One Health 19 (2024) 100941

Contents lists available at ScienceDirect

One Health

journal homepage: www.elsevier.com/locate/onehlt

Association between precipitation events, drought, and animal operations with *Salmonella* infections in the Southwest US, 2009–2021

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ARTICLE INFO

Keywords:
Climate change
Precipitation
Drought
Salmonella
Environmental epidemiology
Enteric diseases

ABSTRACT

Background: Temperature and precipitation have previously been associated with *Salmonella* infections. The association between salmonellosis and precipitation might be explained by antecedent drought conditions; however, few studies have explored this effect.

Methods: Using an ecological study design with public health surveillance, meteorological (total precipitation [inches], temperature [average °F], Palmer Drought Severity Index [PDSI, category]), and livestock data we explored the association between precipitation and *Salmonella* infections reported in 127/141 counties from 2009 to 2021 in the Southwest, US and determined how this association was modified by antecedent drought. To explore the acute effect of precipitation on *Salmonella* infections we used negative binomial generalized estimating equations adjusted for temperature with a 2-week lag resulting in Incidence Rate Ratios (IRR). Stratified analyses were used to explore the effect of antecedent drought and type of animal density on this association.

Results: A one inch increase in precipitation was associated with a 2 % increase in *Salmonella* infections reported two weeks later (IRR: 1.02, 95 % CI: 1.00, 1.04) after adjusting for average temperature and PDSI. Precipitation following moderate (IRR: 1.22, 95 % CI: 1.17, 1.28) and severe drought (IRR: 1.16, 95 % CI: 1.10, 1.22) was associated with a significant increase in cases, whereas in the most extreme drought conditions, cases were significantly decreased (IRR: 0.89, 95 % CI: 0.85, 0.94). Overall, more precipitation (above a 30-year normal, the 95th and 99th percentiles) were associated with greater increases in cases, with the highest increase following moderate and severe drought. Counties with a higher density of chicken and beef cattle were significantly associated with increased cases regardless of drought status, whereas dairy cattle, and cattle including calves had mixed results.

Discussion: Our study suggests precipitation following prior dry conditions is associated with an increase in salmonellosis in the Southwest, US. Public health is likely to see an increase in salmonellosis with extreme precipitation events, especially in counties with a high density of chicken and beef cattle.

1. Introduction

Salmonellosis is caused by infection with *Salmonella* and is usually marked by fever, abdominal pain, diarrhea, nausea, and vomiting. Non-typhoidal *Salmonella* is one of the leading causes of foodborne illness in the United States, resulting in an estimated 1 million infections, 19,000

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https://doi.org/10.1016/j.onehlt.2024.100941
Received 13 June 2024; Received in revised form 12 November 2024; Accepted 17 November 2024
Available online 19 November 2024

hospitalizations, and 378 deaths annually [1].

Salmonella has a range of hosts including livestock, wildlife, and domesticated animals [2]; however, the main animal host of *Salmonella* is poultry. Transmission to humans primarily occurs via the fecal-oral route most commonly through contaminated food, water, or direct animal contact. Environmental-exposure pathways for transmission of *Salmonella* are complicated by a range of biological, ecological, and human factors.

Salmonella can survive for an extended period of time in the environment (up to 332 days) [3,4]. In epidemiology studies, salmonellosis typically peaks in the warmer months and has been associated previously with ambient air temperature, relative humidity, precipitation and extreme heat events [5–11]. Kovats et al. [12] showed that for every 1 °C increase in temperature above 6 °C across 10 European countries, *Salmonella* cases increased 5–10 %. A more recent meta-analysis found a 5 % increase in salmonellosis (95 % Confidence Interval [CI]: 1.04–1.07) for every 1 °C increase in temperature [13]. Other research has found *Salmonella* persists during extreme heat events, particularly in coastal areas or in areas with farming operations [14,15] and human behavior changes during summer months may help to explain some of the increase in infections [9,10]. Hypotheses about this increased association have been attributed to *Salmonella*'s ability to survive in high temperatures and remain ubiquitous in the environment through contamination from various animal hosts.

Although there is ample evidence *Salmonella* is associated with temperature, few studies have explored the effect of cascading weather events [16] such as rainfall (precipitation) and antecedent levels of rainfall on salmonellosis. A related weather variable to drought is relative humidity. Researchers have found there are less *Salmonella* outbreaks in areas with lower relative humidity in China [8] and that relative humidity is positively correlated with *Salmonella* infections in Australia [17]. The concentration-dilution hypothesis explains that antecedent levels of rain may explain why in some areas of the world rainfall following dry periods can increase diarrheal incidence (concentration), whereas rainfall following wet conditions can decrease diarrheal incidence (dilution) [18]. Counter to the concentration-dilution hypothesis, Lee et al. explored the interaction between extreme rainfall and antecedent rainfall conditions in Georgia, finding that wet periods followed by extreme rainfall was associated with an increase in salmonellosis [4].

For *Salmonella*, drought stress and higher temperatures also result in the greater internalization of *Salmonella* in plant structures, particularly lettuce [19,20]. More recent research has found that relative humidity may play an important role in *Salmonella's* fate in plant structures [21]. Combined, these are important findings because *Salmonella* was implicated in 11 % of leafy green vegetable outbreaks during 1973–2012. Further, seeded vegetable outbreaks linked to *Salmonella* frequently involve multiple states and a large number of illnesses and hospitalizations in the US [22].

Because *Salmonella* has been shown to persist in soils and the environment, even when desiccated during drought conditions, more research is needed to explore the risk of *Salmonella* which may occur following antecedent drought and extreme precipitation events. The objective of this work is to explore the association between precipitation and the incidence of *Salmonella* in four states of the southwestern US from 2009 to 2021. We hypothesized that precipitation will increase *Salmonella* incidence, and that this relationship would be modified by antecedent drought.

2. Methods

2.1. Study design & setting

We used county-level public health surveillance data from four states in the Southwest US: (Arizona [AZ], Colorado [CO], New Mexico [NM], and Utah [UT]) to conduct this ecological study. The total land area for these states totals 424,779 mi^2 with a population of almost 19 million. The majority of the states have arid or semi-arid climate zones, with a few continental climate zones in Colorado and New Mexico [23]. Drought occurs frequently in this region and, compared to other regions in the US, the Southwest has also not experienced an increase in total precipitation over time. However, extreme precipitation events (defined as rainfall over one inch) do occur and can cause catastrophic damage to infrastructure [24–26]. Two of the states (AZ and NM) experience Southern Oscillation Index (SOI) events, which include an intensification of temperatures and the North American monsoon during the summer (El Niño), and additional precipitation and cooler temperatures during the winter (La Niña) [27,28]. *Salmonella* infections have overall increased in these four states during the time period, with less cases reported in 2020 and 2021 due to the COVID-19 pandemic.

2.2. Data sources

We use three sources of data: 1) public health surveillance from each state; 2) weather and climate data from Parameter-elevation Regressions on Independent Slopes Model (PRISM) [29], the National Oceanic and Atmospheric Administration (NOAA) [30], and Köppen-Geiger Climate Zone [23]; and 3) animal and farm data from the United States Department of Agriculture (USDA) 2012 and 2017 census [31]. We describe each dataset in depth below.

2.3. Public health surveillance data

Non-typhoidal *Salmonella* data is collected by each state's respective health department and was provided for the earliest and latest available years for each jurisdiction (AZ [15 counties]: 2009–2020; CO [64]: 2009–2021; NM [33]: 2009–2021; UT [15]: 2012–2021). *Salmonella* infections are reportable in the US, meaning identification of *Salmonella* in clinical specimens are reported by healthcare providers to local, state, and territorial health departments. States provided de-identified daily reports of all confirmed, probable, and suspected *Salmonella* cases by county (case definitions [32–35] available in Table S1). In Utah, only counties with >20,000 population were included due to data suppression requirements ($n = 15/29$ counties). We aggregated daily case counts to week of the year (starting on Sunday) for a total of 52 or 53 weeks depending on leap-years using the lubridate [36] week() function in R Studio version 4.2.2.

2.4. Weather and climate data

Weather data were obtained from PRISM [29], including daily county centroid-level precipitation (inches) and temperature (°F). Daily weather data were aggregated to week by totaling all precipitation values in that 7-day time period, and averaging the mean temperature values in a week. We defined three extreme precipitation events comparing weekly PRISM data to 30-year normal from 1990 to 2020: (1) heavy precipitation (defined as total precipitation in the week over the 30-year normal), (2) total precipitation above the 95th percentile, and (3) total precipitation above the 99th percentile. The Palmer Drought Severity Index (PDSI) from the National Oceanic and Atmospheric Administration National Centers for Environmental Information (NCEI) was obtained and applied to every week in a month, for every county in a climate division [30]. PDSI generally considers the drought level in the current month, and the previous 9 months on a rolling basis [37]. The magnitude of the PDSI value indicates the departure from normal conditions and can be categorized as: extremely wet (≥4), very wet (3–3.9), moderately wet (2–2.9), normal (−1.9–1.9), moderate drought (−2 to −2.9), severe drought (−3 to −3.9), and extreme drought (≤ − 4) [37]. Köppen-Geiger Climate Zone was determined by intersecting the gridded zone to county boundary, and determining the majority climate zone for each county using ArcGIS Online.

2.5. Animal and farm data

We obtained data for county level animal density from the US Department of Agriculture (USDA) 2012 and 2017 Farm Census Quick Stats 2.0 [38]. We extracted the number of livestock reported for poultry including chicken broilers (raised for meat) and chicken layers (raised for eggs), and cattle including beef, dairy, and total counts including calves. Data were transformed to calculate the number of livestock per square mile of the county to allow for interpretability across animal types.

A list of all relevant data sources and metadata are available in Table S2.

2.6. Data linkage & transformation

We explored 2-week and 3-week lags between weather and case data based on *Salmonella* incubation period (1–4 days) and laboratory and reporting delays (~7–10 days). These lags were chosen given input from health department co-authors, and differences in incubation periods and laboratory and reporting delays which make concurrent counts or 1-week lags less meaningful. Results from the 2-week and 3-week lags were similar for initial model estimates, so we used a 2-week lag for the remaining analysis. We did not explore weekly lags greater than 3-weeks as our primary interest was to explore the acute effect of precipitation events accounting for antecedent drought. We did not have any missing health, weather, or animal data; we chose to use all available data for all weeks of the analysis.

2.7. Variables

Our exposure of interest was total precipitation in a county in a week during the time period of interest. Our outcome was the weekly total of confirmed, probable or suspected salmonellosis cases reported to the health department in a county in a week with a 2-week lag. We hypothesized that temperature was a confounder, so adjusted for ambient temperature with a 2-week lag to adjust for seasonality and the general rise in cases during the warmer months. We hypothesized that antecedent drought would act as an effect modifier of the association between precipitation and cases. To explore effect modification we categorized the PDSI values and conducted stratified analyses by antecedent drought level using the normal category as the reference.

2.8. Statistical analysis

We used negative binomial Generalized Estimating Equations (NBGEE) [39,40] to investigate the association between precipitation and counts of reported *Salmonella* cases using an autoregressive correlation structure. We used a negative binomial distribution because the variance exceeded the mean for the dependent variable and all associated lags. We added average temperature as a covariate to adjust for seasonality. We chose to not include population as a covariate because the model estimates were largely unstable and led to non-convergence. Finally, we found no spatial autocorrelation in the dataset when testing a subsample of years within each state. The results of model testing using Pan's Quasi likelihood Information Criterion (QIC) and Moran's I statistics are shown in Table S3 and S4.

We performed stratified analyses for the effect of a one-inch increase in precipitation following each PDSI category (with Normal as reference). We estimated the effect of different amounts of precipitation following each PDSI category in counties which experienced extreme precipitation events compared to counties that did not in a given week. Finally, we estimated the association between precipitation and cases for a one-unit increase in types of animal density (per square mile poultry, cattle). The resulting Incidence Rate Ratios (IRRs) can be interpreted as a percent increase/decrease in the number of human *Salmonella* case events following precipitation 2 weeks prior, adjusted for average temperature 2 weeks prior. Datasets were merged in R version 4.2.2 [41] (with the following packages: readxl [42], dplyr [43], purr [44], readr [45], lubridate [36], data.table [46], stringr [47]) and analyzed using Stata 17 [48].

2.9. Sensitivity analyses

We conducted sensitivity analyses identified a-priori. These included exploring different spatial scales and rural vs. urban classification schemes, using a different drought index (US Drought Severity Monitor [USDM]) [49], adjusting for SOI, and restricting the analysis to years prior to the COVID-19 pandemic due to human behavior changes including isolation and quarantine, healthcare seeking behaviors, and other restrictions [50]. In order to understand the association with extreme precipitation events, in a sensitivity analysis we compared counties with heavy precipitation relative to a 30-year normal (mean = 0.98 in, sd = 0.63), and total weekly precipitation above the 95th (≥1.19 in), and 99th percentile (≥2.1 in) to counties without these events in the same week.

2.10. Data access & cleaning

All data, except human case data, are available via the research compendium on GitHub: https://github.com/austhofe/RainDroughtSalmonella. Instructions for collecting data, as well as code for merging and linking data are available to help others reproduce the results and conduct this work in other areas. Although surveillance data in this analysis are not considered protected health information, health data require a data use agreement with each individual state health department in order to gain access.

2.11. IRB approval

This work was reviewed and deemed exempt, minimal-risk human subjects research by the University of Arizona Institutional Review Board (#00001514).

3. Results

A description of each state's weather, human, and animal data are provided in Table 1. Arizona had the highest annual average temperature, whereas Colorado had the lowest annual average temperature and the greatest annual average precipitation. There were 29,350 reported *Salmonella* cases reported across the time periods with incidence ranging from 11.1 to 19.3 per 100,000 across the four states. Density of chicken and poultry were highest in Colorado, whereas density of dairy cattle operations was highest in New Mexico and other cattle highest in Colorado (maps available in Fig. S1 and S2).

Overall, a one inch increase in precipitation was associated with a small, but significant 2 % increase in *Salmonella* cases 2-weeks later (IRR: 1.02, 95 % CI: 1.00, 1.04) after adjusting for average temperature and PDSI. Fig. 1 shows the effect of a one inch increase in precipitation in stratified analyses accounting for antecedent drought level. Precipitation following extremely wet (IRR: 1.12, 95 % CI: 1.00, 1.27) and moderately wet (IRR: 1.07, 95 % CI: 0.99, 1.14) conditions was associated with increased cases, although borderline statistically significant. Precipitation following moderate and severe drought was significantly associated with a 22 % (IRR: 1.22, 95 % CI: 1.17, 1.28) and 16 % (IRR: 1.16, 95 % CI: 1.10, 1.22) increase in cases respectively. Precipitation following extreme drought was associated with a significant decrease in cases (IRR: 0.88, 95 % CI: 0.83, 0.93). The association between increased cases with precipitation following early stages of drought then decreased cases in the extreme stage of drought remained consistent even with using a different drought index (USDM [Table S5]).

When exploring the sensitivity analyses of different levels of precipitation accounting for prior drought conditions, we found that

Table 1
State-specific characteristics for an ecological analysis of *Salmonella* infections in the Southwest US, 2009–2021.

	Arizona	Colorado	New Mexico	Utah *	Total
County Information					
Population, n	7,151,502	5,773,714	2,117,522	3,271,616	18,314,354
Years included in analysis	2009–2020	2009–2021	2009–2021	2012–2021	2009–2021
Counties included in analysis over total counties in state, n	15/15	64/64	33/33	15/29	127/141
Urban counties, n (%)	8 (53 %)	40 (63 %)	26 (79 %)	16 (55 %)	90 (64 %)
Climate					
Koppen-Geiger Climate Zone, number of arid counties n (%)	15 (100 %)	34 (53 %)	31 (94 %)	23 (79 %)	103 (73 %)
Statewide annual precipitation, mean (min, max)	12.26	17.95	13.88	13.39	
Statewide annual temperature, mean (min, max)	59.7 (45.6, 73.8)	44.9 (31.0, 58.7)	53.2 (38.3, 68.1)	47.8 (35.1, 60.5)	
Statewide Palmer Drought Severity Index (PDSI), mean (range)	−1.6 (−6.8–4.1)	−0.9 (−8.0–6)	−1.8 (−6.9–4.7)	−1.6 (−7.4–6.7)	
United States Drought Monitor, % of weeks in analysis drought category ≥1	78.9 %	56.2 %	70.8 %	81.7 %	
Southern Oscillation Index (SOI), mean (min, max) †	–	–	–	–	0.24 (−2.2, 2.9)
Health					
Total Counts of *Salmonella*	11,551	8878	5305	3616	29,350
Count of Confirmed Cases of *Salmonella*	10,906	8255	5132	3387	27,680
Incidence Rate of *Salmonella* per 100,000 population per year	13.5	11.8	19.3	11.1	13.9
Animals					
Density of Animals (USDA), mean (range) per mi^2					
Cattle, Milk	3.9 (0–14.2)	1.5 (0–32.8)	5.2 (0–64.1)	2.3 (0–16)	2.9 (0–64.1)
Cattle, Beef	2.1 (0–9.7)	6.8 (0.1–19.9)	4.3 (1.4–11.4)	5.9 (0.5–32.2)	5.6 (0–32.2)
Cattle, including calves	10.9 (1.5–76.4)	24.4 (0.1–183.5)	16 (2.1–199.2)	13.9 (0.9–53.2)	19.2 (0.1–199.2)
Chicken, Broilers	0.1 (0–0.4)	0.3 (0–1.9)	0.1 (0–0.7)	0.2 (0–1.5)	0.2 (0–1.9)
Chicken, Layers	0.5 (0.1–2.4)	19.8 (0.1–900.8)	0.7 (0–6.8)	1 (0–9.2)	9.7 (0–900.8)

UDSA, United States Department of Agriculture.
* 15 counties with a population > 20,000 people were included in the analysis due to data suppression requirements.
† Southern Oscillation Index value applied to all counties.

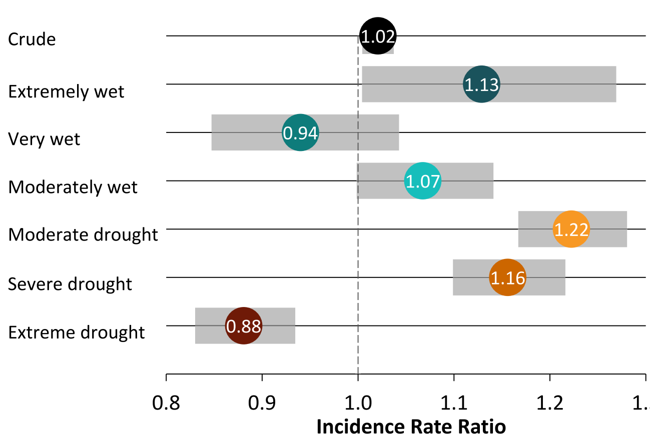

Fig. 1. IRR (marker) and 95 % CI (band) for the association between a one-inch increase in total weekly precipitation during different levels of drought via the PDSI (colors) in an ecological analysis of *Salmonella* infections in the Southwest US, 2009–2021.
IRR, Incidence Rate Ratio; CI, Confidence Interval; PDSI, Palmer Drought Severity Index. IRRs and 95 % CIs for all models available in Table S6 of the Supplemental Material. Dashed line indicates null value, where the risk of the outcome in both the exposed and non-exposed groups are equal. Estimates are based on negative binomial generalized estimating equations. The crude IRR (first marker, in black) provides the estimate for a one-inch increase in total weekly precipitation on *Salmonella* cases adjusted for average temperature. The next estimates are for a one-inch increase in total weekly precipitation, stratified by antecedent conditions. Antecedent conditions are measured via the PDSI (each of the next 6 markers, in color from teal to red: Extremely Wet, ≥4; Very Wet, 3–3.9; Moderately Wet, 2–2.9; Normal, −1.9-1.9; Moderate Drought, −2 to −2.9; Severe Drought, −3 to −3.9; and Extreme Drought, ≤ − 4). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

compared to weeks without these events, weeks with extreme precipitation events were associated with greater increases in cases. Further, as the level of precipitation increased from heavy precipitation above a 30-year normal, above the 95th percentile, and above the 99th percentile, the IRRs were attenuated within each stratified PDSI category (Fig. 2). The greatest association was found for extreme precipitation events following moderate and severe drought conditions which were all statistically significant regardless of the level of precipitation; the greatest risk was heavy precipitation following moderate drought (IRR: 1.30, 95 % CI: 1.23, 1.38).

Compared to counties without farm operations, counties with cattle and chicken or poultry farm operations had an increased risk of salmonellosis following precipitation (IRR cattle 1.37, 95 % CI: 1.31, 1.43; IRR chicken and poultry 2.71, 95 % CI: 2.55, 2.88), regardless of antecedent drought (Table S6). Across animal density types, precipitation following moderate and severe drought categories was associated with increased cases with the greatest increase in counties with a greater density of broiler chickens (IRR moderate drought: 1.49, 95 % CI: 1.38, 1.61; IRR severe drought: 1.41, 95 % CI: 1.31, 1.53). When considering animal density independently, density of broiler chickens was associated with a significant increase in cases, regardless of antecedent conditions (Fig. 3d). Density of beef cattle per square mile was associated with significant increases in cases with the greatest increase when precipitation fell following extremely wet conditions (Fig. 3b). Results for dairy cattle, and cattle including calves were mixed, with some prior wet conditions resulting in decreased cases, and precipitation following moderate and severe drought associated with increased cases (Fig. 3a, Fig. 3c).

Increased cases with precipitation following moderate and severe drought conditions remained consistent across the majority of the sensitivity analyses (Table S6). State-specific analyses showed increased cases for all PDSI categories except for antecedent extreme drought for Colorado; and significantly decreased cases for all other states for precipitation following extremely wet conditions and increased cases

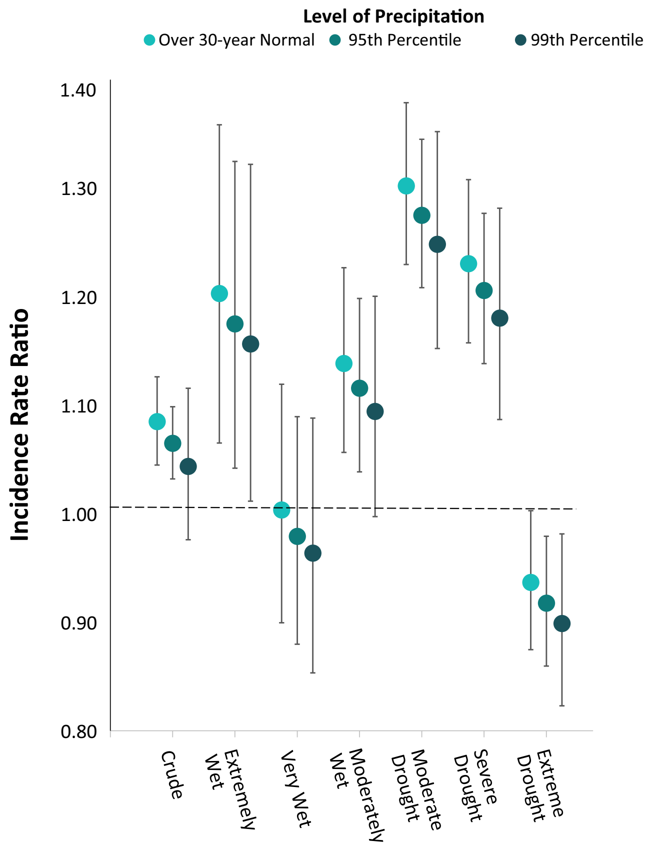

Fig. 2. IRR (marker) and 95 % CI (line) comparing counties which have experienced different levels of extreme precipitation events, compared to those who have not during different levels of drought via the PDSI in an ecological analysis of *Salmonella* infections in the Southwest US, 2009–2021.
IRR, Incidence Rate Ratio; CI, Confidence Interval; PDSI, Palmer Drought Severity Index. IRRs and 95 % CIs for all models available in Table S6 of the Supplemental Material. Dashed line indicates null value, where the risk of the outcome in both the exposed and non-exposed groups are equal. Estimates are based on negative binomial generalized estimating equations. Colors indicate the level of precipitation defined as (light teal) heavy precipitation (defined as total precipitation in the week over the 30-year normal), (teal) total precipitation above the 95th percentile, and (dark teal) total precipitation above the 99th percentile. The first set of markers (crude IRR) provides the estimate for comparing counties which have experienced that level of total weekly precipitation in a given week, to counties which have not. The next estimates compare counties which experienced that level of precipitation, to those that have not, stratified by antecedent conditions. Antecedent conditions are measured via the PDSI (each of the next 6 markers, in color from teal to red: Extremely Wet, ≥4; Very Wet, 3–3.9; Moderately Wet, 2–2.9; Normal, −1.9-1.9; Moderate Drought, −2 to −2.9; Severe Drought, −3 to −3.9; and Extreme Drought, ≤ − 4). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

following moderate and severe drought. Results for analyses exploring urbanicity, adjusting for years prior to the COVID-19 pandemic, and adjusting for SOI all remained consistent with the primary analysis.

4. Discussion

In this study we explored the association between precipitation and drought on *Salmonella* incidence in the Four Corners Region in the southwestern US from 2009 to 2021. We found that *Salmonella* cases increased by 2 % following a one inch increase in weekly total precipitation. Interestingly when we compared weeks with extreme precipitation events over a 30-year normal to weeks without, cases increased by 8 % (95 % CI: 1.04, 1.13) and were still elevated with precipitation above the 95th percentile (6 %) and 99th percentile (4 % although not significant). The attenuation of estimates with more extremes in precipitation indicates that more rain is not necessarily associated with increased cases in this study. Rather, we found the highest increase in cases in weeks when extreme precipitation events follow moderate and severe drought categories across all of our analyses of interest. Finally, we found density of broiler chickens and beef cattle was significantly associated with increased cases regardless of the prior conditions following precipitation.

These results are the first of our knowledge to explore the association between precipitation and drought on salmonellosis in the Southwest US. Our results partially support the concentration-dilution hypothesis [18]. When precipitation fell following dry periods, cases were highest, although cases did decrease in the most extreme drought conditions. This indicates that precipitation following moderate and severe drought conditions is associated with increased salmonellosis. However, precipitation following extreme drought was associated with decreased cases. We found mixed results during wet conditions which may be due to the low number of weeks in the analysis that were considered very wet or moderately wet (as seen in the large confidence intervals for wet conditions). For public health, it is likely that with changes in drought and extreme precipitation events due to climate change [16], public health may also see an increase in cases following these events. Efforts to integrate existing weather notification systems into public health surveillance may help public health prepare for and respond to this increase in cases through changing staff loads to account for additional case investigations.

Our results in this study are in contrast to the stratified analysis in Kraay et al. [18] showing bacterial diarrhea is more common during rainy seasons. Rather, our estimates for precipitation following moderate and extreme drought is consistent with Wang et al. [51] which explored diarrheal risk for children younger than five in a global cohort (risk of 7 % for mild drought, 11 % for severe drought). However, the settings and population are significantly different between Wang et al. and the study reported here, thus results are hard to compare. Our results are partially consistent with results found in Lee et al. [4] in Georgia, US. They found extreme rainfall (above 90th percentile) in wet periods had a 9 % increase in *Salmonella* cases, whereas, in dry periods, there was a 2 % increase (not significant). In contrast, we found extreme precipitation events (precipitation over a 30-year average) were associated with increased *Salmonella* infections in prior extremely wet (IRR: 1.20) and moderately wet (IRR: 1.14) conditions, but our largest increase was during prior moderate (IRR: 1.30) and severe (IRR: 1.23) drought. These conflicting results may be due to the difference in environmental conditions between the Southwest and Southeast US. For extreme precipitation events, we find similar results as Jiang et al. [14] which found an increased risk with an increase in extreme precipitation events in Maryland, US. Overall, these findings suggest the importance of region-specific and pathogen-specific analyses to explore the association between extreme weather events and enteric diseases.

Our results for the density of chicken operations are consistent with two other similar studies. For example, Lee et al. [4] found an elevated risk regardless of antecedent rainfall conditions, consistent with our results. Additionally, Morgado et al. [15] also showed elevated risks in areas with a high density of poultry operations in alignment with our results presented here. We hypothesize that the slight difference in results between studies is likely due to differences in climate region and how antecedent conditions were defined. Although this study did not explore transmission routes, this finding, which is consistent across multiple studies, indicates that presence and density of chicken and poultry operations may be a significant risk factor for salmonellosis. Ecological factors such as on-farm practices, water sources, and climate can significantly impact environmental-exposure pathways for *Salmonella* and it's prevalence (poultry 22 % [52,53]; cattle 9 % [54]). Efforts to comanage agricultural lands including treating upstream agricultural water sources (e.g. ditches, culverts), treating wastewater and effluents

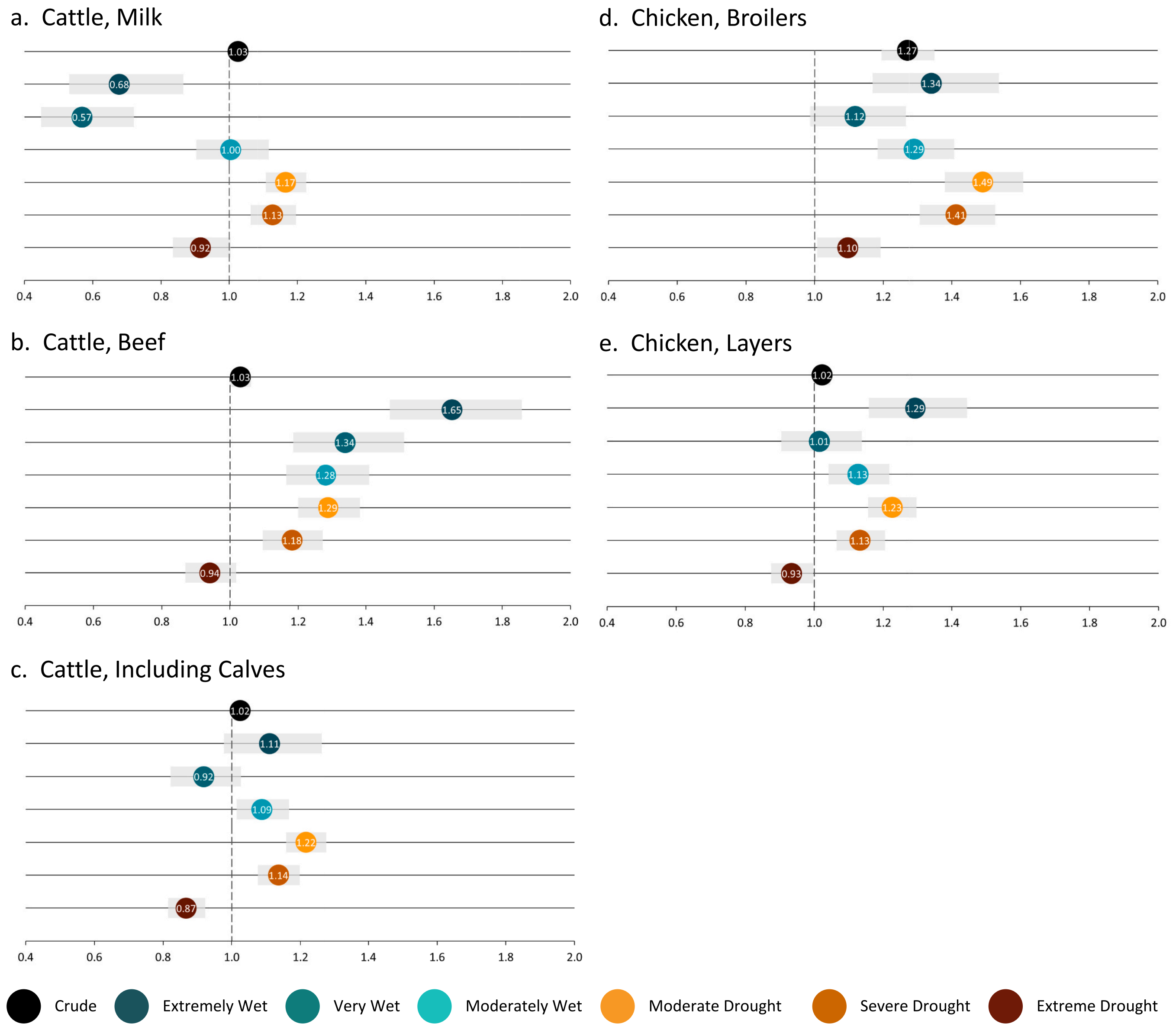

Fig. 3. IRR (marker) and 95 % CI (band) for the association between a one-inch increase in precipitation during different levels of drought via the PDSI adjusted for counties with different animal density types per square mile in an ecological analysis of *Salmonella* infections in the Southwest US, 2009–2021.
IRR, Incidence Rate Ratio; CI, Confidence Interval; PDSI, Palmer Drought Severity Index. IRRs and 95 % CIs for all models available in Table S6 of the Supplemental Material. Dashed line indicates null value, where the risk of the outcome in both the exposed and non-exposed groups are equal. Estimates are based on negative binomial generalized estimating equations. The crude IRR (first marker, in black) provides the estimate for a one-inch increase in total weekly precipitation on *Salmonella* cases adjusted for animal density and average temperature. The next estimates are stratified by antecedent conditions for a one-unit increase in density of each livestock type for a one-inch increase in total weekly precipitation on *Salmonella* cases in counties with these operations compared to those without. Antecedent conditions are measured via the PDSI (each of the next 6 markers, in color from teal to red: Extremely Wet, ≥ 4; Very Wet, 3–3.9; Moderately Wet, 2–2.9; Normal, -1.9-1.9; Moderate Drought, -2 to -2.9; Severe Drought, -3 to -3.9; and Extreme Drought, ≤ -4). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

from farms, and impeding overland flow to reduce surface transport of pathogens from terrestrial to freshwater environments (e.g. via increasing biodiversity around farms, rewilding to improve vegetation and native plant species, and changing ditch hydrology if needed) would all help reduce the environmental-exposure pathways of *Salmonella* transmission.

While our study has many strengths, there are limitations. The weather data from PRISM provides the best estimate of the weather occurring across the county rather than attributing the weather reported from one weather station. This data is also readily available for analyses and therefore finer spatial resolution data could be used in future studies to identify areas of particularly high vulnerability. However, because PRISM is grid-based, not county-based it incorporates data from weather stations and other sources based on their physiographic similarity, regardless of county boundaries. This means that the grid cell prediction (for county centroid in our case) could be influenced by stations both inside and outside the county boundaries. Typically, the denser the station data, the smaller the contributing area, and the larger the county, the more likely that stations within the county contributed to the centroid prediction. This could result in potential misclassification of the exposure (precipitation) as a result of attributing precipitation from the county centroid to the whole county; there is a larger risk of this misclassification in larger counties in the analysis. Future research could use the PRISM gridded weather dataset and point-location data for cases in their modeling to account for this limitation.

For the public health surveillance data we chose to use report date instead of onset date (because report date was more complete), and did not exclude cases based on outbreak-association or for recent travel. These limitations should be taken into account when considering these estimates. Further, due to data suppression requirements, we were not able to include all counties from UT in the analysis; this likely introduced some selection bias into the model if the excluded counties have different environmental exposures than included counties. Thus, results from the model are not generalizable to the whole state.

The model we chose to use for this analysis is also a major strength because it can account for the non-independence in the *Salmonella* data and the correlation between weather variables. However, not being able to account for population in the model due to non-convergence of estimates limits our interpretation of results. We hypothesize that the non-convergence and unstable estimates may be because of the time scale we chose (weekly) or the spatial scale (county). Further studies could explore how these factors may lead to unstable estimates for NBGEE, and include population offsets at a finer spatial resolution to account for this limitation. Future studies should also explore alternate sources for animal data as USDA animal census data for every year for every county was often missing. However, to the best of our knowledge this was the best dataset available at the time of writing for this region of the US.

5. Conclusion

In this study, we found that increased *Salmonella* infections are associated with precipitation events and are increased even more following precipitation in extremely wet, moderate and severe drought conditions. Our results differ from previous work in this area, showing the importance of pathogen-specific and regional estimates of risk. These results contribute to our knowledge about the many ways that weather variability affects our health. As drought becomes more severe and extreme weather events become more common, public health may see increases in *Salmonella* infections following precipitation during moderate and severe drought. Public health officials in this region will likely also see increases in *Salmonella* infections following extreme precipitation events over historic averages.

Funding information

This work was supported by the Colorado Integrated Food Safety Centers of Excellence (Grant number NU50CK000552-03-00).

CRediT authorship contribution statement

Erika Austhof: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Conceptualization, Software. **Kristen Pogreba-Brown:** Writing – review & editing, Validation, Supervision, Project administration, Funding acquisition. **Alice E. White:** Writing – review & editing, Project administration, Funding acquisition, Resources, Validation. **Rachel H. Jervis:** Writing – review & editing, Funding acquisition, Data curation, Resources. **Joli Weiss:** Writing – review & editing, Data curation, Resources. **Sarah Shrum Davis:** Writing – review & editing, Data curation, Resources. **Delaney Moore:** Writing – review & editing, Data curation, Resources. **Heidi E. Brown:** Writing – review & editing, Supervision, Funding acquisition, Project administration, Validation.

Declaration of competing interest

None.

Data availability

All data and code are available via the research compendium on GitHub: https://github.com/austhofe/RainDroughtSalmonella.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.onehlt.2024.100941.

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