Too Hot, Too Wet: Bayesian Spatial Modelling of Climate-Driven Salmonella Risk in New South Wales, Australia, 1991–2022

Oyelola A. Adegboye[1,2]*†, Tehan Amarasena [2]†, Mohammad Afzal Khan[3]†, Hassan Ajulo[2], Anton Pak[4], David Taniar[3]Theophilus I. Emeto[2]

[1]Menzies School of Health Research, Darwin, Charles Darwin University, NT, Australia
[2]Public Health and Tropical Medicine, College of Medicine and Dentistry, James Cook University, Townsville, QLD 4811, Australia
[3]Faculty of Information Technology, Monash University, Melbourne, Australia
[4]Centre for the Business and Economics of Health, The University of Queensland, Brisbane, Queensland, Australia

Key Points:

- High temperatures consistently increased *Salmonella* risk across all LHDs in NSW.
- A J-shaped relationship was observed for all climate variables.
- Inland and rural regions experienced more dramatic risk increases.
- Flooding and humidity were also associated with elevated *Salmonella* risk, especially in coastal and arid regions.
- Spatial modelling revealed significant geographic variation.

Corresponding author: Oyelola Adegboye, `oyelola.adegboye@menzies.edu.au`

Abstract

Salmonella infections contribute significantly to gastrointestinal-related hospitalisations in Australia and remain a major global public health concern. While seasonal patterns in *Salmonella* incidence have been documented globally, there is limited evidence on the influence of climatic factors, particularly rainfall, humidity, flooding, and temperature, in the Australian context. This study investigated the relationship between climatic extremes and *Salmonella*infections across Local Health Districts (LHDs) in New South Wales (NSW), Australia, using a Spatial Bayesian Distributed Lag Non-Linear Model (SP-DLNM). Spatial modelling revealed marked geographical heterogeneity in climate-related *Salmonella* risk across NSW. High ambient temperatures consistently increased the risk across LHDs (relative risk (RR)¿1), while the effects of rainfall and flooding varied by region. A distinct J-shaped relationship was observed for all variables, with the lower risk at cooler/drier extremes and highest during extremes of heat and moisture. In the Far West, the risk of *Salmonella* was markedly higher during extreme heat compared to colder conditions. In contrast, in the Murrumbidgee region, the likelihood of *Salmonella* cases rose substantially during periods of intense rainfall compared to dry conditions. These findings have important public health implications that extend beyond NSW, highlighting the need for broader national and global preparedness in the context of a changing climate.

Keywords: *Salmonella*, Foodborne disease, Climate variability, Environmental drivers, Climate change and health, Spatial Bayesian

Plain Language Summary

Salmonella is a major cause of stomach illness and hospitalisation. This study investigated the impact of temperature, rainfall, and flooding on Salmonella infections in New South Wales (NSW), Australia. It found that warmer temperatures and heavier rainfall were associated with a higher incidence of cases, particularly in urban areas. The strongest link was with warmer night-time temperatures. These results suggest that climate change may increase the risk of *Salmonella*, highlighting the need for improved public health planning in response to extreme weather events.

1 Background

Salmonellosis, the infection caused by *Salmonella* bacteria, contributes significantly to the global burden of disease, with an age-standardised mortality rate of 3 per 100,000 population (Ikuta et al., 2022). Transmission occurs by consuming contaminated food (e.g., undercooked meat, eggs, dairy, raw fruits and vegetables), drinking contaminated water, coming into contact with infected persons' faeces or infected animals (e.g. cattle, chickens, rodents, tropical fish and reptiles) (NSW Health, 2024; World Health Organization, 2018). The incubation period can vary from 6 hours to 72 hours, and individuals are considered infectious while their stools test positive for *Salmonella* (NSW Health, 2024; World Health Organization, 2018). A person can potentially be infectious for days to weeks after acquiring the infection (NSW Health, 2024). In developed countries such as Australia, it is usually less likely to be fatal, typically manifesting as an acute gastroenteritis (Darby & Sheorey, 2008). However, it can spread rapidly and still cause severe illness, particularly in vulnerable populations with underlying health conditions. In 2015, *Salmonella* was associated with an estimated 3013 hospitalisations and 13 deaths, resulting in a societal cost of over $100 million (Akil et al., 2014).

Salmonella, a leading cause of food-borne gastroenteritis and sepsis, has been associated with a rising incidence of foodborne illness in Australia (Ford et al., 2016; Ratnayake et al., 2024). National Notifiable Diseases Surveillance System (NNDSS) data show that notifications almost doubled from 9,058 cases in 2009 to a peak of 18,044 in 2016, before falling sharply during the COVID-19 period to 10,129 in 2022 and rebounding modestly to 11,205 in 2023 (Australian Government Department of Health and Aged Care, 2024). The pattern in New South Wales (NSW) mirrors the national trend: notifications climbed from 2,651 in 2009 to 4,519 in 2016 and have since declined by about one-third, stabilising at about 3,031 cases in 2023 (Australian Government Department of Health and Aged Care, 2024). Despite this recent decrease in notifications, current counts remain higher than a decade ago, underscoring the continuing burden.

A growing international literature demonstrates that *Salmonella* transmission is climate-sensitive, exhibiting seasonal variation (Tack et al., 2021; Thindwa et al., 2019; Morgado et al., 2021; Akil et al., 2014; Manchal et al., 2024). Time-series studies in the Democratic Republic of Congo and Malawi have linked heavy rainfall and elevated ambient temperature, respectively, to surges in invasive non-typhoidal *Salmonella* (Tack et al., 2021; Thindwa et al., 2019), while warmer, wetter months are associated with faster bacterial replication and increased case counts, particularly in the southern United States (Akil et al., 2014).

Australian evidence, though sparse, points in the same direction. In Adelaide, a 1°C increment in warm-season temperature increased notifications by 1–4 % (Milazzo et al., 2016), and a national study covering 1991–2019 found that a 1°C rise in mean monthly temperature anomaly was associated with a 3.4 % increase in cases, with El Niño periods elevating risk in NSW and Queensland (Davis et al., 2022). NSW is highly exposed to hydrometeorological hazards such as floods, bushfires, cyclones and hailstorms, which cost the state an estimated $5.1 billion in 2020–21 and are projected to escalate under climate-change scenarios (Treasury, 2021).

However, the combined influence of rainfall, temperature, humidity and discrete flood events has not been examined at finer spatial scales, and no study has systematically assessed these drivers across NSW Local Health Districts (LHDs). Therefore, this study aims to evaluate the influence of key meteorological factors, including temperature, rainfall, and discrete flood events, on the incidence of *Salmonella* infections across NSW, Australia. Building on limited but consistent national evidence linking temperature with enteric disease, this study addresses a critical gap by integrating multiple exposures to climate and examining their effects at the LHD level. By employing spatial and temporal data, the study seeks to identify geographic disparities in climate-related enteric risk and to assess whether metropolitan and regional LHDs exhibit differential vulnerability. Ultimately, the findings aim to inform climate-resilient food safety policies, strengthen early-warning surveillance systems, and provide a scalable framework for enteric disease preparedness in the face of escalating hydrometeorological hazards under future climate change scenarios.

2 Materials and Methods

2.1 Study area and data sources

NSW is one of eight Australian states and territories, with LHDs categorised into six metropolitan and nine rural/regional districts (Figure 1).

2.1.1 Health data

Monthly non-identifiable notifications of *Salmonella* cases from 1991 to 2022 were obtained from the NSW Health Notifiable Conditions Information Management System (NCIMS), via the Communicable Diseases Branch and the Centre for Epidemiology and Evidence. These data were aggregated by LHD and used to calculate monthly incidence rates. LHD population data were sourced from the NSW Department of Planning (NSW Department of Planning, Housing and Infrastructure, 2024). For years before 2001, historical population estimates were retrospectively calculated using the department's earliest available annual growth rates (from 2002), applied separately for each LHD.

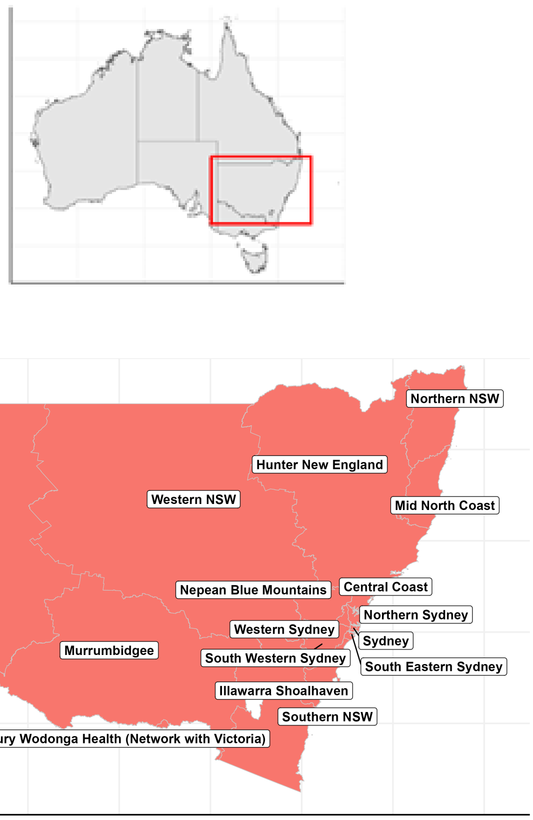

Figure 1: Map of Australia and the study area.

2.1.2 Meteorological data

Meteorological and hydrological data were extracted from the Australian Bureau of Meteorology at the weather station level, including mean temperature (°C), mean maximum temperature (°C), mean minimum temperature (°C), daily total rainfall (mm) and streamflow (ML/day)for the years 1991 to 2022 (Zippenfenig, 2024). Monthly Flood wave events were defined as the number of days with river discharge/streamflow exceeding the 95th percentile of the distribution. As the meteorological records are georeferenced but not labelled by LHD, the coordinates of each weather station were manually assigned to the corresponding LHD using Google Maps. Where multiple stations existed within an LHD, values were averaged as appropriate.

2.2 Data analysis

Preliminary analysis includes yearly *Salmonella* incidence rates per 100,000 population calculated for each LHD. To explore exposure-response relationships, we produced scatter plots with regression lines to visualise the association between *Salmonella* incidence and climate variables, rainfall by LHD. Additionally, autocorrelation and partial autocorrelation functions (ACF and PACF) were computed to assess temporal dependence in *Salmonella* incidence (Supplementary Material).

2.2.1 Climate–*Salmonella* associations

To investigate how climatic factors influence *Salmonella* incidence across NSW, we applied spatial Bayesian distributed lag non-linear models (SP-DLNMs), constructing distributed lag non-linear terms for each climate exposure to capture potentially non-linear and delayed associations flexibly (Quijal-Zamorano et al., 2024; Gasparrini et al., 2010). Monthly *Salmonella* counts for each LHD were linked with corresponding climate data, including mean temperature, total rainfall, a flooding index, and mean humidity. These data were structured into two formats to support complementary modelling strategies: a case-crossover dataset, where each month was nested within LHD-month strata (allowing within-stratum comparisons), and a time-series dataset, indexed by year and month per LHD (Figure 2).

For each climatic exposure, we defined a cross-basis using natural cubic splines to flexibly capture both the non-linear exposure–response relationships and lagged effects up to two months. Exposure splines used knots at the 10th, 50th, and 90th percentiles of observed values, while lag splines spanned lags 0 to 2 months. All exposures were mean-centred prior to basis construction, and the resulting basis matrices were appended to the datasets to model both immediate and delayed risk.

We modelled monthly *Salmonella* counts y_i using a Poisson likelihood, with the log of the expected count $\log(\lambda_i)$ specified as the linear predictor (Maclure, 1991; Besag et al., 1991). Two Bayesian models were fitted to estimate the association between climate variables and *Salmonella* risk, allowing for spatial and temporal variation in exposure-response relationships.

Firstly, a time-stratified case-crossover design (Maclure, 1991) was employed, using LHD–month strata as fixed intercepts, inherently controlling for time-varying confounders like seasonality and long-term trends:

$$\log(\lambda_i) \;=\; \alpha_{\text{stratum}(i)} \;+\; \sum_{\text{exposures}} f_{r(i)}(X_i) \;+\; \phi_{r(i)},$$

where $\alpha_{\text{stratum}(i)}$ is the stratum-specific intercept for the LHD $\times$ (month–year) stratum of observation i, $f_r(X_i)$ represents the DLNM basis contribution for each exposure X in region r, and $\phi_{r(i)}$ is the spatial random effect for the region of observation i. The long-term trends and seasonality are handled implicitly via a time-stratified case-crossover design, where each LHD $\times$ month–year combination is treated as a fixed-effect stratum $\alpha_{\text{stratum}(i)}$, absorbing time-varying confounders without requiring explicit temporal terms.

Secondly, a full Bayesian hierarchical time-series structure with random intercepts for LHD and calendar month was included, along with temporal random effects to capture region-specific long-term trends and anomalies. A spatially structured random effect (ϕ_r) was included using an intrinsic conditional autoregressive (iCAR) prior to account for spatial correlation between neighbouring LHDs(Besag et al., 1991). Region-specific exposure–response curves were estimated using partial pooling around a global mean curve, with shrinkage determined by variance hyperparameters. This framework allowed estimation of both overall and LHD-specific climate–*Salmonella* associations, accounting for spatial and temporal dependencies:

$$\log(\lambda_i) \;=\; \alpha_{r(i),\,m(i)} + \gamma_{r(i)}(\text{trend}_i) + \delta_{r(i),\,y(i),\,s(i)} + \sum_{\text{exposures}} f_{r(i)}(X_i) + \phi_{r(i)},$$

where $\alpha_{r,m}$ is the intercept for region r in month m (capturing baseline seasonal variation), $\gamma_r(\text{trend})$ is a region-specific long-term trend term (modeled with basis functions of time), and $\delta_{r,y,s}$ is a region- and year-specific seasonal deviation (an adjustment for season s in year y). These terms allow the model to account for secular trends and inter-annual variability in seasonal peaks.

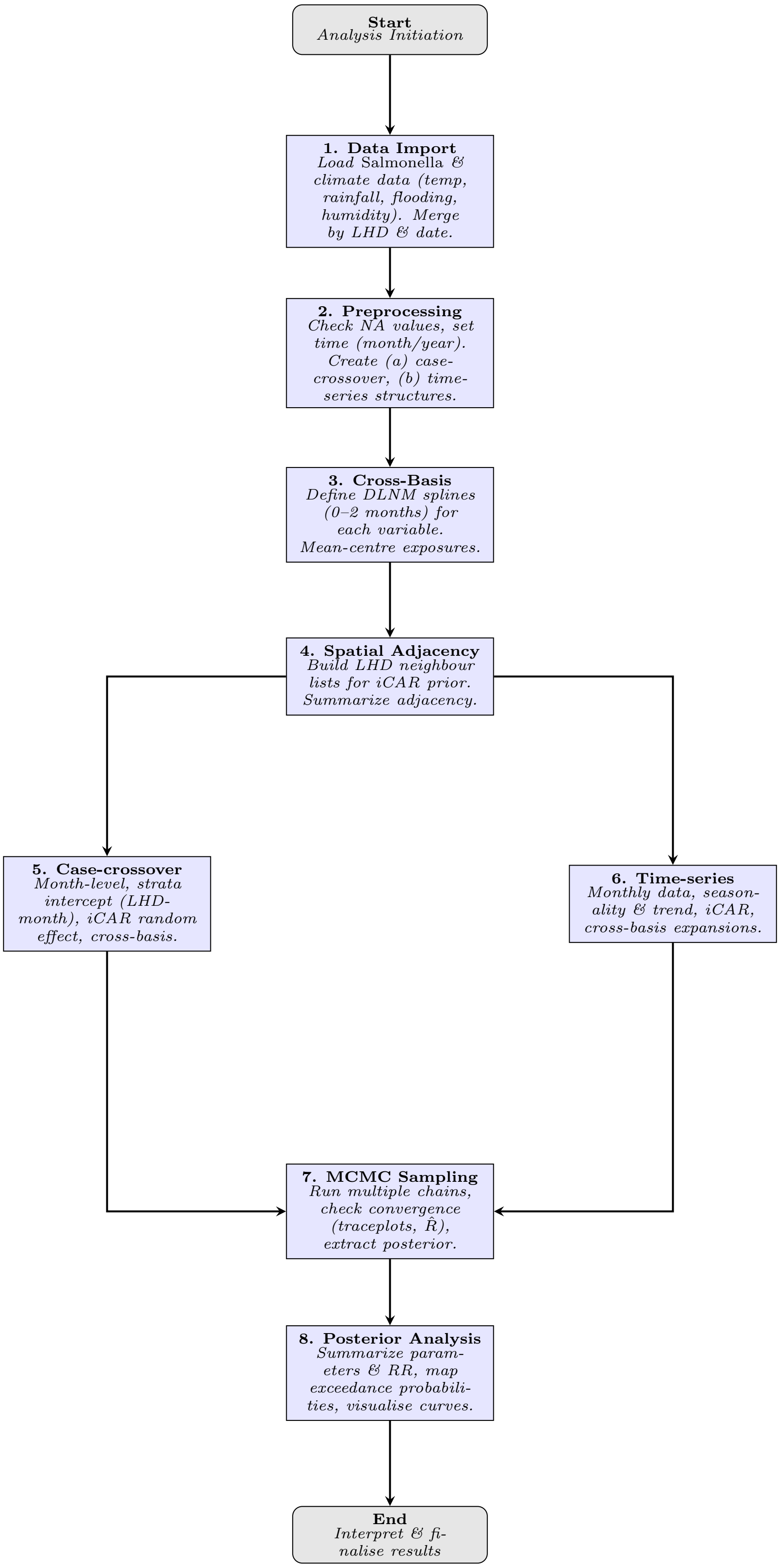

Figure 2: Methodological flowchart

2.3 Model priors

For both models, priors for all regression coefficients in the exposure cross-basis were given hierarchical normal distributions:

$$\beta_{r,j}^{(X)} \; = \; \mu_j^{(X)} + \sigma_j^{(X)}\, \theta_{r,j}^{(X)}, \quad \theta_{r,j}^{(X)} \; \sim \; N(0, \tau_X^{-1}),$$

with vague hyperpriors such as

$$\mu_j^{(X)} \sim N(0, 10^3), \quad \sigma_j^{(X)} \sim U(0, 10), \quad \tau_X \sim \text{Gamma}(0.1, 0.1).$$

Intercepts and other random effects were given diffuse priors (e.g., $\alpha \sim N(0, 10^3)$), and the iCAR precision τ_ϕ also had a Gamma(0.1,0.1) prior. The models were fitted with three MCMC chains of 5,000 iterations each (after burn-in), and convergence was assessed by traceplots and $\hat{R}$ statistics. Posterior samples of all key parameters (including derived quantities such as relative risks) were extracted for inference.

All models were fitted in a Bayesian framework using the `NIMBLE` package (de Valpine et al., 2017) in R version 4.3.3.

2.3.1 Model comparison

A comparison between the time-stratified case-crossover model (CCM) and the full Bayesian spatiotemporal model (BSM) is provided in Supplementary **Table SS.1**. Across nearly all performance metrics, BSM demonstrated superior model fit and predictive accuracy. Specifically, it yielded lower root mean squared error (RMSE) and mean absolute error (MAE) in case predictions, and a higher pseudo-R^2 (0.854 vs. 0.827), indicating greater explanatory power. Model selection criteria also favoured BSM, with markedly lower values for deviance information criterion (DIC), Akaike information criterion (AIC), and Bayesian information criterion (BIC). Although CCM showed marginally better performance based on quasi-AIC (QAIC) derived from an overdispersion-adjusted likelihood, the Bayesian QAIC from posterior deviance supported BSM. Given BSM's enhanced ability to account for seasonality and long-term trends, all subsequent results presented in this main manuscript are based on the BSM. Results from CCM models are presented in the Supplementary material.

2.4 Ethics

No specific ethics approval was required for this study as data analysis was based on publicly available data. *Salmonella* data were obtained from de-identified notifiable disease data, whilst the climate data were obtained from the Australian Bureau of Meteorology.

3 Results

3.1 Exploratory Spatial Data Analysis

Between 1991 and 2022, the mean monthly number of *Salmonella* cases was 13.3 (SD = 13.3), with a median of 9 cases. The maximum monthly count was 190 cases, recorded in South Eastern Sydney in January 2016, while none were recorded in NSW during the 1990s (Table 1). Figure 3 shows peaks of *Salmonella* cases recorded during the years 2007-08, 2010-12, 2014-16 and 2020-21. Increased flood wave events were recorded over 2007, 2011-13, 2016-17 and 2020-22. These are in keeping with recorded major flooding events in NSW, such as the Hunter Valley and Central Coast floods in 2007, Wollongong floods in 2011, Northern NSW floods in 2012-13, Central West and Riverina floods in 2016, Cyclone Debbie in 2017 and NSW North Coast floods in 2020-21. The figure also illustrates numerous flood wave events recorded during the 1990s, which coincide with increased *Salmonella* case recordings; however, these rises are not as pronounced as those seen in the 2000s.

Table 1: Summary *Salmonella* cases and climatic variables

Variable	Mean	SD	Min	25th	Median	75th	99th	Max
1. Max. temp	21.51	5.34	7.15	17.5	21.46	25.1	34.5	40.2
2. Mean Temp	16.75	5.09	2.75	12.9	16.92	20.7	28.1	34.1
3. Min. Temp	12.53	5.08	-0.6	8.52	12.7	16.7	21.9	27.9
4. Rainfall (mm)	60.66	55.7	0	0	0	2	275.8	493
5. Flood Events	1.25	2.53	0	0	0	2	12	19
6. *Salmonella* Cases	13.33	13.3	0	4	9	18	60	190

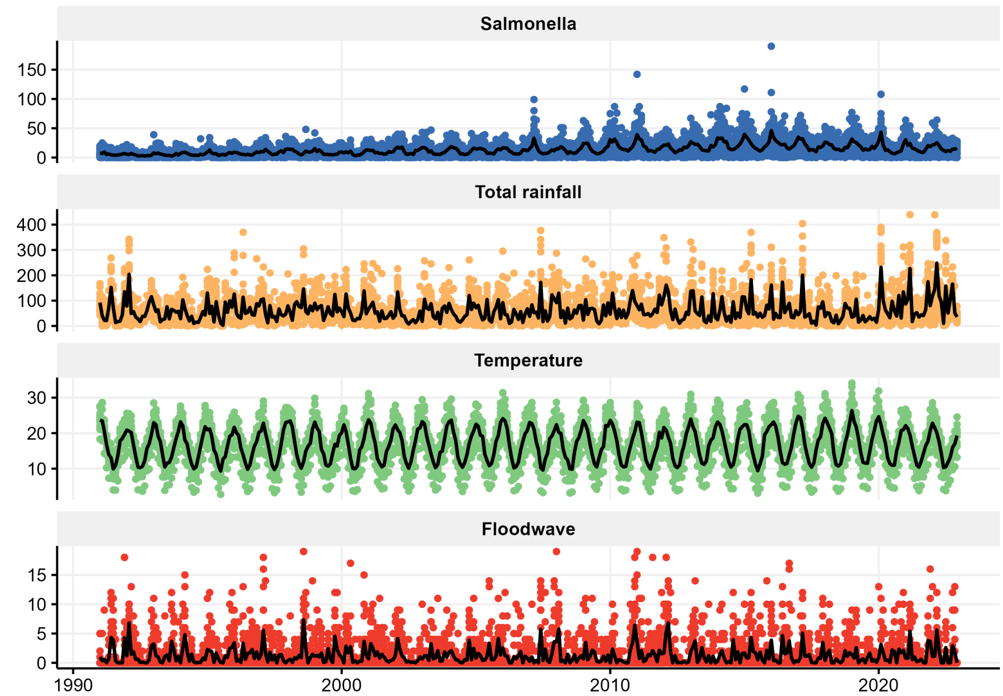

Figure 3: Time series plot of *Salmonella* cases, total rainfall, mean temperature and floodwaves over the study period, 1991-2022

. Thick lines represent monthly averages.

Time series decomposition of *Salmonella* cases in NSW reveals a gradual upward trend, particularly between 2000 and 2015, and a consistent seasonal pattern with annual peaks (Figure SS.1). Irregular spikes in the residual component suggest sporadic outbreaks. Associations between monthly mean temperature and *Salmonella* cases across 15 LHDs (Figure SS.2), and total monthly rainfall (Figure SS.3), indicate that temperature has the strongest association.

3.2 Spatial temporal association

Figure 4 presents the estimated relative risk (posterior mean of RR) in each LHD for an extreme value of the exposure (95th percentile) relative to a low reference value (5th percentile) from BSM. There is substantial spatial heterogeneity in the strength of associations. All regions show RRs above 1, confirming a positive association between high ambient temperature and *Salmonella* risk. However, the magnitude varies: coastal and metropolitan LHDs generally have moderate increases, whereas some inland areas see considerable effects. High rainfall exhibits an inverse association in many coastal LHDs (median RR < 1), whereas some inland areas show slightly positive effects. Flood events are associated with modestly higher *Salmonella* risk in most LHDs, although confidence intervals often include 1, indicating some uncertainty. High humidity is consistently associated with elevated risk, particularly in arid inland areas.

We also mapped the posterior probability that RR exceeds thresholds such as 1.0, 1.2, and 1.5 (Figure 5). This approach highlights where climate effects on *Salmonella* are most likely to be high. For temperature, nearly the entire state shows $P(RR > 1.0) \approx 1.0$. Rainfall probability maps confirm that many coastal LHDs are likely to have $RR < 1.0$ under heavy rainfall, while a few inland LHDs might experience $RR > 1$. Similar patterns appear for flooding and humidity, although with generally smaller effect sizes than those for temperature.

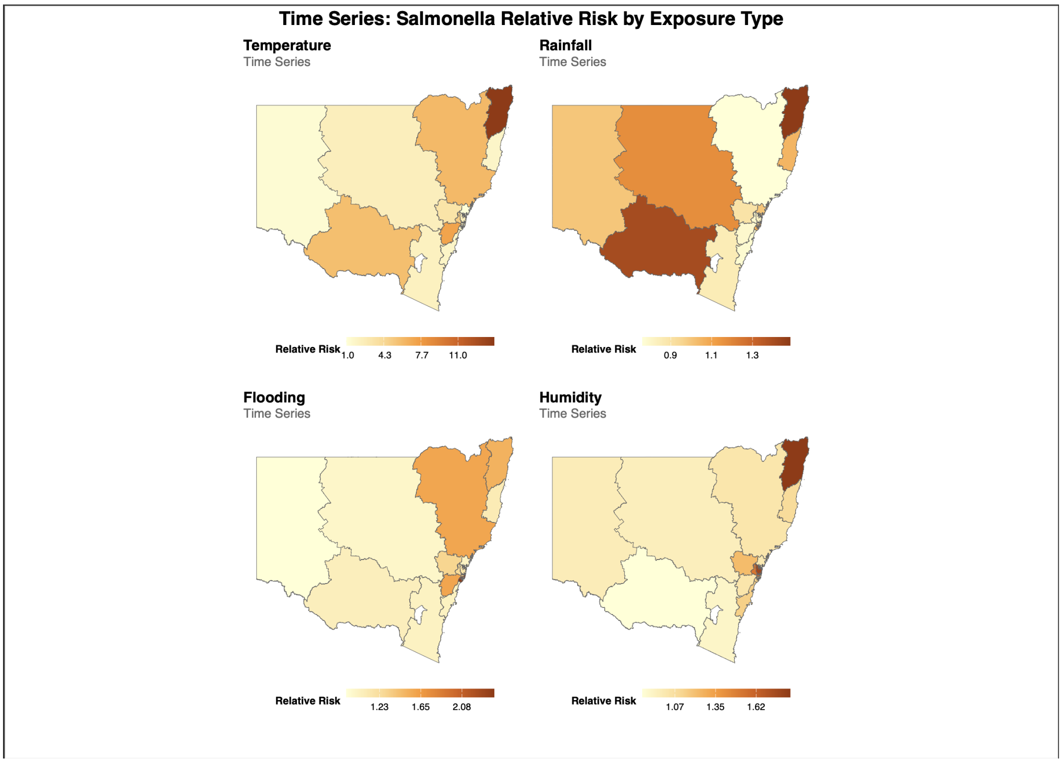

Figure 4: Spatial distribution of the estimated relative risk (RR) of *Salmonella* associated with extreme values of each climate variable under BSM. Panels show posterior median RR by Local Health District for: Temperature (hot vs. cool conditions), Rainfall (wet vs. dry conditions), Flooding (occurrence of a flood-wave vs. none), and Humidity (high vs. low). Darker colours indicate higher risk. Temperature and humidity display positive associations across most of NSW, while rainfall shows mostly neutral or negative associations (coastal areas in lighter shades). Flooding has a modest positive effect in a few regions.

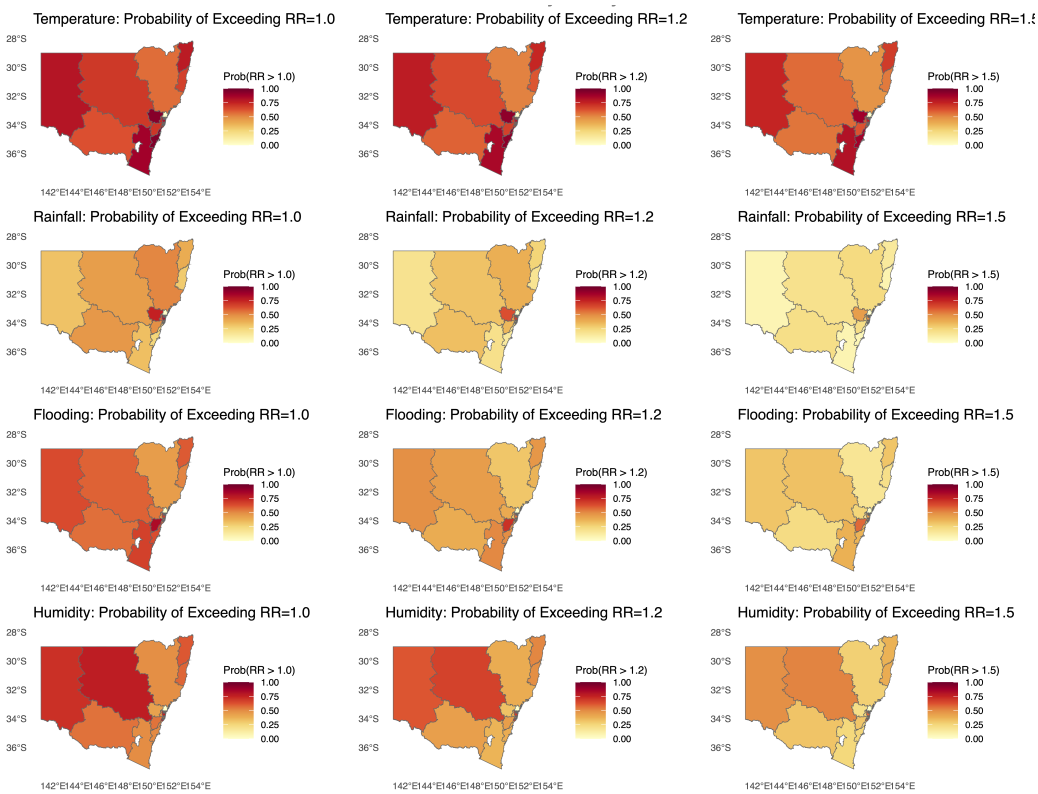

Figure 5: Posterior probability that the relative risk (RR) exceeds thresholds (1.0, 1.2, 1.5) for each exposure in BSM. Shading indicates the probability level in each LHD.

Table 2: Percentile-based Relative Risk (RR) of *Salmonella* by LHD and Climate Variable (Model 4).

LHD_Region	Exposure_Variable	Percentile_01	Percentile_05	Percentile_95	Percentile_99
Central Coast	Temperature	1	1	1	1
Central Coast	Rainfall	1	1	1	1
Central Coast	Flooding	1	1	1	1
Central Coast	Humidity	1	1	1	1
Far West	Temperature	0.08	0.21	73.93	267.53
Far West	Rainfall	0.23	0.33	1.63	2.26
Far West	Flooding	0.38	0.52	3.88	8
Far West	Humidity	0.29	0.5	5.41	8.52
Hunter New England	Temperature	0.03	0.1	16.86	44.86
Hunter New England	Rainfall	0.2	0.38	2.52	3.81
Hunter New England	Flooding	0.1	0.26	2.27	4.46
Hunter New England	Humidity	0.17	0.28	3.3	5.57
Illawarra Shoalhaven	Temperature	0.64	1.02	46.12	160.8
Illawarra Shoalhaven	Rainfall	0.3	0.39	1.61	2.37
Illawarra Shoalhaven	Flooding	0.42	0.55	10.87	22.27
Illawarra Shoalhaven	Humidity	0.28	0.41	2.55	3.79
Mid North Coast	Temperature	0.1	0.26	20.22	46.97
Mid North Coast	Rainfall	0.24	0.36	1.71	2.43
Mid North Coast	Flooding	0.2	0.37	2.73	6.25
Mid North Coast	Humidity	0.15	0.29	3.98	6.43
Murrumbidgee	Temperature	0.02	0.07	38.16	120.79
Murrumbidgee	Rainfall	0.29	0.41	4.88	10.76
Murrumbidgee	Flooding	0.28	0.49	2.66	5.37
Murrumbidgee	Humidity	0.19	0.35	3.29	5.59
Nepean Blue Mountains	Temperature	0.32	0.88	44.3	90.17
Nepean Blue Mountains	Rainfall	0.42	0.6	3.53	5.3
Nepean Blue Mountains	Flooding	0.24	0.4	2.62	4.22
Nepean Blue Mountains	Humidity	0.15	0.28	2.57	3.76
Northern NSW	Temperature	0.22	0.41	33.44	91.58
Northern NSW	Rainfall	0.26	0.39	2.31	3.97
Northern NSW	Flooding	0.34	0.51	5.39	9.82
Northern NSW	Humidity	0.21	0.35	4.61	9.57
Northern Sydney	Temperature	0.13	0.35	891.46	3404.4
Northern Sydney	Rainfall	0.62	0.79	2.97	3.8
Northern Sydney	Flooding	0.45	0.61	6.16	12.53
Northern Sydney	Humidity	0.33	0.53	7.5	13.8
South Eastern Sydney	Temperature	0.05	0.16	31.12	57.8
South Eastern Sydney	Rainfall	0.28	0.35	2.41	5.26
South Eastern Sydney	Flooding	0.27	0.4	4.65	9.18
South Eastern Sydney	Humidity	0.44	0.62	6.54	14.36
South Western Sydney	Temperature	0.02	0.1	15.87	32.31
South Western Sydney	Rainfall	0.44	0.55	2.8	5.23
South Western Sydney	Flooding	0.6	0.76	13.52	20.92
South Western Sydney	Humidity	0.28	0.42	3.31	5.67
Southern NSW	Temperature	0.24	0.5	101.29	232.39
Southern NSW	Rainfall	0.15	0.32	1.63	2.05
Southern NSW	Flooding	0.52	0.64	11.09	17.66
Southern NSW	Humidity	0.32	0.43	2.94	4.15
Sydney	Temperature	0.03	0.1	30.61	63.63
Sydney	Rainfall	0.22	0.35	1.99	2.89
Sydney	Flooding	0.18	0.36	2.66	4.89
Sydney	Humidity	0.16	0.26	2.87	4.46
Western NSW	Temperature	0.12	0.24	19.96	54.95
Western NSW	Rainfall	0.32	0.41	2.25	3.14
Western NSW	Flooding	0.41	0.55	7.25	15.95
Western NSW	Humidity	0.31	0.53	4.86	10.36
Western Sydney	Temperature	0.13	0.25	19.96	37.63
Western Sydney	Rainfall	0.33	0.49	3.31	6
Western Sydney	Flooding	0.2	0.34	2.62	6.92
Western Sydney	Humidity	0.16	0.26	3.15	5.7

Table 2 illustrates how *salmonella* risk varies non-linearly with climate extremes across different LHDs. Generally, we observe a J-shaped pattern for each climate variable: at the low extreme (1^{st} and 5^{th} percentiles), the relative risk (RR) of salmonella is often below 1.0 (indicating lower risk than under typical conditions), whereas at the high extreme (95^{th} and 99^{th} percentiles) the RR is above 1.0, in many cases dramatically so.

High ambient temperatures show the most pronounced effect on *Salmonella* risk. Nearly every LHD exhibits a steep rise in RR at the 95^{th} and especially 99^{th} percentile of temperature. For example, in the Far West LHD (an arid inland region), the RR for S*almonella* jumps from about 0.08 at the 1^{st} percentile (extremely cool days) to 267.5 at the 99^{th}

percentile (extreme heat). Likewise, Sydney (urban central) rises from ≈ 0.03 at the coldest end to 63.6 at the hottest end. Several rural or southern districts (e.g., Southern NSW, Nepean Blue Mountains) also reach very high RRs (well above 50) under extreme heat. An extreme case is Northern Sydney, with an estimated RR exceeding 3400 at the 99th percentile of temperature—although this value is likely an outlier with wide uncertainty, it underscores the potential for exponential increases in risk at the furthest temperature extremes. At the opposite end, extremely low temperatures are associated with RRs near 0 (e.g., Murrumbidgee ≈ 0.02, Sydney ≈ 0.03 at the 1st percentile), indicating minimal risk during cold conditions.

In other words, very cool or dry conditions tend to suppress salmonella incidence, while very hot or wet conditions significantly increase the risk. This non-linear behaviour suggests that salmonella rates remain relatively stable around moderate climate conditions (baseline ≈ 1.0 RR), but decrease at one end and surge at the other end of the climate spectrum.

Extreme precipitation events also show a clear impact on salmonella risk, though generally the magnitude is less extreme than for temperature. In most LHDs, drought-like conditions (very low rainfall, 1st percentile) correspond with RR below 1 (often in the 0.2–0.5 range), whereas heavy rainfall (95th–99th percentiles) pushes RR above 1. For example, in the Murrumbidgee LHD (a rural agricultural region), the RR rises from 0.29 at the 1st percentile of rainfall to 10.76 at the 99th percentile—indicating more than a tenfold higher risk during periods of extreme rainfall. Several other districts see roughly 2- to 6-fold increases in risk at high rainfall extremes (e.g., Western Sydney RR ≈ 6.0 at the 99th percentile rainfall, vs. 0.33 at the 1th).

Notably, when heavy rain leads to flooding, the risks can spike further: e.g., Illawarra Shoalhaven (coastal) shows RR ≈ 22.3 at the 99th percentile of flooding, and South Western Sydney has RR ≈ 20.9 at 99th percentile flooding. In contrast, at the 1st percentile of flooding (essentially no flooding), RRs are < 0.5 in those same areas, indicating much lower baseline risk when significant flooding is absent.

High relative humidity emerges as another factor amplifying salmonella risk, though its effects are somewhat intertwined with temperature (hot periods are often humid). Still, the data show that at the 99th percentile of humidity, RRs are elevated in many LHDs, while at very low humidity (dry air) RRs are below 1. For instance, South Eastern Sydney has RR ≈ 14.4 at the most humid extreme, compared to 0.44 at the 1st percentile. Even the arid Far West LHD exhibits an increase from RR ≈ 0.29 at minimal humidity to ≈ 8.5 at the highest humidity percentile, suggesting that occasional surges in moisture (e.g., storms in desert regions) can facilitate outbreaks.

The relative impact of these climate extremes varies considerably between LHDs, highlighting specific regional vulnerabilities. Some districts exhibit far greater sensitivity to certain climate variables than others. The Far West stands out for its extreme temperature effect, an unsurprising finding given its desert-like climate. Meanwhile, the Central Coast shows minimal change in risk across all percentiles (RR ≈ 1.0), indicating that climate factors had lesser influence in this region's mild environment. Most other areas fall between these extremes. Generally, rural and inland LHDs (Far West, Western NSW, Southern NSW, Murrumbidgee) face more dramatic swings in climate and thus exhibit more pronounced climate-related RRs. In the Murrumbidgee region, for instance, aside from its temperature effect, it also had one of the highest rainfall-related risks. On the other hand, urban/metropolitan LHDs like Sydney and Western Sydney also show significant increases with climate extremes, but typically not as steep. Notably, Illawarra Shoalhaven and South Western Sydney show very high RRs for flooding (over 20-fold increase), suggesting specific local vulnerabilities (e.g., low-lying areas or stormwater overflow).

4 Discussion

Our analyses highlight the significant influence of meteorological factors, specifically temperature, humidity, and, under certain conditions, rainfall and flooding, on the incidence of *Salmonella* in NSW. By employing two complementary Bayesian modelling approaches, a case-crossover design and a spatiotemporal time-series framework, this dual approach allowed for robust validation of climate-disease associations and underscored the importance of accounting for seasonality, long-term trends, and localised spatial heteregeneity in epidemiological modelling.

4.1 Non-linear relationships and extreme percentiles

A principal finding of this study is the markedly non-linear relationship characterising the association between climatic variables and the risk of *Salmonella*. The summary of RR at the 1$^{\text{st}}$, 5$^{\text{th}}$, 95$^{\text{th}}$, and 99$^{\text{th}}$ percentiles of each exposure reveals a pronounced "U" or "J" shape, across most LHDs. Specifically, at the lower percentiles (cooler or drier conditions), RRs frequently fall below unity, suggesting a potential reduction in risk. Conversely, at higher percentiles, particularly above the 95$^{\text{th}}$, RRs increase substantially, indicating a disproportionate rise in risk under extreme conditions. Notably, several LHDs exhibited substantial increases; for instance, the Far West LHD showed a significantly high RR at extreme heat percentiles, while Illawarra Shoalhaven demonstrated 20-fold or greater increases at the highest flood index percentile. These dramatic increase underscore the potential for rapid escalation of *Salmonella* risk under intense climatic conditions, such as heatwaves, extreme rainfall, or periods of unusually high humidity. These non-linear patterns align with prior research demonstrating exponential increases in *Salmonella* growth rates above specific temperature thresholds and the mobilisation of environmental pathogens by precipitation events (D'Souza et al., 2004; Baker et al., 2019). Such a pattern aligns with known seasonality and environmental survival of *Salmonella*. For instance, infections tend to decrease during cold spells and increase during hot weather (D'Souza et al., 2004). These findings reinforce that hot weather is a major driver of *Salmonella* outbreaks (Scallan et al., 2011). Each degree of warming has been shown to elevate *Salmonella* infection rates by roughly 5% per 1 °C in pooled analyses (Williams et al., 2020). Here, we observe that at very high percentiles, these increases compound into enormous relative risks. Even short-term heatwaves can significantly boost cases; for instance, one Australian study found a 34% increase in salmonella risk when temperatures exceeded 41 °C (Bennett et al., 2014). Thus, the relationship between temperature and *Salmonella* is highly nonlinear, beyond a certain threshold, the risk appears to accelerate sharply with each additional degree of heat.

Probability of exceeding thresholds

Complementing the point estimates, the probability maps for exceeding specific risk thresholds provide valuable insights into the spatial distribution and certainty of these climate effects. These maps illustrate that extensive areas across NSW have a high probability ($P > 0.7$) of increased *Salmonella* risk associated with extreme heat or humidity. Coastal LHDs generally appear less susceptible to rainfall-associated risk (with $P(\mathrm{RR} > 1)$ often below 0.5 for heavy rain), whereas inland or semi-rural districts demonstrate higher vulnerability. Overlaying these exceedance probabilities onto specific regions allows for the identification of potential local hotspots. For example, while western Sydney might face a moderate probability of a flood-induced surge, the likelihood of a temperature-driven increase in the Far West LHD above a certain heat threshold is markedly higher. These probability-based findings add a crucial dimension to the RR estimates by quantifying the confidence with which we can assert that extreme climatic conditions will elevate Salmonella risk above defined thresholds (e.g., RR¿1.5). Consequently, these findings can inform targeted public health strategies, enabling authorities to prioritise interventions, such as enhanced food safety inspections or public health advisories, when meteorological forecasts indicate a high probability of exceeding relevant climatic thresholds.

4.2 Climate specifics

Consistently across all LHDs, elevated ambient temperatures were associated with a significantly increased risk of *Salmonella*, which aligns with the known temperature-dependent growth and survival characteristics of textitSalmonella bacteria. The dozens-fold increase in RR exemplifies the disproportionate effect at the upper extreme observed in many districts at the 99$^{\text{th}}$-percentile of heat. The relationship with rainfall was more complex. While moderate precipitation sometimes showed minimal or potentially protective associations in some coastal areas, likely related to dilution or flushing effects, extreme rainfall events have the potential to mobilise pathogens in the environment, contaminate water sources, and contribute to localised flooding, thereby increasing case counts. The observed vulnerability of certain inland or semi-rural LHDs (e.g., Murrumbidgee, Western Sydney) to extreme rainfall echoes prior findings linking rainfall-runoff, sewage overflow, and infrastructure failures during flood events, which can contaminate water and food supplies (Ebi et al., 2006; Hall et al., 2012).

Flood-linked risks demonstrated marked spatial heterogneity, with specific LHDs (e.g., Illawarra, South Western Sydney) showing substantial surges in risk at the highest flood index percentiles. This is likely attributable to the flood-induced disruption of critical infrastructure, such as sewage and water treatment systems, resulting in widespread environmental contamination. However, the negligible flood impacts observed in some areas may reflect more resilient infrastructure or a lower frequency of significant flood events. Elevated humidity was also positively associated with increased risk, albeit generally to a lesser degree than extreme temperature or flooding in most LHDs. Nonetheless, a subset of inland districts (Far West, Western NSW) exhibited notable increases in RR with high humidity, suggesting that atmospheric moisture can exacerbate bacterial persistence, particularly when coupled with elevated temperatures (Baker et al., 2019).

Mechanistically, high humidity can prolong the survival of *Salmonella* on surfaces and foods by preventing desiccation, further exacerbating the effect of heat (Baker et al., 2019). Similarly, dry periods tend to suppress *Salmonella*, while intense rainfall elevates it, consistent with the “concentration–dilution” hypothesis in environmental microbiology (Curriero et al., 2001). During extended dry spells, pathogen levels in the environment may decrease, resulting in a lower disease risk; however, heavy rainfall can wash pathogens from soil or animal waste into water sources and food-production areas (Hall et al., 2012).

4.3 Spatial heterogeneity and local vulnerabilities

A key insight from this study is the substantial spatial heterogeneity in climate sensitivity observed across the 15 LHDs. Regions such as the Far West exhibited exceptional sensitivity to extreme heat and humidity. In contrast, others, such as the Central Coast, showed comparatively minimal changes in risk across temperature and humidity extremes. Importantly, densely populated urban LHDs (e.g., Sydney, Western Sydney) were not immune to the impacts of climate stressors, particularly concerning acute heatwaves and flooding events. These findings reinforce the understanding that the effect of broader climate signals on local health outcomes is mediated by the interplay of region-specific factors, including baseline climate characteristics, the resilience of critical infrastructure (e.g., water and sanitation systems), and population behaviours (e.g., food handling practices, reliance on rainwater tanks) (Schramm et al., 2020). Consequently, effective adaptation measures must be tailored to address these localised vulnerbilities. For instance, interventions in rural areas prone to intense rainfall- or heat-driven spikes might focus on fortifying water storage practices or enhancing agricultural hygiene. At the same time, urban strategies could prioritise the implementation of effective heatwave alert systems and improvements to stormwater drainage to mitigate flood impacts (Ferrand, 2014; NSW Government, 2024).

4.4 Implications for surveillance and intervention

These findings carry significant implications for public health surveillance and intervention, particularly in the context of projected increases in the frequency and intensity of extreme weather events under climate change (Semenza & Menne, 2012). Our results underscore the potential for increased frequency and severity of *Salmonella* outbreaks in susceptible regions. Public health agencies can leverage these findings by integrating climate metrics into disease early-warning systems, enabling the issuance of targeted alerts when forecasts indicate extreme heat or rainfall. This proactive approach allows the pre-emptive deployment of targeted interventions, including enhanced food safety inspections, rigorous water quality monitoring, and timely public advisories. Strengthening critical infrastructure, including sewer systems and stormwater drainage, as well as ensuring reliable refrigeration capacity, is especially vital in regions identified as highly vulnerable. Furthermore, public health education campaigns promoting safe food handling practices during heatwaves or floods (e.g., preventing cross-contamination, recommending boiling water in post-flood scenarios) can play a crucial role in mitigating the severity of outbreaks (Organization, 2018). Ultimately, the development and implementation of regional adaptation strategies that specifically address the localised climate risks identified in this study, such as extreme heat in the Far West, flooding vulnerabilities in Illawarra, and combined risks in areas like Western Sydney, are likely to be the most effective.

4.5 Strengths and Limitations

Strengths

This study leverages a long-term dataset to explore the relationship between environmental exposures and *Salmonella* risks across multiple LHDs in NSW. The inclusion of distributed lag structures and spatial disaggregation enables a robust investigation of temporal and regional variations in risk.

Limitations

We acknowledge the following limitations in this study. First, residual confounding by unmeasured variables such as air pollution, socioeconomic status, or individual-level comorbidities cannot be excluded. The reliance on aggregated data limits the ability to examine effect modification by demographic factors (e.g., age, sex) or behavioural exposures. Second, the analysis does not distinguish between sporadic and outbreak-associated cases, which may confound estimates of climate sensitivity, particularly during extreme weather events. Third, potential compound events were not explicitly modelled, limiting insight into more complex exposure scenarios. Lastly, we did not explore how serotype-specific data may constrain understanding of transmission dynamics across different Salmonella strains under climate stress.

5 Conclusion

This study provides evidence that high ambient temperatures and elevated humidity levels are significant drivers of increased *Salmonella* risk in NSW, with effects manifesting over short lags. While high rainfall was often associated with a reduced risk in many areas, particularly in coastal and temperate regions, suggesting a disruption of transmission pathways, extreme rain and flood events showed a more complex or modest potential to elevate risk, albeit with notable spatial variability and associated uncertainty. Overall, temperature and humidity emerge as key meteorological factors associated with increased risk of *Salmonella*, displaying regionally varying effects and short-term associations. Understanding this climate-disease interplay is paramount for developing effective public health strategies and adaptation measures to safeguard food safety and prevent future *Salmonella* outbreaks in a changing climate.

Authors Contribution

OAA: Conceptualization, Data curation, Formal analysis,Investigation, Methodology, Visualization, Writing – original draft TA: Data curation, Formal analysis, Investigation, Writing – original draft MAK: Data curation, Formal analysis, Investigation, Writing – original draft HA: Data curation, Formal analysis, Investigation AP: Methodology, Validation, Investigation, Writing – reviewing and editing DT: Methodology, Validation, Investigation, Writing – reviewing and editing TIE: Methodology, Validation, Investigation, Writing – reviewing and editing

Open Research Section

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