Chapter 13

Effects of Environment and Socioeconomics on *Salmonella* Infections

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Additional information is available at the end of the chapter

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Abstract

Objectives: *Salmonella* is a major public health concern particularly in areas of low socioeconomic status (SES) and high temperature. In this chapter, we examined several socioeconomic and environmental factors that may increase the spread of *Salmonella* in the southern states of the USA.

Methods: In our recent studies, relevant US-southern states data of foodborne illnesses, from 2002 to 2011, were collected and used in various analytical models. The associations among low socioeconomic status, climatic variables and *Salmonella* infections were determined using several software packages.

Results: Our studies showed a significant increase in *Salmonella* outbreaks in Mississippi during the observed periods with regional and district variations. Regression and neural network models revealed a moderate correlation between *Salmonella* infection rates and low socioeconomic factors. A seasonal trend was observed for *Salmonella* infections. In one of our study, an increase of 1°F (0.556°C) was shown to result in four new cases of *Salmonella* infection in Mississippi.

Conclusions: Geographic location besides socioeconomic status may contribute to the high rates of *Salmonella* outbreaks. There are consistent evidence that gastrointestinal infections with bacterial pathogens are positively correlated with ambient temperature. Warming trends in the USA may further increase rates of *Salmonella* infections.

Keywords: *Salmonella* infection, socioeconomic status, climate change, global warming

1. Introduction

Salmonella is a serious foodborne pathogen with an estimated 94 million human cases of gastroenteritis and 155,000 deaths around the world each year [1]. It causes around 1.4 million human cases with 15,000 hospitalizations and more than 400 deaths in the USA annually [2].

Contaminated eggs and poultry meat are common source of human salmonellosis. Wide range of domestic and wild animals, such as poultry and swine, can act as reservoirs for *Salmonella*. Institutions such as schools and nursing homes have often been linked to *Salmonella* outbreaks with devastating effects [3].

Salmonella rates in USA fluctuate considerably by geographic regions, with particularly higher rates in the Mid-Atlantic and New England States. This variation may be partly attributed to reporting differences. Salmonellosis rates between geographically and socio-economically similar to USA have been documented with as much as 200% differences between neighbouring states [1]. Southern USA, due to its socioeconomic status (SES), climatic changes and agricultural practices, is more vulnerable to increased outbreaks of foodborne illnesses compared to other parts of the country.

Emergence or resurgence of numerous infectious diseases is strongly influenced by environmental factors, such as climate or land use change [4]. Climate, weather, topology, hydrology and other geographical characteristics of the crop-growing site may influence the magnitude and frequency of transfer of pathogenic microorganisms from environmental sources [5].

2. Geographical variation and socioeconomic status effects

Socioeconomic status (SES) is an important predictor of diseases. SES is frequently measured based on individual and community-level education, income, wealth, employment and family background when compared with other individuals or groups. Low SES is generally associated with greater morbidity and mortality of diseases [6]. Socioeconomic and demographic indicators can be used to predict the individuals and communities that are at an increased risk of acquiring infections. Generally, low socioeconomic status is an important predictor of several poor health outcomes including chronic diseases, mental illnesses and mortality.

In our previous study [7], we examined the extent of *Salmonella* infections in Mississippi and compared it with other southern states and with two referenced northern states of the USA (**Figure 1**) to determine the infections' correlation with socioeconomic status. Several analytical modelling approaches including geographical information system (GIS) and neural network (NN) were employed. Laboratory confirmed data of *Salmonella* cases, from 2002 to 2011, were collected for Mississippi, Alabama, Tennessee, Louisiana, Montana and Michigan. Southern states including Alabama, Tennessee and Louisiana were selected as neighbouring states of Mississippi, while Montana and MI were selected as reference states based on their geographical and climatic conditions. Monthly *Salmonella* outbreak cases were grouped by year and districts. Data sources for this study included the US Centers for Disease Control and

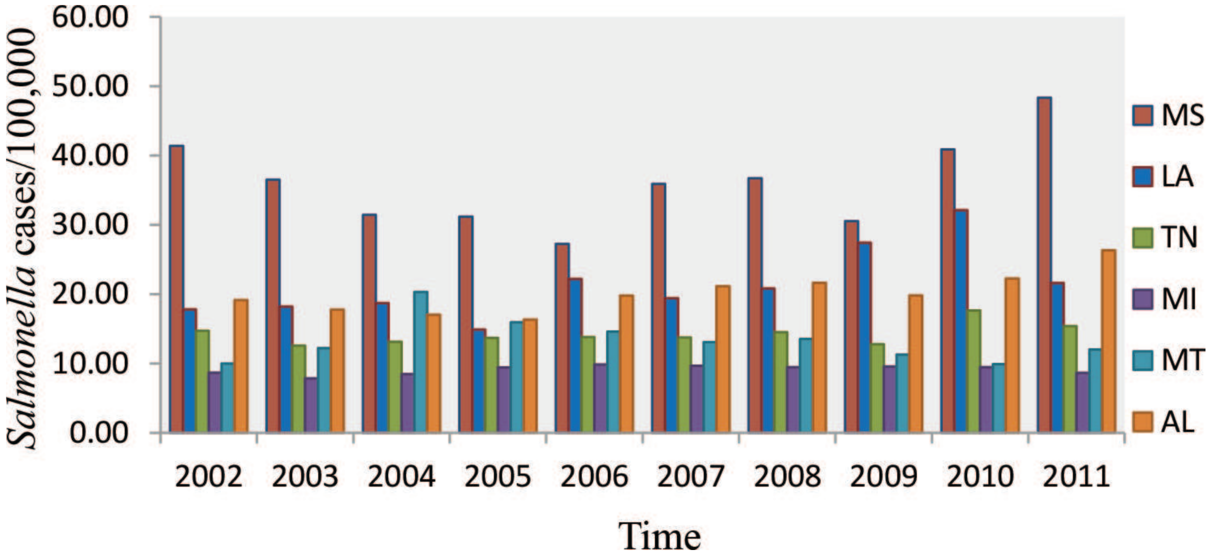

Figure 1. *Salmonella* Rates in Selected US States. MS-Mississippi; LA-Louisiana; TN-Tennessee; MI-Michigan; MT-Montana; AL-Alabama.

Prevention (CDC) and the respective States Department of health and Epidemiology [8–11]. Data were adjusted to 100,000 of population [12]. In addition to *Salmonella* infections, data for Mississippi, socioeconomic variables for its various counties, categorised by public health districts, for the year 2010–2011, were also retrieved [13]. The selected variables included poverty, uninsured, unemployment and primary care providers' rates.

Results of the study showed mostly positive correlation between low socioeconomic variables and increased rates of *Salmonella* infections; however, poverty rates were negatively correlated with *Salmonella* outbreaks.

Results of this study also revealed *Salmonella* rates in Mississippi to be twice than the average US *Salmonella* rates (36 cases/100,000 vs. 16.42 cases/100,000, respectively) [14]. Substantial regional differences in the incidence of *Salmonella* infections have also been reported previously [15]. A significant variation was observed in *Salmonella* outbreaks among the Mississippi districts through GIS mapping, regression analysis and NN models.

2.1. Poverty, education and unemployment

Underreporting of enteric infections is a critical issue in disease surveillance systems. Generally, patients with severe symptoms tend to visit the doctor and are subsequently notified to health authorities. As of 2011, almost 23% of Mississippi populations are living under poverty with average per-capita income of $32,000, although rural per-capita income lagged at $29,550, according to the USDA Economic Research Service. There are 96 hospitals in Mississippi, 163 Rural Health Clinics, and 21 Federally Qualified Health Canters that provide services at 170 sites in the state. An average of 19% of Mississippi residents lacks health insurance [12, 13].

The west-central region of Mississippi showed higher rates of *Salmonella* infections and lower poverty rates (36%), when compared to the Delta region of high poverty. However, more medical facilities are available in west-central region, resulting in higher identification and reporting of diseases. In 2011, 20% of the populations in west-central region were college graduate, with 10% unemployment rate, while only 14% of populations in Delta region were college graduate and 13% were unemployed. Lower rates of shigellosis and salmonellosis in communities with high rates of unemployment were identified. It was speculated that the reduced access to health care due to lack of employment may lead to under-detection of a disease among the unemployed individuals [16].

Geographical variations in poverty rates were also observed in different districts of the state (**Figure 2**). In the Delta region of Mississippi, the poverty rate was 44.2%. The lowest *Salmonella*

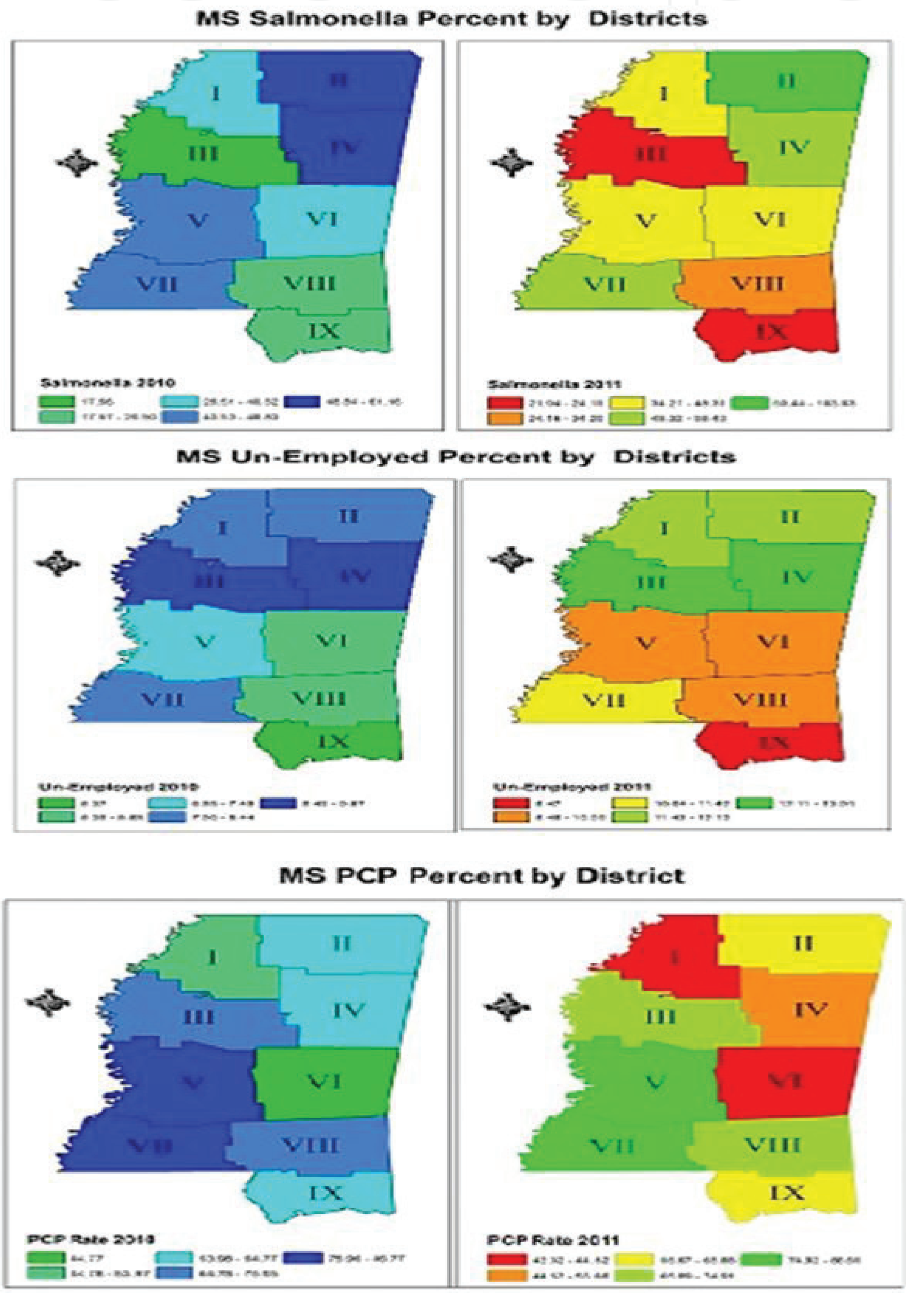

Figure 2. Geographical variations in *Salmonella* rates and socioeconomic factors in Mississippi.

rates were observed in this region as well. With high rates of poverty, many individuals cannot afford to seek medical care, which suggested underreporting of the disease.

The northern region of the state including northeast, northwest, Tombigbee and Delta district had the highest rates of unemployment. An average of 42% increase in unemployment rate was observed in the region in 2011. Primary care provider rate was the lowest in the northwest and east-central regions of Mississippi. An average of 17% decrease in primary care provider rates was observed in these regions. On the other hand, highest rates of primary care providers were found in west-central and southeast regions of the state, with 2% increase from 2010 to 2011.

Our results are different from reported individual level epidemiologic studies that had found higher levels of foodborne infections among low education and low-income groups. Studies suggested that high socioeconomic status (HSES) groups may be overrepresented in incidence statistics. It is possible that lower socioeconomic status (LSES) groups tend not to have health insurance or do not seek medical care when needed due to financial constraints. Access to health care may be an important influence on rates of reported bacterial infections. In an economy without universal health care coverage, tendency to seek care for GI infection has been associated with having health insurance [17, 18]. However, the Affordable Care Act (ACA) is expected to expand insurance coverage to millions of people in the USA. As a result, rates of reported cases of diseases and infections are expected to increase. In future projects, we will try to understand the impact of Affordable Care Act of 2010 on diseases reporting, especially among minority and LSES groups.

It is quite possible that various SES groups have different exposures because of dietary differences, or differences in food safety behaviours [8]. Behavioural studies have revealed that high SES groups are more likely to eat undercooked foods, such as raw oysters and rare beef [9, 12]; while low SES groups are less likely to have adequately cool refrigerators [4].

Other studies had similarly utilised GIS to examine the relationships between area-based socioeconomic measures and incidence of salmonellosis [18, 19]. The results showed higher incidences of salmonellosis in groups with high education compared to the less educated groups suggesting the role of education in health-seeking behaviour and the predisposition for *Salmonella* infections at the population level [19].

Neural network modelling was shown to be a useful tool in this study to predict the correlation between socioeconomic factors and *Salmonella* outbreaks. A moderate correlation between actual and network predicted output was observed at 41%, a reasonable level considering the biological system. Artificial neural networks (ANNs) are non-linear mapping structures comparable to human brain. They have been shown to be universal and highly flexible function to approximate any data. ANNs were developed initially to model biological functions [20–23]. Neural network melding has been used previously for prediction of T-Cell epitopes [24], prediction of cancer using gene expression profiling [25], temperature prediction [26], diabetes prediction [21], poultry growth modelling [27], egg price forecasting [28], in addition to predicting the relation between obesity and high blood pressure [23].

In the USA, Mississippi ranked 50th among all the states for health care, according to the Commonwealth Fund, a non-profit foundation working to advance performance of the health care system. For the past 3 years, obese populations were accounted for more than 30% of Mississippi's residents and 22.8 % of the state's children. On top of obesity, Mississippi had the highest rates in the nation for high blood pressure, diabetes and adult inactivity [24].

Social and economic conditions underpin poverty and can directly or indirectly affect health status and health outcomes. Major epidemics emerge and chronic conditions cluster persist wherever poverty is widespread [5].

3. Effects of climatic variables

3.1. Temperature

Diseases associated with climate change are estimated to comprise 4.6% of all environmental risks and hazards. Climate change, in the year 2000, contributed to about 2.4% of all diarrhoea outbreaks in the world, 6% of malaria outbreaks in certain developing countries and 7% of the episodes of dengue fever in some industrial countries. In total, the estimates showed that climate change related mortalities were 0.3%, whereas the related burden of disease was 0.4% [29].

Global average temperature, from 1906 to 2005, has warmed by 0.74°C; and since 1961, sea level has risen on average by 2 mm per year. On the other hand, Arctic sea ice has declined by 7.4% per decade while snow cover and glaciers have diminished in both hemispheres [4]. The climate change rate is faster now than in any other period during the last 1000 years. According to the United Nations Intergovernmental Panel on Climate Change, average global temperatures will increase between 1.8 and 4.0°C in next 90 years along with sea level rise of 18–59 cm [30, 31].

Changes in expected weather patterns can lead to the transfer of microbial contaminants to leafy vegetables and herbs. Dry periods can cause dust storms that settle dust particles on leafy vegetables. The rate of microbial growth was shown to increase with rise in temperature. It influences the population of insects and pests found in and around farms that transfer human pathogens to leafy vegetables as well. Relative humidity has been shown to have an effect on survival of human pathogens [32]. Climate change scenarios predict a change distribution of infectious diseases with warming temperature and changes in outbreaks associated with weather extremes, such as flooding and droughts.

Several infectious agents, vector organisms, non-human reservoir species, and rate of pathogen replication are sensitive to climatic conditions. Both *Salmonella* and *Vibrio cholera*, for example, proliferate more rapidly at higher temperatures, *Salmonella* in animal gut and food, cholera in water. In regions where low temperature, low rainfall, or absence of vector habitat restrict transmission of vector-borne disease, climatic changes could tip the ecological balance and trigger epidemics [31]. Furthermore, strong linear associations have been noted between temperature and notifications of Salmonellosis in European countries and Australia [31]. The USA is likely to experience increases in extreme heat, extreme cold, hurricanes, floods, wildfires, droughts, tornadoes and severe storms [33]. The health impacts of global climate change are expected to be widespread, geographically myriad and profoundly influenced by pre-existing social and economic disparities [34].

The southern states, including Mississippi's climate, has been fluctuating with extreme patterns. The average temperatures in Mississippi have varied significantly over the past century, with an average of 1°F increase, since the late 1960s. Extreme rainfall events, primarily thunderstorms, have increased as well. While rainfall totals have changed little, seasonal trends are apparent, summers have become slightly drier and winters slightly wetter [33]. On an average, 29 tornadoes are reported annually in Mississippi; the highest number was in 2008 with 109 tornadoes. In addition, during the past decade, Mississippi had experienced multiple hits by hurricanes including the devastating Katrina in 2005 [33].

Global warming and the climate change have contributed to the spread of several foodborne pathogens [5, 30]. In our previous research, we determined the extent of *Salmonella* infections in Mississippi along with its correlation to climate variations [35]. Monthly data of *Salmonella* outbreaks from 2001 to 2011 were obtained from Mississippi State Department of Health and Department of Epidemiology. In addition, meteorological data, including average air temperatures, minimum and maximum, and total precipitation for the selected station across the state were collected from the Southeast Regional Climate Center, available at: http://www.sercc.com/climateinfo/monthly_seasonal.html.

Analysis of variance was performed to determine the seasonal change in *Salmonella* outbreaks during the study period. Time series analysis, including the Mann-Kendall test and a Seasonal trend test, was applied to quantify the relationships between the temperature and the number of notified cases of *Salmonella*.

Our results indicated an increase in temperature is positively correlated with *Salmonella* infections. A seasonal trend was also observed in this study with the highest outbreaks during the summer to early fall (**Figure 3**).

The positive relationship between temperature and *Salmonella* infections, observed in our study, using regression and NN models, was similar to recent findings from Australia, Europe, North America and Asia with similar trends [36–38]. Endemic regions for *Salmonella* outbreaks include developing countries in South Central and South East Asia; and many parts of Africa, Middle East and Latin America. In the same study, we found that an increase of 1°F (0.556°C) in Mississippi was shown to result in four new cases of *Salmonella* (**Figure 4**). Studies also found that weekly counts of enteric bacterial disease cases generally increased with weekly temperature after adjusting for seasonal and long-term trends [37, 39]. Another study [40] had suggested that a potential 1°C rise in mean weekly maximum temperature may be associated with an 8.8% increase in the weekly number of cases, and a 1°C rise in mean weekly minimum temperature may lead to a 5.8% increase in the weekly number of cases.

The US-southern states climate is generally warm and wet, with mild and humid winters. The average annual temperatures in the region have increased by about 2°F since 1970, and the average annual temperatures in the region are projected to increase by 4 to 9°F by 2080 [41].

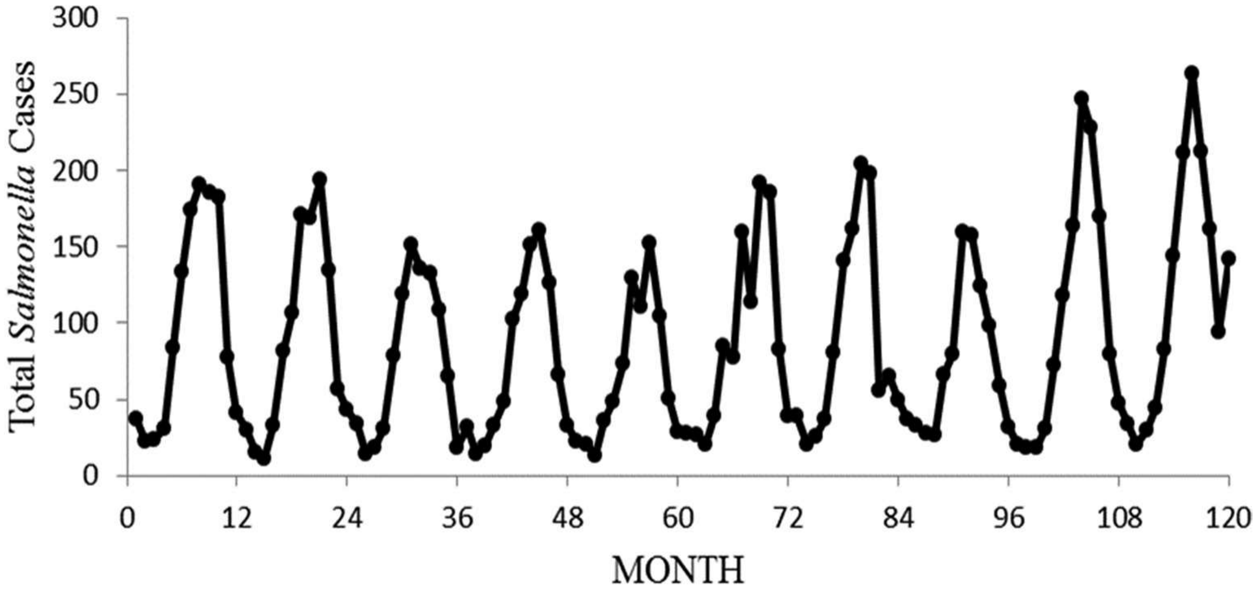

Figure 3. Seasonal trend in *Salmonella* cases.

Climate change and extreme events may increase the spread of foodborne diseases in this region, particularly in the disadvantaged states, such as Mississippi.

Increased growth *of Salmonella* at higher temperatures leads to higher concentration of *Salmonella* in the food supply, particularly during the warmer months. Poor cooking practices are also more common during these summer months (picnics, barbecues, etc.). Temperature

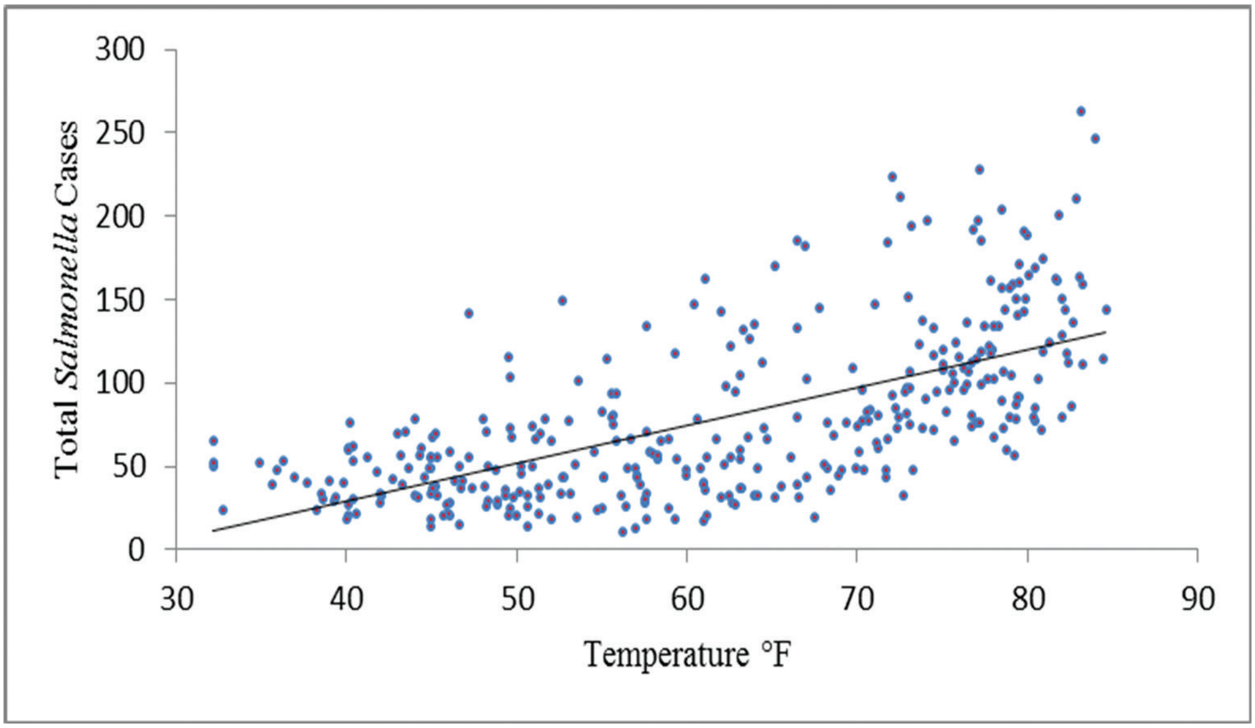

Figure 4. Correlation between *Salmonella* outbreaks and increase in temperature.

may affect the transmission of *Salmonella* infections via several causal pathways, such as direct effects on bacterial proliferation and indirect effects on eating habits during hot days. The optimum temperature for the growth of *Salmonellae* is between 35 and 37°C. The growth is greatly decreased at less than 15°C. Ambient temperature influences the development of *Salmonella* at various stages in the food chain, including bacterial loads on raw food production, transport and inappropriate storage [37, 42].

Studies showed that an increase in the ambient temperature correlated positively with an increase in human *Salmonella* with a delay of approximately five weeks. *Salmonella* has the ability to multiply itself within 20 min at ambient temperatures; this growth rate however, is increased at 30°C or higher temperature. Additionally, cross-contamination and undercooking of meat during barbecuing is more likely to occur during summer months [43].

There is consistent evidence that gastrointestinal infection with bacterial pathogens is positively correlated with ambient temperature, as warmer temperatures enable rapid replications of pathogens. *Salmonella* notifications peak in summer and the rate of notifications has been shown to be positively and linearly correlated with the mean temperature of the previous month or week [44, 45]. Some of this increase in summer months may be due to changed eating behaviours (more 'eating out' while on holidays and attending outdoor functions such as barbecues). Ambient temperatures contribute directly to pathogen multiplication in foods and thus the likelihood of infection. Furthermore, it was noted that enteric diseases in temperate latitudes have a seasonal pattern, with the highest incidence of illnesses during the summer months. A study of foodborne illnesses in the UK found a relationship between the incidence of disease and the temperature in the month preceding the illness [46]. It is believed that the survival and growth of certain enteric pathogens are, within limits, positively correlated with ambient temperature [39].

Rates of *Salmonella* are expected to increase in the future as climate change causes ambient temperatures to rise above the average, contributing to around 1000 extra cases annually. This links to an annual difference of approximately 1200 lost workdays and $120,000 in the cost of health care and surveillance by 2050 [44]. By considering a suite of future climate scenarios, the UN-Intergovernmental Panel on Climate Change projected global surface temperature increases between 1.1 and 6.4°C over the next century. Studies had shown that the main health risks caused by climate change include health impacts of weather disasters, health impacts of temperature extremes, including heat waves, mosquito-borne infectious diseases, foodborne infectious diseases (including those due to *Salmonella, Campylobacter* and many other microbes), water-borne infectious diseases and other health risks from poor water quality. In addition, diminished food availability, costs/affordability, nutritional consequences, and increases in urban air pollution are also reported as health risks from climate change [44, 47, 48].

Higher ambient temperatures are main concerns on farm and during food processing and should be considered as an early warning for increased numbers of foodborne infections with 4–6-week lag time. Heightened surveillance during such times may act as a mitigation and enhance the preventive measures. Proper hygiene during slaughter, processing, wholesale and retail sale should be carefully implemented and monitored for further safeguards.

More importantly, active consumer education through mass media and other sources regarding the potential danger of consuming contaminated food with *Salmonella* or *Campylobacter*, especially during the summer months should be properly disseminated to mitigate the increased infection rates of *Salmonella*.

3.2. Precipitation effect

In our previous study [35], no correlation between monthly average precipitation rate and *Salmonella* was observed. A better association with *Salmonella* outbreaks was noted in studies using daily or weekly rates of precipitation. Other studies, however, indicated that maximum and minimum temperatures, relative humidity and rainfall were positively correlated with the number of cases of *Salmonella* with a lag time of 2–8 weeks. It was reported that rainfall, especially heavy rainfall events, may affect the frequency and level of contamination of drinking water, and consequently enteric infection. A strong association between drinking water quality, precipitation and gastroenteritis was reported [49].

A study by Jiang *et al*. [50] suggested that extreme temperature and precipitation events are associated with salmonellosis. It was shown that the frequency and intensity of such extreme events are increasing and will continue to do so in the coming decades as a result of changing climate [50]. The influence of precipitation on salmonellosis is not always immediate but most often delayed by 2–4 weeks [51]. Precipitation likely increases salmonellosis incidence shortly after a rainfall event by increasing pathogen loads in household rainwater tanks through runoff. The delayed effect of rainfall on salmonellosis is also likely to be through increased pathogen loads in surface water which is then used to irrigate or process fresh produce that later may be consumed raw [51].

Climatic changes impact the emergence or re-emergence of infectious disease agents. There are some general principles of pathogen emergence, which are associated with changes in ecology and agriculture, technology and industry, globalization, human behaviour and demographics, epidemiological surveillance and microbial adaptation [52, 53]. It is important to recognise that pathogen emergence usually occurs as a consequence of a combination of two or more specific factors [54].

4. Modelling approaches

4.1. Regression analysis

Multiple regression analysis were carried out to test the relationship between *Salmonella* rates and socioeconomic factors, including poverty, uninsured, unemployment and primary care providers' rates. Socioeconomic factors were used as classification variables and *Salmonella* infection rate as a response variable. Regression analysis was also performed for climate factors, where temperature and precipitation were used as independent (classification) variables and *Salmonella* outbreaks as dependent (response) variable.

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4.2. Neural network modelling of *Salmonella* and temperature

Neural network models for temperature effects on *Salmonella* outbreaks were developed using @RISK and NeuroShell2 software packages. NeuroShell2 is a program that mimics the human brain's ability to classify patterns or to make predictions or decisions based upon past experience. The network is exposed to the problem being predicted or classified, and the software will 'learn' the patterns from training data and will make its own classifications, predictions or decisions when presented with new data. NN models are particularly useful when there are implicit interactions and complex relationships in the data.

Over the last few years, artificial neural networks, as nonlinear modelling techniques, had been proposed for use in predictive microbiology [55–61]. In our study, two neural network models, General Regression Neural Network (GRNN) model and Polynomial Net model, were used to predict the effects of temperature on *Salmonella* outbreaks in Mississippi. Several architectures of neural network models were developed to establish the best fitting models. Both of the reported models showed a significant correlation between temperature and *Salmonella* outbreak. GRNN model and Monte Carlo simulation for predicting survival and growth of *Salmonella* on raw chicken skin, as a function of serotype, temperature and time, were used in previous studies as well [62].

Monthly data for temperature and *Salmonella* data in Mississippi from 2001 to 2011 were used to build these models. Temperature was used as an input while *Salmonella* outbreaks as output variables (**Figure 5**). A General Regression Neural Network Model and Polynomial Net Models were selected from the software design architecture. Twenty per cent of the data were extracted for testing, and 80% were used for training the NN models. A test data file was applied to previously saved trained NN models and outputs were generated. Results were exported to Excel, and graphs were created to show the association between actual data and the predicted model.

Salmonella outbreaks and socioeconomic data for Mississippi districts were used for NN models. Mean and Standard deviation were calculated for each variable, including *Salmonella*, poverty, uninsured and unemployment and primary care providers' rates. Those means and SD were subsequently used to generate data with 500 iterations using @RISK in Risk Normal distribution. The simulated data were then used as training examples for the NN models, while the original data were used for testing with NeuroShell2 software.

Advanced NNs were selected and the simulated data files were imported. The network was built by defining input variables as poverty, uninsured, unemployment and primary care providers' rates, while *Salmonella* outbreaks as output. A General Regression Neural Network (GRNN) model was selected from the software design architecture. This model was trained with the simulated data. The test file containing the original data was imported to the system and applied to previously saved trained NN models. Results were exported to Excel where graphs were created to show the association between actual data and the predicted model.

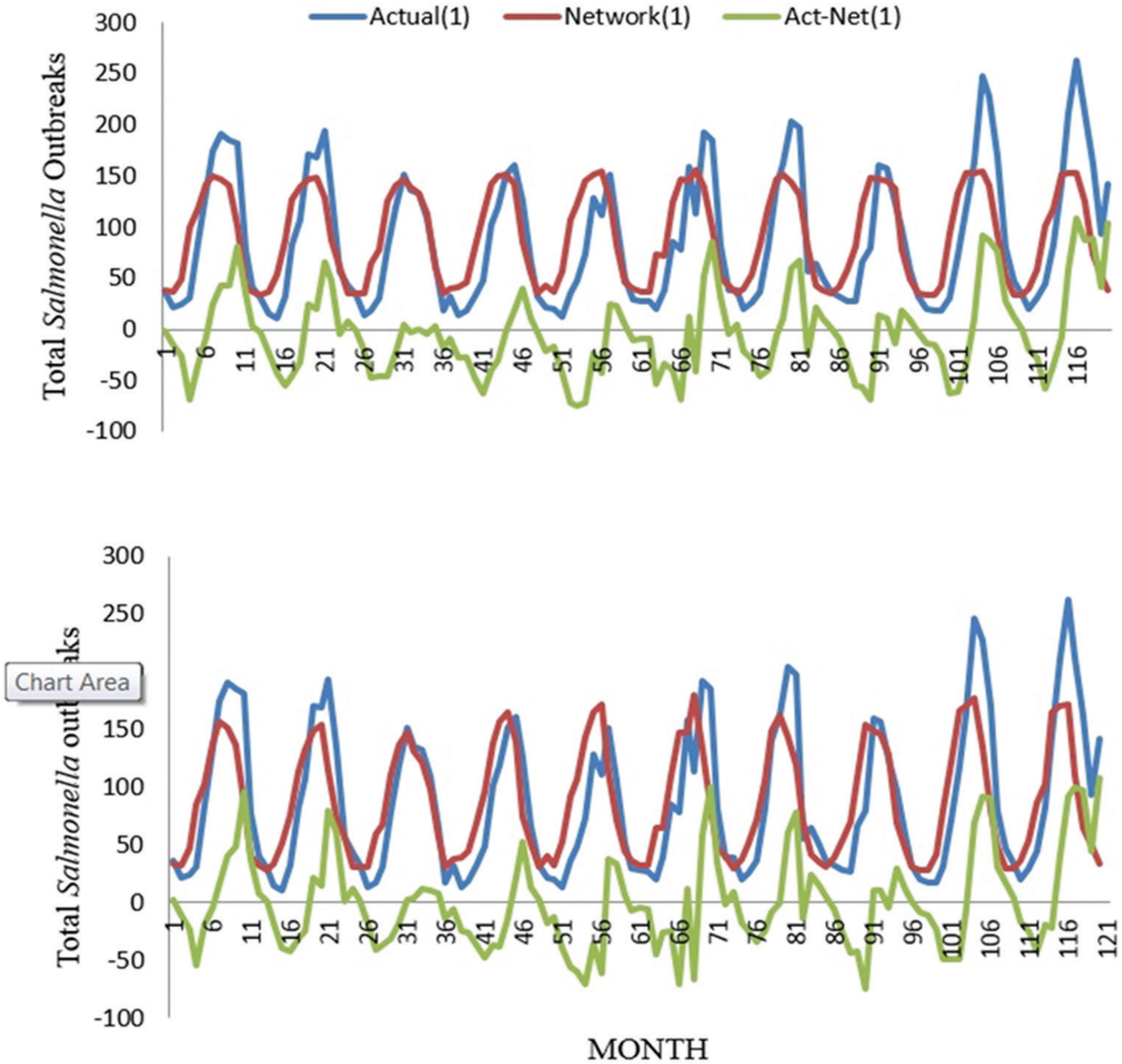

Figure 5. Neural network models for *Salmonella* and temperature correlation.

4.3. GIS mapping

A GIS incorporates hardware, software and data for capturing, managing, analysing and displaying all forms of geographically referenced information.

Study area for GIS map: Mississippi (32.9906° N, 89.5261° W) is located in the southern USA. It is bordered by TN on the north, Gulf of Mexico on the south, AL on the east and Arkansas and LA on the west. It covers a total area of 47,689 square miles. GIS allows for the integration and analysis of geographic data, such as coordinates and area perimeters, and tabular data (i.e., attributes of geographic data points). Data are imported into mapping software in layers, where each layer represents a different visual component of the map. Shape files are layers which provide visual output of coordinates and area perimeters on the map.

Mississippi counties' data were grouped by public health districts. Background map was obtained from ESRI ArcGIS online resources. Maps' layers for *Salmonella*, unemployment and primary care providers' rates were created for the years 2010 and 2011, to visually analyse areas with higher disease rates and socioeconomic status (**Figure 2**).

5. Conclusions

Human foodborne illnesses are significant public health concerns. Socioeconomic status and climate changes contribute to the increased rates of *Salmonella*. A significant correlation between increase in outbreaks of *Salmonella* and the lower socioeconomic status was observed in several studies. Understanding the geographical and economic relation with infectious diseases will help to determine effective methods to reduce outbreaks within these communities. Climate changes in the USA are likely to increase the severity, frequency, timing and duration of extreme weather events, which consecutively will increase the associated health risks. The transmission of *Salmonella* to humans is a complex ecological process; warmer temperatures in combination with differences in eating pattern, may contribute to enteric infections.

Modelling approaches, such as neural network were shown to be a useful tool to model and predict outbreaks. Neural network models accounting for non-linearity may predict better association than regression models. Geographical information system mapping was also shown to be a very useful instrument to map and visualise the areas and districts of highest *Salmonella* outbreaks in addition to socioeconomic status.

Regression and neural network models were used to determine the correlation between increase in temperature and increase in *Salmonella* outbreaks. Considering the seasonal variation, neural network models turned out to be better predictor models.

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