

Impacts of short-term weather on communicable enteric infectious diseases in western Europe: A case study of the Republic of Ireland, 2009–2020

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Abstract

The incidence of sporadic enteric infections at temperate latitudes, including much of western Europe, vary seasonally, and as such are forecasted to shift in response to global climate changes. Understanding the associations between weather patterns and infection incidence is crucial to focus future surveillance efforts and minimise disease transmission. Accordingly, the relationship between antecedent mean ambient temperature, cumulative rainfall and weekly de-seasonalised incidence rates of three communicable pathogens, *Campylobacter*, *Cryptosporidium*, and Shiga-toxigenic *Escherichia coli* (STEC), delineated by five distinct settlement type classifications across the Republic of Ireland were investigated. A two-phase modelling strategy was employed, initiated via seasonal decomposition and followed by Bayesian structural time-series (BSTS) modelling of infection incidence using 0–20-week distributed temperature and rainfall lags. Models indicate that STEC enteritis is the most “climate driven” infection studied ($R^2=0.577$), followed by cryptosporidiosis ($R^2=0.355$) and campylobacteriosis ($R^2=0.207$). Associations between antecedent local weather variables and infection differed significantly with respect to settlement type: national-scale patterns of campylobacteriosis reflected a combination of i) urban incidence characterised by an association with short-term (0-4 weeks) antecedent temperature (suggesting shifting social behaviours e.g., food consumption), and ii) rural incidence driven by long-term temperatures (10-18 weeks) and short-term precipitation (1-2 weeks) (indicating bimodal transmission mechanisms). Conversely, STEC enteritis exhibited high levels of variance with respect to antecedent hydrometeorological variables across both urban commuter ($R^2=0.495$) and rural commuter ($R^2=0.407$) areas, settlement types often characterised by high concurrent reliance on private water supplies, domestic wastewater treatment systems, and livestock grazing across much of Western Europe. Study findings may be used to inform development of risk-based, pathogen-specific surveillance strategies based on observed and future weather conditions to mitigate the human health impacts of climate change across temperate high-income regions.

1. Introduction

Short-term hydrometeorological conditions have long been acknowledged as a driver for the transmission of infectious diseases [1]. Warmer mean temperatures and distinct wet seasons in tropical countries are frequently identified as primary factors for vector-borne diseases including malaria and

49 Lyme disease [2]. Likewise, survival and transmission of waterborne pathogens are predicated on
50 temperature and precipitation across climactic regions [3], while the occurrence of extreme weather
51 events (EWEs) including flooding or drought have been identified as the source of numerous outbreaks
52 [4-6]. Considering ongoing and projected climatic change, myriad concerns have been raised around
53 the rising incidence of environmentally associated infections driven by weather conditions. Mora *et al.*
54 predict that 58% of known pathogenic diseases are likely to increase due to climate change effects [5],
55 with Semenza *et al.* reporting that abnormally warm weather conditions during Spring 2018 across
56 Europe initiated an early breeding season for mosquitoes, resulting in a significant increase in the
57 incidence of West Nile Virus [6].

58 Multiple studies have focused on elucidating the associations between weather and infectious
59 diseases via time-series analyses; Lal *et al.* employed Seasonal Auto-Regressive Integrated Moving
60 Average (SARIMA) models to identify a positive relationship between cryptosporidiosis incidence and
61 the previous month's (i.e., 4-5 week lagged) mean temperature, in addition to salmonellosis incidence
62 and the current monthly temperature across New Zealand [7]. Similarly, Cheong *et al.* used Generalised
63 Additive Models (GAMs) to identify a positive relationship between cumulative rainfall, mean minimum
64 temperature, and dengue incidence across Malaysia at 1- and 2-month lags, respectively [8]. In the
65 Republic of Ireland (ROI), a country characterised by extremely high rates of gastroenteric infection
66 compared to EU mean figures, no time-series analyses focusing on the association between infectious
67 disease incidence and short-term weather conditions have been undertaken to date, representing a
68 notable knowledge gap.

69 The ROI is particularly likely to experience significant hydrometeorological fluctuations due to global
70 warming, with a 2-3°C increase in average temperature expected by 2100, in concurrence with higher
71 winter rainfall, significantly drier summers, and an increased frequency of EWEs [9]. These changes will
72 likely increase the incidence of environmentally acquired infections across the country; for example,
73 Boudou *et al.* recently reported that the 2015-2016 Winter flood event series (November - January)
74 across Ireland was associated with an atypical synchronous increase in both cryptosporidiosis and shiga
75 toxin-producing *E. coli* (STEC) incidence during late Spring 2016, while conversely, the European
76 summer 2018 heatwave was responsible for significant excess case notifications of campylobacteriosis
77 ($n = 101$) and STEC enteritis ($n = 68$). [10]. Accordingly, the current study employed Bayesian Structural
78 Time-Series modelling with distributed lags to identify associations between short- and medium-term
79 meteorological parameters (mean temperature, cumulative rainfall) and the incidence of three
80 gastroenteric infections, namely cryptosporidiosis, campylobacteriosis and STEC enteritis. All three
81 infections exhibit particularly high incidence rates in the ROI; a STEC enteritis crude incidence rate (CIR)
82 of 17.6 cases/100,000 was notified for 2022, the highest across the European Union [11], with Irish
83 cryptosporidiosis CIRs the highest reported across the European Union in 2021 (14.5 cases/100,000 vs
84 EU/EEA mean 1.8 cases/100,000) [12]. Campylobacteriosis is consistently reported as the most
85 common cause of bacterial gastroenteritis in the ROI with 71.5 cases/100,000 notified in 2022 [13]. The
86 current study is the first to directly assess the relationship between weather and the incidence of
87 enteric infection in Ireland. Findings may be used to inform development of risk-based, pathogen-
88 specific surveillance strategies based on observed and future weather conditions to appropriately
89 mitigate the human health impacts of climate change.

90

91 2. Methods

92 2.1 Infection data

93 Irreversibly anonymised data for laboratory-confirmed cases of campylobacteriosis, cryptosporidiosis
94 and STEC infection were obtained from the national Computerised Infection Diseases Reporting (CIDR)
95 database (<http://www.hpsc.ie/CIDR>). The CIDR database comprises a national Irish database of
96 notifiable infectious disease events notified to regional departments of Public Health in accordance
97 with the Infectious Diseases (Amendment) Regulations 2011 (S.I. No. 452 of 2011). For inclusion in the
98 CIDR database, a 'confirmed' infection case is defined as any person satisfying both clinical and
99 laboratory criteria for any given disease.

100 Individual cases were geographically linked to the geographical centroid of a Central Statistics Office
101 (CSO) 2016 Census Small Area (SA, N = 18,681), currently the smallest administrative unit used in the
102 Republic of Ireland, following the geocoding protocol previously developed for spatial attribution of
103 infection in the Republic of Ireland by Domegan et al. [14]. CSO SAs were designed as the lowest level
104 of geography for compilation of statistics in line with data protection guidelines and contain between
105 50 and 200 dwellings. However, for context, while the overall population density for the ROI currently
106 equates to approximately 70 persons/km², urban and rural areas average 2,008 and 27 persons/km²,
107 respectively. Previous work by the research group has shown that the incidence of all three infections
108 included as part of the current study are significantly affected by settlement type, and as such, these
109 delineations were used as a proxy measure for exposure and subsequent transmission mechanisms.
110 For example, the relative ubiquity of private (unregulated) groundwater wells, onsite wastewater
111 treatment systems, and pastoral agriculture across rural Ireland have been shown to associate with
112 elevated levels of primary transmission via direct animal contact and untreated water consumption,
113 while rates of secondary (person to person) transmission are significantly higher in urban areas [15-17].

114

115 Primary settlement type for each SA was extracted from the 2016 CSO Census Classification [18] (Figure
116 1), as follows:

- 117 • Rural areas, describing remote areas with little or no influence on urban areas (N = 3,101, 16.6%
118 of total SAs)
- 119 • Urban areas, identifying main cities (populations greater than 50,000) and satellites towns
120 (populations between 1,500 and 49,999) (N= 10,771, 57.8%)
- 121 • Commuter zones, areas having a moderate or high influence on urban areas (n = 4,769, 25.6%)

122

123 To further assess potential relationships between commuter zones dominated by rural or urban areas,
124 commuter zones were aggregated based on the abovementioned CSO classification [18] to create two
125 new categories, namely rural-commuter areas (rural areas with moderate urban influence, N =
126 7,820, 42.2% of total SAs) and urban-commuter areas (rural areas with high urban influence, N =15,540,
127 83.4% of total SAs).



128

129 **Figure 1. Settlement type classification in the Republic of Ireland based on the CSO Census 2016**
130 **[18]**

131 2.2. Weather data pre-processing

132 Mean weekly temperature and cumulative antecedent rainfall was acquired from Met Eireann, the
133 national meteorological agency, following a research protocol agreement. Data comprised NetCDF
134 raster files covering the period January 2009 to December 2020. Weekly time-series of cumulative
135 antecedent rainfall and mean temperature were extracted at the national scale via ArcMap v 10.7 for
136 each infection. Cumulative rainfall calculations were undertaken on an individual case by case basis,
137 based on the “date of infection” field included within the CIDR (communicable disease notification)
138 database e.g., 1-day lagged rainfall was the total volume of measured rainfall occurring on the data
139 prior to “date of infection”, while 5-day lagged rainfall was the sum of total rainfall volume occurring in
140 the five days prior to “date of infection”. To assess potential associations between antecedent weather
141 and infection, seasonal adjustments were undertaken using the STL() function in Rstudio (v 4.0.5), based
142 on the LOESS method and an additive seasonal decomposition formula whereby the incidence rate of
143 cases (I_v) is equal to the sum of seasonal variations (S_v), long-term trend (T_v) and residuals (R_v) [19], as
144 follow:

145

$$I_v = S_v + T_v + R_v$$

146 Seasonally adjusted (deseasonalised) time-series, corresponding to the sum of long-term trend (T_v) and
147 residuals (R_v), were extracted and used as primary inputs for analyses. This approach permits
148 examination of the “real” effect of short-term weather on infection incidence by avoiding any potential
149 bias introduced by typical seasonal patterning [20].

150

151 **2.3 Time-series modelling** Bayesian Structural Time-Series (BSTS) was employed for time-series analyses to
152 identify the presence and magnitude of synchronicity between antecedent cumulative rainfall and mean
153 temperature on infection incidence. BSTS is a stochastic state-space modelling approach commonly used for
154 time-series forecasting, nowcasting, inferring causal relationships or selection of best regressors. BSTS is
155 equivalent to dynamic linear modelling but relies on prior distribution experience and a likelihood (Bayesian)
156 function to build an analytical model for forecasting the posterior distribution [21]. Compared with ARIMA and
157 Additive Model Time Series Analysis, BSTS is considered superior as it effectively deals with much larger scale
158 exogenous data (e.g., antecedent climactic variables), leading to increasingly precise forecasting [21]. Weekly
159 seasonally adjusted time-series for each infection CIR delineated by settlement type (rural, urban, commuter,
160 rural-commuter and urban-commuter) were used as primary inputs, with weather variables employed as
161 regressors. Weather variables were lagged from 0 to 20 weeks (i.e., distributed lag) to identify delayed effects
162 [15] (Boudou *et al.*, 2021). The 0-20 week distributed lag framework was selected for use based on the
163 overarching study objective (national scale assessment of the effects of short-term weather patterns on endemic
164 (non-outbreak) cases of enteric infection), biological plausibility and previous work by the research team on
165 extreme weather events in Ireland. A recent study by Boudou *et al.* (2025) reports that the longest lagged effects
166 found between human infection and the 2018 European heatwave was approximately 4-5 weeks (STEC
167 enteritis, $p < 0.001$) [16], while an earlier Irish study reports that the longest lagged effect associated with the
168 1:500-year 2015/16 flood event was 19 weeks in the lower Shannon Basin (cryptosporidiosis) [15]. Accordingly,
169 20-weeks was used to truncate the current lag framework, however the authors that future studies at a regional
170 or local scale may wish to examine lag periods greater than this. The overarching BSTS computational approach
171 was adapted from Vavilala *et al.* (2022) who previously sought to predict the incidence of malaria in northeastern
172 India based on a battery of lagged antecedent climactic variables [22]. Both Vavilala *et al.* [22] and Scott & Varian
173 [23] provide excellent mechanistic overviews of the BSTS approach. All BSTS modelling was implemented using
174 the 'bsts' package (v 0.9.10) in Rstudio (v 4.0.5). State specification was defined using the `AddLocalLevel()`,
175 `AddSeasonal()`, and `AddRegression()` functions, with the `AddAR()` function not employed due to the absence of
176 serial correlation in the de-seasonalised time-series based on tests of autocorrelation and partial
177 autocorrelation. Model specifications integrated a local level trend state component with the infection time-
178 series, based on the assumption of a "random walk" trend, with the `SdPrior()` function included to create an
179 object describing the prior distribution for the standard deviation of the random walk increments via a
180 `sigma.prior` argument. The time-series component (`AddRegression`) was characterised using the spike-slab prior
181 regression approach, an optimal variable selection method which reduces a larger dataset of correlated variables
182 to a smaller dataset comprising important variables by imposing prior beliefs on the model. The prior distribution
183 for the variance of the regression coefficients was not explicitly defined or fixed, meaning the prior on the
184 variance was estimated from the data, allowing for more flexibility and adaptability in the model, by allowing
185 for simultaneous error variance estimation. The spike and slab method can also remove the multicollinearity
186 among independent predictors in the regression coefficients. Here, the term "spike" handles the probability of
187 inclusion or omission of any predictor variable by using Bernoulli distribution as prior and the term "slab"
188 escalates the calculation of probabilities of coefficients for a predictor (non-zero) if it had already been selected
189 [23]. The seasonal component was characterised as `period = 52`, `season.duration = 1`. Using the input dataset,
190 state specification, and priors, models were run with an `expected.model.size = 5`, referring to the anticipated
191 number of non-zero coefficients in the model, indicating the complexity of the model in terms of the number of
192 predictors or features included to guide the spike and slab prior. All models comprised a 1000x modelling cycle
193 (`niter = 1000`), with the `SuggestBurn()` function used to determine the number of Monte Carlo iterations to
194 discard as burn-in when making predictions. The six distributed lags with highest inclusion probabilities have
195 been employed for reporting, with multiple r^2 values used to assess model accuracy (generalisability).

196

197 3. Results

198 3.1 Descriptive analyses

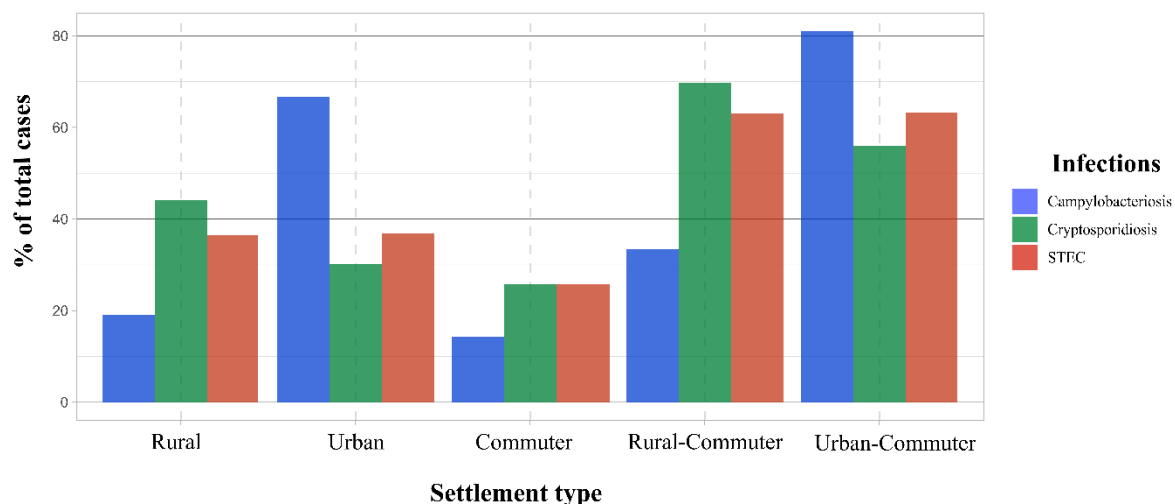
199 Of 25,161 laboratory-confirmed cases of campylobacteriosis notified between January 2011 to
200 December 2018, 14,375 cases (72.3%) were successfully geo-linked to one CSO SA. Further, 4,158 (97%)
201 cases of cryptosporidiosis occurring between January 2009 and December 2017 were geo-linked, while
202 the STEC infection dataset comprised cases occurring between January 2013 to December 2020 with
203 5,120 cases (68%) successfully geo-linked.

204 As shown (Figure 1), campylobacteriosis cases were more frequently notified in urban areas (N
205 = 9,580; 66.7% of total cases), with commuter areas reporting the lowest proportion of cases (N = 2,057,
206 14.3%). Conversely, cryptosporidiosis cases were most frequently notified in rural areas (N = 1,830,
207 44.1%), while STEC cases were evenly distributed between rural (N = 1,969, 37.8%) and urban areas (N
208 = 1,963, 37.7%).

209 Campylobacteriosis (2011-2018) exhibited a weekly mean incidence of 34.7 cases with an
210 annual seasonal peak from April to June. Cryptosporidiosis (2009-2017) exhibited a weekly mean
211 incidence of 8.8 infections with highest incidence rates occurring in April, while STEC infections were
212 characterized by a mean incidence of 12.5 cases/week with a primary annual peak in mid-Summer (i.e.,
213 July) and a secondary peak in September. Weekly incidence rates for all three infections are presented
214 in Figure 3, with developed seasonally adjusted time series provided in Figures 4 and 5.

215

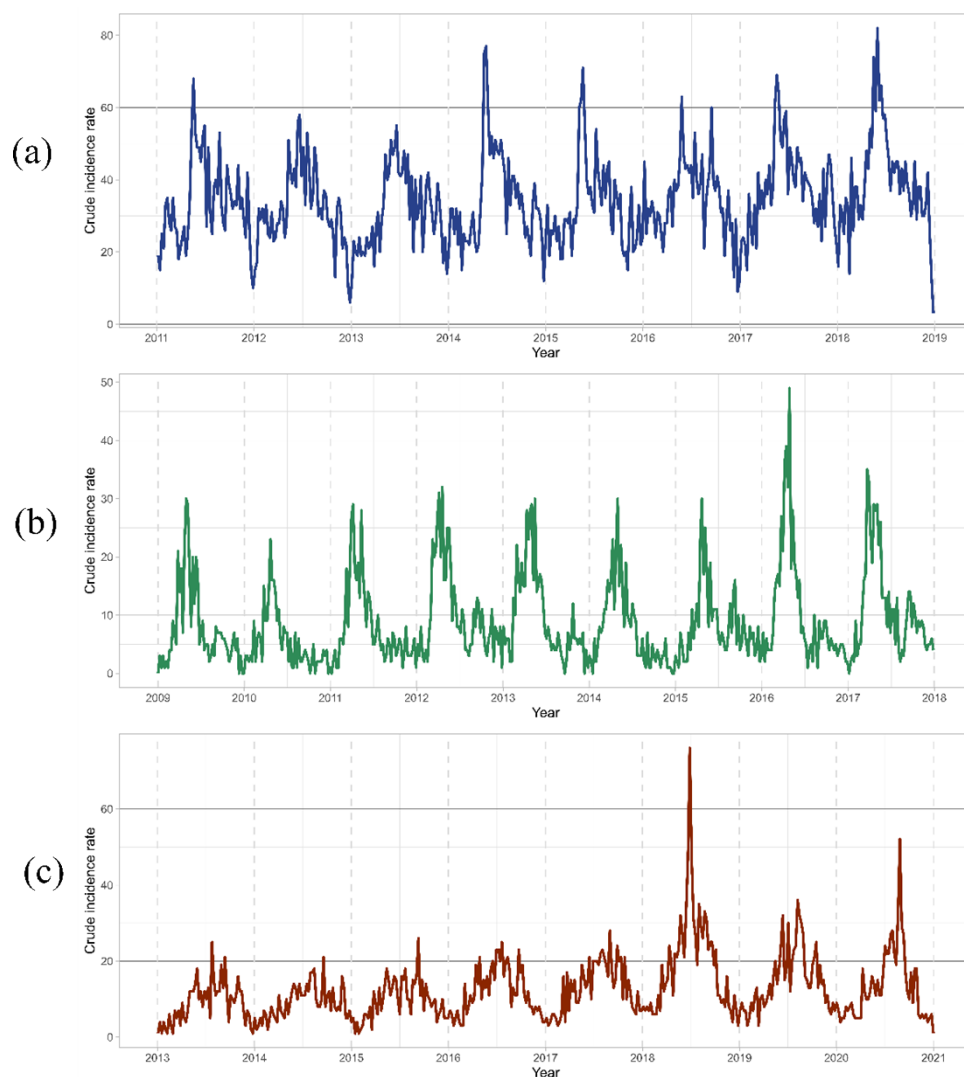
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217

218 Figure 2 Settlement type classification attributed to notified cases of campylobacteriosis (2011-2018),
219 cryptosporidiosis (2009-2017) and STEC enteritis (2013-2020) across the Republic of Ireland

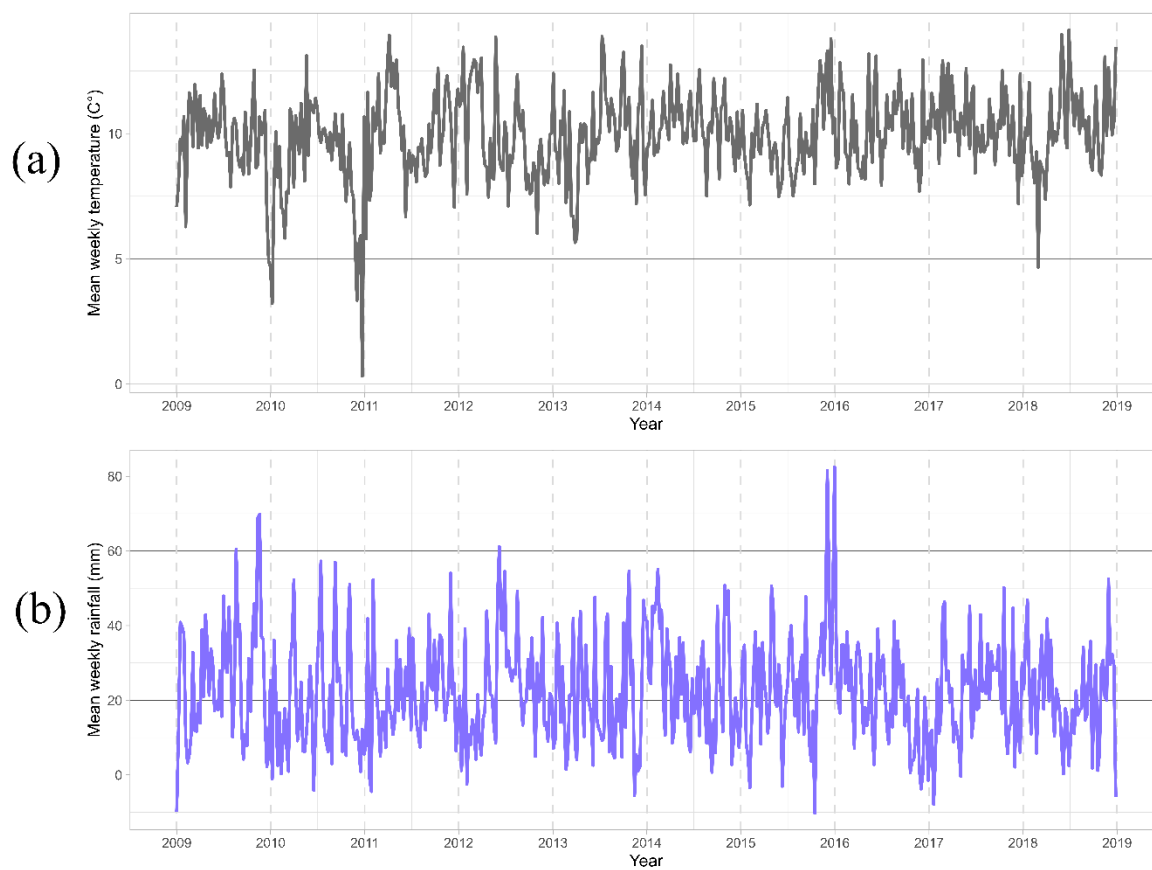
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221

222 Figure 3 Weekly incidence rates of: (a) - campylobacteriosis (2011-2018) – (b) cryptosporidiosis (2009-
223 2017) – (c) STEC (2013-2020) across the Republic of Ireland

224

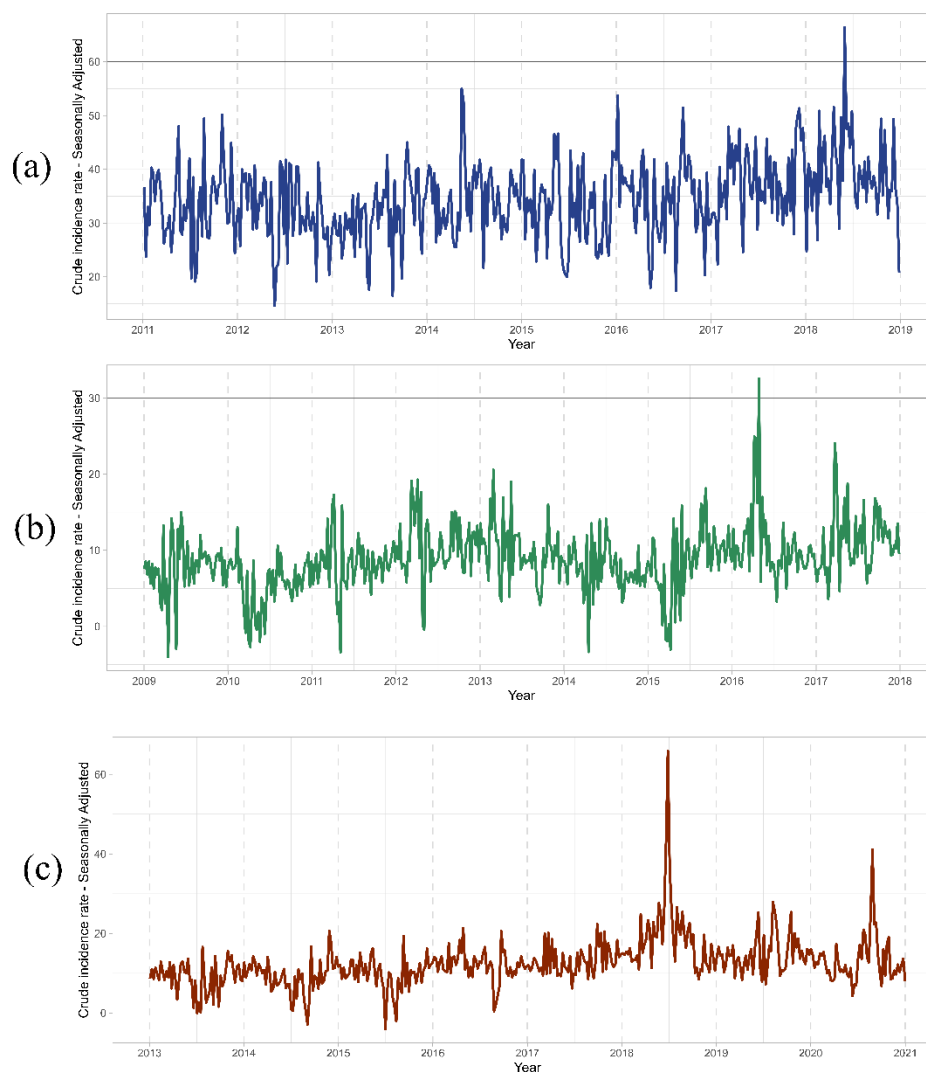


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226

227

Figure 4. Seasonally adjusted time series of (a) weekly mean temperature (°C) and (b) weekly antecedent cumulative rainfall (mm) across the Republic of Ireland (2009-2018)



228

229 **Figure 5. Seasonally-adjusted time series of crude incidence rate of: (a) - campylobacteriosis (2011-**
230 **2018) – (b) cryptosporidiosis (2009-2017) – (c) STEC (2013-2020)**

231

232 3.2 Distributed Lag Bayesian Structural Time-series Models

233 *Campylobacteriosis*

234 Antecedent temperature was shown to be a significant precursor for campylobacteriosis cases across
235 all settlement types (Table 1). Notably, antecedent precipitation did not appear as a significant
236 predictor for Campylobacteriosis infection in urban areas. The most frequently reported associations
237 for temperatures were negative and identified as occurring at week 15 in the ROI (OR: 0.62), rural (OR:
238 0.81), urban (OR: 0.95), rural-commuter (OR: 0.82) and urban-commuter areas (OR: 0.97). A 3-week
239 lagged temperature was identified as having the highest positive association with campylobacteriosis
240 incidence at the national scale (ROI model) (OR: 1.07), urban (OR: 1.07), and urban-commuter areas
241 (OR: 1.05) (i.e., 1°C increase in temperature associated with 5-7% increased incidence rate). Regarding
242 rainfall, positive association with a 1-week lag were exhibited across all non-urban models. Highest
243 model R² values were obtained for the ROI (national) model (R²: 0.206).

244

245 **Table 1. Peak inclusion probabilities (n = 6) from BSTS for seasonally adjusted weekly incidence rate of**
 246 **campylobacteriosis, antecedent rainfall and mean temperature**

Model	Variable	Lag	Incl. Prob.	Estimate	OR	R ²
ROI (National scale)	Temp	15	0.670	-0.4746	0.6222	0.207
	Rainfall	1	0.321	0.0279	1.0283	
	Temp	3	0.127	0.0729	1.0757	
	Temp	10	0.024	-0.0100	0.9900	
	Temp	19	0.017	-0.0039	0.9961	
	Temp	4	0.015	0.0054	1.0054	
Rural	Temp	15	0.696	-0.2002	0.8186	0.111
	Temp	18	0.065	0.0130	1.0131	
	Rainfall	2	0.018	0.0004	1.0004	
	Rainfall	1	0.015	0.0004	1.0004	
	Temp	10	0.014	-0.0017	0.9983	
	Temp	12	0.009	0.0014	1.0014	
Urban	Temp	3	0.137	0.0702	1.0727	0.145
	Temp	15	0.130	-0.0443	0.9566	
	Temp	0	0.047	-0.0100	0.9900	
	Temp	20	0.039	-0.0066	0.9935	
	Temp	19	0.038	-0.0108	0.9893	
	Temp	4	0.026	0.0099	1.0100	
Comm	Temp	11	0.547	-0.1480	0.8624	0.052
	Rainfall	1	0.169	0.0048	1.0049	
	Temp	10	0.033	-0.0059	0.9941	
	Temp	19	0.012	-0.0003	0.9997	
	Temp	1	0.012	0.0011	1.0011	
	Temp	0	0.011	0.0013	1.0013	
Rural Comm	Rainfall	1	0.538	0.0280	1.0284	0.160
	Temp	15	0.535	-0.2037	0.8157	
	Temp	10	0.267	-0.1006	0.9043	
	Temp	11	0.093	-0.0286	0.9718	
	Temp	18	0.040	0.0100	1.0100	
	Rainfall	2	0.026	0.0008	1.0001	
Urban Comm.	Temp	3	0.076	0.0486	1.0498	0.152
	Rainfall	1	0.066	0.0038	1.0039	
	Temp	15	0.046	-0.0259	0.9744	
	Temp	11	0.026	-0.0085	0.9916	
	Temp	20	0.019	-0.0070	0.9930	
	Temp	13	0.017	-0.0061	0.9939	

247

248

249

250 *Cryptosporidiosis*

251 Bayesian time-series models identified antecedent temperature as the primary meteorological
 252 predictor of cryptosporidiosis incidence, with rainfall entirely absent from the highest inclusion
 253 probabilities (N=6) across categorically rural areas (Table 2), albeit the national-scale model comprised
 254 three antecedent precipitation periods, all of which were positive. Positive associations between
 255 cryptosporidiosis incidence and mean temperature were identified at week 19 for the ROI (OR: 1.03),
 256 rural (OR: 1.42) and rural-commuter areas (OR:1.17). The association between mean temperature at
 257 week 19 and cryptosporidiosis CIRs was particularly notable, with results indicating a 1°C increase in
 258 temperature above the seasonal mean is associated with a 42% increase in the incidence rate of
 259 infection. Similarly, the 17-week temperature lag was positively associated with cryptosporidiosis
 260 incidence rates in rural, urban, rural-commuter and urban-commuter areas. Antecedent rainfall was
 261 also linked to positive relationships according to model results, with the most common lags
 262 corresponding to weeks 14 and 19 for the ROI, commuter, rural-commuter and urban-commuter areas.
 263 It is important to note that while the odds ratios for rainfall are considerably low (OR 1.001-1.0021),
 264 they represent an increased odds per millimetre of rainfall and thus are aggregated for significant
 265 rainfall events. Highest R² values were obtained for the ROI (national) model (R²: 0.365).

266

267 **Table 2. Peak inclusion probabilities (n = 6) from BSTS for seasonally adjusted weekly incidence rate of**
 268 **cryptosporidiosis, antecedent rainfall and mean temperature**

Model	Variable	Lag	Incl. Prob.	Estimate	OR	R ²
ROI	Temp	18	0.086	-0.0327	0.9678	0.355
	Temp	19	0.074	0.0262	1.0265	
	Rainfall	14	0.014	0.0005	1.0005	
	Rainfall	19	0.008	0.0001	1.0001	
	Rainfall	7	0.006	0.0001	1.0001	
	Temp	16	0.005	0.0000	1.0000	
Rural	Temp	19	0.980	0.3514	1.4210	0.154
	Temp	18	0.977	-0.3344	0.7158	
	Temp	6	0.026	-0.0040	0.9961	
	Temp	0	0.022	-0.0025	0.9975	
	Temp	4	0.017	-0.0016	0.9984	
	Temp	17	0.016	0.0022	1.0023	
Urban	Temp	17	0.046	0.0041	1.0041	0.236
	Temp	5	0.022	0.0017	1.0017	
	Temp	10	0.014	0.0009	1.0009	
	Temp	8	0.012	0.0009	1.0009	
	Rainfall	19	0.008	0.0001	1.0001	
	Temp	18	0.008	0.0002	1.0002	
Comm	Temp	7	0.124	-0.0117	0.9884	0.137
	Rainfall	14	0.122	0.0021	1.0021	
	Temp	8	0.104	-0.0123	0.9878	
	Temp	9	0.033	-0.0040	0.9960	
	Temp	16	0.017	-0.0013	0.9987	
	Temp	11	0.012	-0.0005	0.9995	
Rural Comm	Temp	19	0.469	0.1491	1.1608	0.238

	Temp	18	0.395	-0.1235	0.8838	
	Temp	0	0.044	-0.0076	0.9924	
	Rainfall	14	0.026	0.0007	1.0007	
	Temp	8	0.016	-0.0027	0.9973	
	Temp	17	0.015	0.0022	1.0022	
Urban Comm.	Temp	17	0.042	0.0035	1.0035	0.301
	Temp	4	0.034	0.0027	1.0027	
	Temp	7	0.031	-0.0022	0.9978	
	Temp	14	0.017	0.0006	1.0006	
	Temp	12	0.015	0.0013	1.0013	
	Rainfall	14	0.010	0.0002	1.0002	

269

270 *STEC Enteritis*

271 Overall, model results suggest that STEC enteritis was the most “weather affected” infection of the
 272 three investigated (ROI Model R²: 0.477); perhaps unexpectedly, meteorological variables explained a
 273 higher level of variability in urban areas (R²: 0.587) than their rural counterparts (R²: 0.310). Antecedent
 274 temperatures exhibited the highest inclusion probabilities for the ROI, rural, urban and urban-
 275 commuter areas (Table 3). Within urban areas, rainfall was not identified as a primary predictor of STEC
 276 infections. The most frequently reported significant and positive temperature lags for temperature
 277 occurred between weeks 0 and 5, i.e., relatively rapid response, with week 4 antecedent temperatures
 278 exhibiting the maximum inclusion probability within the national model (OR: 1.003). Negative
 279 associations were found from weeks 0 to 2 in urban areas and weeks 8 to 17 in rural-commuter areas,
 280 while positive associations were identified for week 0 for urban and urban-commuter areas.
 281 Antecedent rainfall was consistently identified as having positive associations across all settlement
 282 types, apart from urban areas. The most frequently identified precipitation lags were week 0 for the
 283 ROI, rural and rural-commuter areas, and week 2 in commuter, rural-commuter and urban-commuter
 284 areas. Maximum odds-ratios for temperature and rainfall were obtained in the ROI (national) model
 285 (Week-4, OR: 1.033) and rural areas (Week 0: 1.0011), respectively.

286

287 **Table 3. Peak inclusion probabilities (n = 6) from BSTS for seasonally adjusted weekly incidence rate of**
 288 **STEC enteritis, antecedent rainfall and mean temperature**

Model	Variable	Lag	Incl. Prob.	Estimate	OR	R ²
ROI	Temp	4	0.0231	0.0033	1.0033	0.587
	Temp	5	0.0121	0.0016	1.0016	
	Temp	14	0.0085	0.0012	1.0012	
	Rainfall	0	0.0073	0.0001	1.0001	
	Temp	20	0.0061	0.0008	1.0008	
	Temp	10	0.0061	0.0005	1.0005	
Rural	Rainfall	0	0.0495	0.0011	1.0011	0.31
	Temp	0	0.0085	0.0000	1.0001	
	Rainfall	18	0.0057	0.0001	1.0001	
	Temp	17	0.0057	0.0000	1.0001	
	Temp	16	0.0057	0.0000	1.0001	
	Temp	5	0.0057	0.0003	1.0003	
Urban	Temp	5	0.0681	0.0104	1.0105	0.477

	Temp	0	0.0307	-0.0001	0.9999	
	Temp	4	0.0204	0.0018	1.0018	
	Temp	1	0.0187	-0.0010	0.9990	
	Temp	2	0.0153	-0.0011	0.9989	
	Temp	3	0.0085	0.0006	1.0006	
Comm	Rainfall	2	0.0086	0.0001	1.0001	0.241
	Rainfall	13	0.0049	0.0000	1.0001	
	Rainfall	1	0.0049	0.0000	1.0001	
	Temp	15	0.0049	0.0000	1.0000	
	Rainfall	4	0.0037	0.0000	1.0001	
	Rainfall	19	0.0024	0.0000	1.0001	
Rural Comm	Temp	15	0.0337	-0.0044	0.9956	0.407
	Temp	8	0.0232	-0.0031	0.9969	
	Temp	17	0.0116	-0.0012	0.9988	
	Temp	9	0.0116	-0.0017	0.9983	
	Rainfall	2	0.0105	0.0002	1.0002	
	Rainfall	0	0.0105	0.0002	1.0002	
Urban Comm.	Rainfall	2	0.0104	0.0002	1.0002	0.495
	Temp.	0	0.0092	0.0006	1.0006	
	Temp.	9	0.0058	0.0001	1.0001	
	Rainfall	7	0.0046	-0.0001	0.9999	
	Temp	2	0.0046	-0.0001	0.9999	
	Temp.	14	0.0035	0.0001	1.0001	

289

290 4. Discussion

291 In the current study, distributed lag Bayesian structural models were employed to investigate
 292 time series of three enteric infection incidence rates and antecedent meteorological variables. Overall,
 293 study findings suggest that while both antecedent cumulative precipitation and mean temperature are
 294 significantly associated with the incidence of enteric infection across temperate regions, the
 295 directionality and magnitude of estimated effects differ by settlement type. Thus, changing climate
 296 patterns will lead to shifting spatiotemporal distributions of infection, which should be considered for
 297 future climate planning, mitigation and resilience.

298

299 *Campylobacteriosis*

300 Overall, models suggest that campylobacteriosis is the least “weather affected” infection of the
 301 three studied, with relatively low R² values (i.e., fraction of explained variance) ranging from 0.052 to
 302 0.257. Nationally, a bimodal effect was noted, with the short-term period 1-4 weeks and longer-term
 303 period 10-19 weeks recurring across campylobacteriosis models. Further delineation showed that this
 304 national pattern reflected a combination of urban incidence rates which were characterised by an
 305 association with short-term (0-4 weeks) antecedent temperature, and rural incidence rates associated
 306 with long-term temperatures (10-18 weeks) and short-term rainfall (1-2 weeks). The positive
 307 associations found between short-term temperature and campylobacteriosis indicates a direct effect
 308 of short-term temperature fluctuations on infection incidence. The link between temperature and
 309 campylobacteriosis has been partially attributed to a higher prevalence of vectoral drivers i.e., warmer
 310 ambient temperatures increase vector activity (e.g., flies), triggering increased contamination of broiler

311 flocks and subsequent foodborne infection [24,25]. Likewise, human behaviours are inherently linked
312 with weather conditions, with drier and sunnier weather co-occurring with an increase in outdoor
313 activities including recreational bathing and shifting dietary habits (i.e., higher consumption of
314 barbecued meats, fruits and salads) resulting in higher rates of food- and recreational waterborne
315 infection [26,27]. Accordingly, the authors consider the primary effects of temperature on urban
316 campylobacteriosis incidence in Ireland to be relatively rapid and indirect (vector ecology, human
317 behaviour) in nature. Patrick *et al.* previously identified a 3-week cumulative increase in mean
318 temperature as the primary meteorological parameter predicating human campylobacteriosis
319 incidence in Denmark [28], with analogous results reported in England and Wales [29] and Germany
320 [25]. Within the current study, the identified short-term lag may be indicative of the mean incubation
321 period for campylobacteriosis (2-5 days) [30] in concurrence with behavioural changes (diet, outdoor
322 recreation) due to bright and warm conditions. Notably, Danis *et al.* (2009) identified consumption of
323 chicken, lettuce and take-away foods as primary risk factors for campylobacteriosis in Ireland, with a
324 recent study by Burke *et al.* reporting the existence of distinct “urban” and “rural” diets, thus potentially
325 elucidating the absence of short-term temperature as a precursor to campylobacteriosis incidence in
326 rural areas [31].

327 All models, excluding the urban model, identified positive associations between lagged weekly
328 cumulative rainfall 1-2 weeks prior and campylobacteriosis incidence (Table 1). This mirrors previous
329 findings from Denmark [28] and the UK [32] where similar positive relationships between
330 campylobacteriosis and short-term (1 week) cumulative rainfall was identified. Kuhn *et al.* have shown
331 that a concurrent increase in heavy rainfall and mean temperature, based on climate change scenarios,
332 increase the number of cases of campylobacteriosis in Scandinavia [33]. Moreover, *Campylobacter spp.*
333 has been shown to exhibit longer periods of viability in wetter conditions [34], with heavy rainfall events
334 previously acknowledged as being responsible for an increase in campylobacteriosis incidence [35] and
335 the source of potential outbreaks due to groundwater contamination [36]. While campylobacteriosis
336 is typically attributed to foodborne transmission in temperate latitudes, one of the few
337 campylobacteriosis case-control studies to be undertaken in Ireland reported that mains (municipal)
338 water supplies showed a protective effect (amOR=0.2; 95 CI 0.1-0.9) [37], thus indicating a potentially
339 causative relationship with private supplies, which are primarily sourced from groundwater in Ireland.
340 Both Hynds *et al.* [38] and Andrade *et al.* [39] have identified a 5-day antecedent rainfall periods as
341 being a risk factor for bacterial contamination of Irish private wells, and when considered in
342 concurrence with the typical incubation period, would seem to add credence to 1-2-week rainfall as a
343 driver of groundwater-borne campylobacteriosis in Ireland.

344 The negative relationships between campylobacteriosis incidence and temperatures during
345 weeks 10-19 (i.e., 2-4 months) may be indicative of a delayed reaction between lower winter
346 temperatures and the usual campylobacteriosis peak of infection in Ireland during early summer [16],
347 however more work is required to explore this association.

348

349 *Cryptosporidiosis*

350 Nationally, a bimodal effect was noted, with the short-term period 1-4 weeks and longer-term
351 period 16-19 weeks recurring across cryptosporidiosis models. Further delineation showed that the
352 national pattern reflected a combination of urban incidence rates characterised by an association with
353 short-term (0-4 weeks) antecedent temperature, and rural incidence rates associated with long-term

354 temperatures (16-19 weeks) and medium- to long-term rainfall (14-19 weeks). Overall, short-term
355 weather patterns represented a more significant precursor to cryptosporidiosis incidence in urban
356 areas, than rural or commuter areas.

357 Numerous studies have reported positive relationships between cryptosporidiosis and mean
358 temperature [7,40,41], variously explained by extended oocyst viability concurring with increased
359 temperatures and increased outdoor activities (i.e., swimming in river and lakes, contact with infected
360 animals). Likewise, the current study identified positive relationships at 16 to 19 weeks between
361 cryptosporidiosis and mean temperature within all settlement type delineations (Table 2). Significantly
362 longer lags obtained by the current study may be indicative of specific agricultural practices and climatic
363 conditions in the Republic of Ireland, with the annual cryptosporidiosis peak (April to June) in the ROI
364 traditionally attributed to agricultural cycles (e.g., calving season) [15]. King & Monis previously
365 demonstrated that cryptosporidiosis oocysts can survive up to 24 weeks when temperatures are
366 between 1 and 15°C [42]; the annual mean temperature in Ireland typically ranges from 9 to 10°C [43].
367 The delayed association identified by the current study may be a result of relatively mild temperatures
368 during Winter months in the ROI contributing to a longer survival capacity of cryptosporidiosis oocysts
369 within the environment. Notably, the highest odds-ratio was obtained in rural areas, with a 1°C increase
370 in mean temperature 19 week before onset date was shown to increase the probability of reporting an
371 increase in cryptosporidiosis incidence by 42% (Table 2). This significantly delayed response points to
372 complex mechanisms associated with environmentally acquired cryptosporidiosis transmission in
373 Ireland. Boudou *et al.* previously identified a link between the extreme rainfall events of Winter 2015-
374 2016 across Ireland with a significantly increased cryptosporidiosis incidence rate up to 19 weeks after
375 event occurrence due to the complex interplay between subsoil conditions, overland flow, oocyst
376 survival and prolonged subsurface residence times i.e., groundwater recharge [15]. The authors
377 consider that these results are reflective of a more complex role than previously thought of mean
378 temperatures in rural areas at temperate latitudes (i.e., combined effects on (sub)soil conditions,
379 oocyst survival, local agricultural cycles), with more research required to elucidate the mechanisms
380 underlying this association.

381 Previous studies have identified significantly shorter temperature lags, albeit these studies
382 were not delineated by settlement type, for example, both Lal *et al.* [7] and Lake *et al.* [40] found an
383 association between cryptosporidiosis incidence and the mean previous months (i.e., 4-6 weeks)
384 temperature in New-Zealand and England/Wales, respectively. Similarly, Hu *et al.* reported a positive
385 relationship between cases of cryptosporidiosis and a lagged mean temperature from 1 to 3 months
386 (i.e., up to 14 weeks) in Brisbane, Australia [44]. Contaminated drinking and recreational waters and
387 international travel account for most of the reported *Cryptosporidium* spp. exposures in high-income
388 countries [45]. The association identified in the current study between urban incidence rates and with
389 short-term (0-4 weeks) antecedent temperature may be indicative of relatively rapid individual and/or
390 community behavioural responses to seasonal weather patterns. A recent report by the ECDC stated
391 that comparisons with available data from four regions in England and Wales during 2022 suggest a
392 greater exposure to swimming as a primary driver for atypically high cryptosporidiosis rates (OR: 1.61;
393 95% CI: 1.04–2.48) [46]. Likewise, in mid-October 2023, the Irish Health Protection Surveillance Centre
394 (HPSC) posted a press release concerning a rise in cases of cryptosporidiosis being reported among Irish
395 tourists during the 2-month period August-September returning from areas of Spain [46] (ECDC, 2023).

396 The most frequently identified association between cryptosporidiosis and rainfall across
397 settlement types was found at week 14, with a 10 mm increase in cumulative weekly precipitation

398 shown to increase the cryptosporidiosis incidence rate by up to 20% (2% per mm) approximately 3
399 months later (Table 2, Commuter Zones). A relatively similar result was reported by Curriero *et al.* who
400 found a significant relationship between the occurrence of waterborne cryptosporidiosis cases and a 2-
401 month precipitation lag in the United States [47]. An increase in cryptosporidiosis cases after periods
402 of higher rainfall has been documented internationally; Britton *et al.* identified an increased
403 rainfall/evaporation ratio as a key precursor to increased cryptosporidiosis cases in New-Zealand [48],
404 with medium-term rainfall identified as a trigger for an increase in *C. hominis* cases in Germany [49]. A
405 direct link between extreme rainfall events, flooding and occurrence of cryptosporidiosis outbreaks has
406 also been demonstrated [50]; high rainfall associated with increased runoff coefficients has been shown
407 to support mobilization and concentration of oocysts in water, thus increasing the risk water supply
408 contamination [51].

409

410 *STEC Enteritis*

411 STEC enteritis was the most “weather affected” infection studied, with presented models
412 accounting for up to 58.7% (national model) of total variance (Table 3). Models identified a clear
413 association between STEC incidence and short-term rainfall, with a positive association identified at
414 Weeks 0 (National scale model) and 2 (rural and rural-commuter areas) (Table 3). The relationship
415 between short-term rainfall and STEC has previously been shown as a proxy for rapid mobilisation of
416 STEC during and immediately after rainfall events, resulting in contamination of surface and
417 groundwater reservoirs via rapid overland and/or preferential flow [52,53]. Recent work undertaken
418 across the Ottawa Health Region reported that cumulative rainfall 2 weeks prior was significantly
419 associated with an increase in STEC case notification across study area, likely due to increased transport
420 of pathogens within watersheds (hydrological catchments) [54]. Likewise, Carlton *et al.* identified heavy
421 rainfall with a 2-week lag as being associated with an increased incidence of gastrointestinal diseases
422 across Ecuador [55]. Several studies have identified 30-day antecedent rainfall periods as a primary risk
423 factor for *E. coli* contamination of private wells in Ireland [38,39,56] - when considered in concurrence
424 with the mean STEC incubation period (7-10 days) and environmental time of travel to susceptible
425 wellheads, this would seem to further highlight private groundwater sources as a major reservoir for
426 STEC infection in rural temperate regions. Garvey *et al.* have previously reported that the most common
427 transmission pathway for STEC infection in rural areas of Ireland is characterised by a combination of
428 susceptible private water supplies and high livestock densities [57]. Perhaps unexpectedly, STEC
429 enteritis was the only infection with high levels of model variance explained by antecedent
430 hydrometeorological variables across both urban commuter ($R^2=0.495$) and rural commuter ($R^2=0.407$)
431 areas. Modern peri-urban/rural development, in concurrence with climate change dynamics, have
432 previously been cited as representing a significant health risk to the Irish population via contamination
433 of potable groundwater [56,57]. Peri-urban (i.e., commuter) development in Ireland is often
434 characterised by concurrently high densities of private groundwater source, onsite domestic
435 wastewater treatment systems (septic tanks) and livestock grazing, compared to significantly lower
436 densities being present in “truly” rural areas [56].

437 Time-series models identified positive associations between STEC enteritis incidence and
438 temperature from weeks 1-5 across the ROI, urban and urban-commuter areas, with weeks 4 and 5
439 exhibiting particularly significant positive odds ratios (Table 3). While increased temperatures typically
440 limit the presence of *E. coli* species in the environment, with warmer temperatures inducing higher
441 bacterial die-off rates, several studies have reported temperature as a potential risk factor for STEC

442 infection. O'Dwyer *et al.* estimated that a 1°C temperature increase enhanced the likelihood of a
443 waterborne STEC outbreak by 37% in Ireland [58]. Likewise, Fleury *et al.* identified ambient
444 temperatures 6 weeks prior as a likely driver for STEC infections [52], thus closely mirroring findings
445 from the current study. The absence of antecedent rainfall, in concurrence with the prevalence of short-
446 term temperature periods in the presented urban mode indicates an absence of waterborne mobility
447 and/or transmission in urban areas. Moreover, the recent report on *Gastroenteric and Zoonotic*
448 *Diseases in Ireland, 2022* [59] identified “animal/environmental contact” (n = 162, 48%) and
449 “foodborne” (n = 39, 12%) as the 1st and 4th most frequently encountered sources of STEC infection,
450 respectively, accounting for approximately 60% of all notified cases (where known). Previous studies
451 have shown increasing temperatures as a driver for both recreational and foodborne exposures
452 [60,61], with results from the current study indicating that these predominate in urban Irish regions.

453

454 *Study Limitations* It is important to note that like all retrospective ecological studies, the current study
455 comprises a number of inherent limitations. Firstly, this study used aggregate-level data (e.g., infection
456 incidence by geographical area), which may not fully capture individual-level exposures or behaviours.
457 Consequently, findings are subject to ecological fallacy, whereby inferences made about individuals
458 based on area-level data may be inaccurate. Secondly, owing to difficulty with geolocation analyses,
459 not all confirmed cases were successfully geo-linked to Small Areas (SAs), particularly for STEC infection
460 (68% linked). This could lead to underrepresentation in certain regions and potentially bias results.
461 Similarly, the dataset includes only laboratory-confirmed cases reported to the CIDR system. As such,
462 cases not seeking healthcare, untested cases, or those with mild symptoms are not captured,
463 potentially underestimating the true incidence of the disease and thus, the impacts of meteorology on
464 the spatiotemporal distribution. The inclusion of several mean temperature lags within presented
465 models raises an issue of (multi)collinearity which should be considered when reporting and
466 interpreting models e.g., 5-day mean temperature pertaining to an individual case of infection will
467 inherently include all mean temperature lags <5 days as part of the calculation process. While
468 numerous methods including regularization, feature engineering and the spike and slab prior regression
469 component were employed to avoid this issue, it is likely that moderate levels of collinearity remain
470 and as such, may exaggerate model efficacy and/or precision. However, based on the potential utility
471 of short-term temperature means as a proxy for human behaviours, it was decided to include for the
472 current study. It is recommended that future studies, and particularly those focused on forecasting for
473 healthcare service planning, seek to avoid this potential limitation via the use of population behavioural
474 surveillance and/or mobility data, if available. Finally, while every effort was made to include high
475 resolution meteorological data, weather data are interpolated meteorological grids, which may not
476 capture hyper-local variability (e.g., microclimates, flood zones). This could affect associations in
477 localised areas, especially in regions with diverse topography.

478

479 **6. Conclusion**

480 The current study identified significant associations between three gastroenteric infections and
481 two temporally distributed meteorological variables in the Republic of Ireland. Both antecedent
482 cumulative rainfall and mean temperature were shown to forerun n change in reported cases for all
483 infections. Study findings raise significant concerns regarding climate change scenarios, which project
484 an increase in mean annual temperature and the frequency of heavy rainfall events in Ireland and other

485 regions characterised by temperate climate and high economic development. Accordingly, there is an
486 urgent need to develop evidence-based, pathogen-specific surveillance strategies based on observed
487 and future weather conditions to appropriately mitigate the human health impacts. Time-series
488 modelling demonstrated the existence of several specific temporal patterns for each infection.
489 Significantly longer lags were obtained for cryptosporidiosis compared to STEC and campylobacteriosis,
490 highlighting the inherent differences between pathogens (e.g., environmental viability, incubation
491 period, transmission pathways). This highlights the complexity of transmission mechanisms associated
492 with sporadic protozoan infections, which remain misunderstood. Rainfall was typically shown to be
493 associated with significantly shorter lag periods, and therefore a quicker response than temperature
494 on infection incidence rates, highlighting the multifaceted and indirect role played by temperature (e.g.,
495 changes in individual and/or community behaviour) in comparison with rainfall (i.e., relatively direct
496 contamination of water supplies and subsequent human exposure). Delineation by settlement type
497 demonstrated the presence of specific temporal patterning, again emphasising the differing infection
498 mechanisms and risk factors at play based on location. Study findings permit an improved
499 understanding of infection mechanisms as they pertain to short-term weather conditions and may be
500 used to forecast the human health effects of extreme weather events and climate change in Ireland
501 and other temperature maritime regions.

502

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507

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