily maximum temperature (Mote, 2003), this climate change trend has implicated for population health. In the future, nights in Oregon may not be able to retard proliferation of *Campylobacter* and *Salmonella.* In addition to colder temperatures in the winter, the amount of rainfall may also limit the proliferability of *Campylobacter* and *Salmonella.* This would explain why we seasonally see a decrease in reported cases in the winter and why precipitation is inversely associated with disease. Floods and droughts are thought to be associated with increased risk of diarrheal disease, though much of the evidence is anecdotal (Hales et al, 2014). It is biologically plausible that heavy rainfall can cause increased risk of diarrheal disease because the rainfall can wash contaminants into water supplies and fields. Additionally, periods of drought may concentrate bacterial loads, which would increase the risk of disease. The rain during the winter months in Oregon is consistent from October-April, but these rainfalls are not prolonged periods of heavy rain. Instead, the rainfalls can range from a light drizzle (lovingly called "Portland Mist") to some days of heavy rainfall. Until recently, floods only occurred one in four years in the Willamette Valley (WRCC, 2014). The lack of floods in the winter months could explain why we do not see an increased rate of reported *Campylobacter* and *Salmonella* illnesses during the wet winter months.

El Niño/Southern Oscillation

El Niño events are associated with an increased rate of reported *Campylobacter* and *Salmonella* infections in Oregon, while La Niña events are inversely associated with the rate of reported *Campylobacter* and *Salmonella* infections in Oregon. This opposing effect was observed for both *Campylobacter* and *Salmonella* models aggregated on the county and the regional levels. For all models, the strongest association observed for weak El Niño events and the strongest inverse association was observed for weak La Niña events. Moderate El Niño and moderate La Niña events were not significantly associated with the rate of reported *Campylobacter* and *Salmonella* infections except for *Campylobacter* aggregated at the regional level. Strong La Niña events were inversely associated with the rate of reported *Campylobacter* and *Salmonella* infections. The association between ENSO events and the rate of reported *Campylobacter* and *Salmonella* infections remained even after adjusting for seasonal trends for all models. This indicates that the association between ENSO events and the rate of reported *Campylobacter* and *Salmonella* infections is above seasonal trends.

The climate of the PNW can vary dramatically during ENSO events. El Niño events can cause winter temperatures to be ~0.7 to 2.7 ^{o}F warmer than La Niña events (CIG, 2013). El Niño events are also known to be drier than La Niña events and winters have on average 14% less precipitation during El Niño events than La Niña events (CIG, 2013). Although the weak-moderate-strong categorization of the ENSO events seems as though the strong El Niño and strong La Niña events have the greatest effect on Oregon's climate, this is not the case. The categorization of ENSO events is for the strength of sea surface temperature warming or cooling in the Pacific Ocean. This study shows that the most extreme changes in Oregon's climate occur during moderate El Niño and moderate La Niña events (Table 6). This study established an association between increased temperature and increased rate of reported *Campylobacter* and *Salmonella* illnesses. This study has also established an inverse association between precipitation amounts and the rate of reported *Campylobacter* and *Salmonella* illnesses. These associations concur with the rate of reported *Campylobacter* and *Salmonella* illnesses and the changes in climate during ENSO events. We see that El Niño events (hotter and drier climate) are associated with increased rate of reported *Campylobacter* and *Salmonella* illness and La Niña events (wetter and colder climate) are associated with a decrease rate of reported *Campylobacter* and *Salmonella* illnesses.

To date, there has not been much research on the association of ENSO events and the incidence of foodborne illnesses. Much research has been completed on the association of ENSO events and waterborne and vector borne diseases, such as cholera, dengue fever, and malaria. One study showed a two-fold rate in hospital administrations due to diarrheal disease in Peruvian children during a strong El Niño event (Hall et al, 2002). Although there has not been much research that shows the association between ENSO events and foodborne illnesses, it is biologically plausible that ENSO events are associated with the rate of reported *Campylobacter* and *Salmonella* infections.

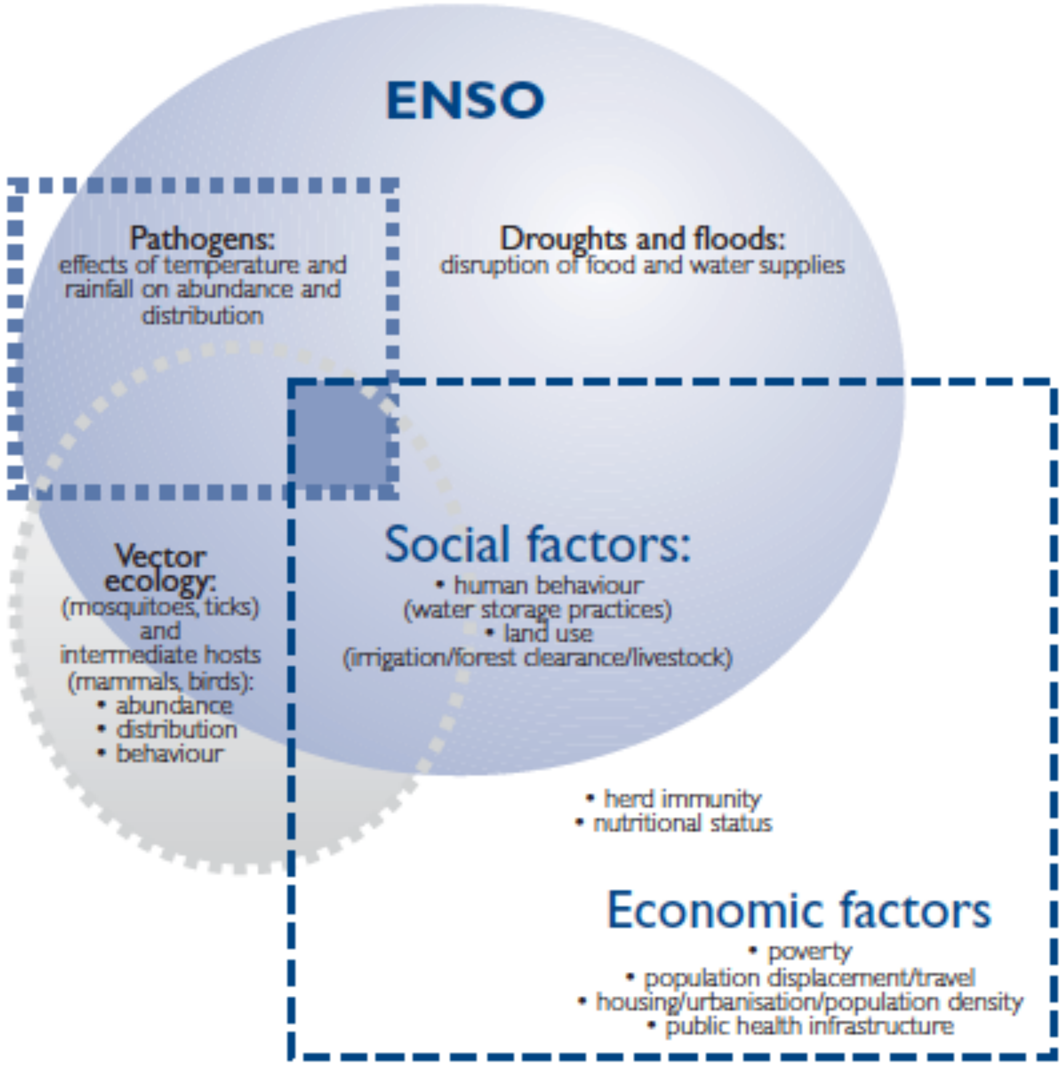

Figure 10. ENSO events can cause physical effects (blue circle). The overlap and interaction between suitable ecological and socioeconomic conditions (within dotted lines) may cause disease outbreaks (dark shaded area). Image from *http://www.who.int/globalchange/publications/climatechangechap5.pdf* accessed 09/03/2014

It is important to remember that a range of physical, ecological, biological, and social mechanisms can explain the association between climate and disease (Fig. 10). Our analysis included environmental factors and biological factors that are routinely monitored and accessible. We were not able to consider other demographic and behavior factors that could cause disease and confound or modify this complex relationship. For example, the warmer and drier weather associated with El Niño can cause the population to host more potlucks or barbeques, or poor food handling practices, which could lead to increased opportunity for proliferation of bacteria and infection. The biological properties of these bacteria, especially the direct effects of temperature and rainfall on the growth and proliferation can further explain the association between reported *Campylobacter* and *Salmonella* infections and the climate of Oregon.

Strengths and Limitations

There were a number of strengths and some limitations to this study. This study only uses cases of *Salmonella* and *Campylobacter* that were reported to the state public health department. Only those that have health insurance or can afford to the visit the doctor are tested for foodborne illnesses. Thus, this sample is biased towards those that are able to visit a doctor and are able to submit a sample. Additionally, many others do not visit their doctor if they have diarrhea. Thus, State's surveillance system captures cases with disease severe enough to visit a physician.

Another potential limitation that arises in this analysis is that the onset date may not be accurate. Onset date is self-reported information that the case provides during the interview with the county health nurse. Although most cases are aware of their day of onset, there are instances where the day of onset is vague. These cases usually have a chronic diarrheal condition. To reduce inaccuracy associated with self-report, our analysis used the date of the first specimen collection. First specimen collection date is the date at which the case first provided a stool specimen for analysis. This date is reported to the state public health department through the reporting laboratory. Although reasonably argued to be more accurate than self-report, use of the first specimen collection is not a perfect solution, because the specimen collection date may vary from 1 day after onset to months after onset. The variance in the time between specimen collection date and onset date is a limitation to this study because cases that had earlier onset dates may be associated with the wrong exposure period. This would then associate the case with a different period of climate and a false association may be found. To circumvent this error, cases that had onset dates more than one week prior to specimen collection date were excluded from analysis.

The Oregon State Public Health database that captures foodborne illnesses not only captures cases that have had diarrheal symptoms and provided a stool sample, but also cases with foodborne illnesses that were cultured from other samples. *Salmonella* in particular, can be found in urine, cerebral spinal fluid, and even wound cultures. *Salmonella* found in non-stool samples are likely not due to food or water contamination, but more likely due to contamination from the person's own fecal matter. These non-stools sample cases also frequently do not have an onset date, and frequently have had non-diarrheal symptoms for more than one week prior to first specimen collection date. Since the onset date is ambiguous, it would be hard to pinpoint the meteorological period associated with the case. If these cases were included in the study, then the association between meteorological data and onset may be untrue. Therefore, we excluded all non-stool sample cases of *Salmonella*.

Previously published studies have evaluated the association between climatic variables and *Salmonella* infections using seasonal autoregressive integrated moving average (SARIMA) modeling methods. We were unable to apply SARIMA models due to the small number of cases in this data set limited to 10 years of Oregon data. However, we employed Poisson regression, a valid statistical method, and we controlled or seasonality using a sin and cosine function validated in other studies to control for temporal correlation. Additionally, we used GEE methods to control for correlation among counties in regions.

In our analyses, meteorological data was averaged within a region and within a county, and assumed that the temperature and precipitation is fairly homogenous across the region. The error associated with this analysis approach is believed to be small and non-differential, causing a bias towards the null.

The high quality of meteorological data is a major strength of this study. The Environmental Public Health Tracking (EPHT) Division assembled data from the National Oceanic Atmospheric Administration (NOAA), which had undergone quality assurance certifications. The EPHT used advanced GIS techniques to match meteorological data to the population center of each zip code. This ensured that the temperature data as accurate for the area with the densest population per zip code.

Future studies

Future investigators should use modeling methods that allow for adjustment of case demographics. It would be beneficial to adjust for age or even stratify by age because it is known that *Salmonella* disproportionately affects those who are young (<5 years) and the elderly. This approach would allow evaluation of the responsiveness of potentially vulnerable subgroups. Additionally, future studies should evaluate a longer time period in order to capture a broader range of ENSO conditions and a strong El Niño event. Expanding the analysis of Oregon data from 1995 to 2015 would incorporate two strong El Niño events (1997-1998, 2014-2015). The strong El Niño events may modulate the association between weak and moderate El Niño events, and in turn, is expected to influence the observed association between reported *Campylobacter* and *Salmonella* illnesses in Oregon. Lastly, future studies should strive to generate a prediction model. A prediction model would allow public health officials to prepare for periods of higher incidence of enteric infections, and provide health education programs to reduce the risk of disease to the population.

Implications for public health

Our finding may be informative to Oregon public health officials who are developing interventions to reduce food borne illnesses and who are planning public climate change adaptation policies. The results of our analysis confirm that the incidence of reported *Campylobacter* and *Salmonella* illnesses was higher in the summer season and during El Niño events. These data can be used to prevent further disease in Oregon by warning Oregonians of potential increases in foodborne illnesses related to increased temperature and El Niño events. For example, public health officials can plan to educate Oregonians on ways to prepare and store foods to decrease the risk of transmission of *Campylobacter* and *Salmonella* in late spring and before El Niño events. Additionally, public health officials can use these data for climate change adaptation policies, anticipating warmer temperatures in regions of the state and boosting food safety messages. These data provide a compelling story, one that provides local evidence that there is an association between meteorological conditions and the incidence of foodborne illnesses. In addition to prevention of foodborne illnesses, public health officials can use these data to compel Oregonians to limit their own ecological footprints by not driving as often, or converting to solar energy. After all, it is up to humans to slow down climate change and the devastating ecological effects.

Conclusion

This study determined that there was a association between meteorological variables (temperature, precipitation, and ENSO events) and the incidence of reported *Campylobacter* and *Salmonella* infections in the Oregon between 2000 and 2010. Overall, we found an opposing effect between the association of El Niño events and the rate of reported *Campylobacter* and *Salmonella* infections and La Niña events and the rate of reported *Campylobacter* and *Salmonella* infections. El Niño events were associated with an increased rate of reported *Campylobacter* and reported *Salmonella* infections while La Niña events were associated with a decreased rate of reported *Campylobacter* and reported *Salmonella* infections even after adjusting for seasonal trends. We also found that increased temperature was associated with an increased rate of both reported *Campylobacter* and *Salmonella* infections and that increased precipitation was inversely associated with the rate of both reported *Campylobacter* and *Salmonella* infections. However, these associations did not persist after adjusting for seasonal trends. The results of this study indicate that meteorological condition was associated with the rate of reported *Campylobacter* and *Salmonella* infections. We except to see further changes in the meteorological properties of Oregon, which may lead to changes in the incidence of not only *Campylobacter* and *Salmonella* infections but also other foodborne illnesses such as *Shigella* or *E. coli* as well. Additionally, public health planning should incorporate food safety interventions into climate change adaptation efforts.

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