Extreme Weather, Soil Moisture, and Drinking Water Quality: Evidence from Kentucky

Munib Inam* Steven Buck†

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Abstract

Climate change is increasing the frequency and intensity of extreme weather events, posing new challenges for drinking water safety. This paper examines the impact of weather extremes on public water systems in Kentucky, focusing on key contaminant concentrations. While previous studies often rely on daily data, this study uses high-resolution, sub-daily weather data and satellite-derived soil moisture data to provide an understanding of contamination pathways. Using a panel of 450 community water systems from 2005–2022, we use fixed-effects models to estimate the effects of different weather measures, and soil moisture condition on nitrate, haloacetic acids (HAA5), total trihalomethanes (TTHM), Total Coliform and *E. coli*.

The results show distinct and often opposing contamination mechanisms. Extreme temperature significantly increases the formation of disinfection byproducts (DBPs) like HAA5 and TTHM, with a 1°C increase in average temperature raising TTHM levels by over 2%. Conversely, warmer temperatures are associated with lower nitrate concentrations, likely due to increased denitrification. Precipitation effects are nuanced: intense, short-lasting extreme rainfall mobilizes nitrate thereby increasing its concentration, while sustained wet conditions tend to dilute DBPs. Furthermore, we find that soil moisture is a significant predictor of water quality. High soil moisture significantly increases nitrate levels but reduces DBPs,

*University of Kentucky, munib.inam@uky.edu. Corresponding author.
†University of Kentucky.

highlighting the crucial role of antecedent hydrological conditions in mediating contamination risk. These findings highlight the need for adaptive regulatory strategies and infrastructure investments that account for contaminant-specific responses to a changing climate, particularly in vulnerable regions like Kentucky.

Keywords: Drinking Water Quality, Climate Change, Extreme Weather, Soil Moisture, Contamination, Environmental Economics.

1 Introduction

Climate-driven shifts in the hydrologic cycle are leading to more frequent and intense weather extremes, which in turn pose serious challenges for drinking water quality and public health (**vanVliet2023**). Extreme precipitation events can overwhelm aging water infrastructure, causing runoff, flooding, and treatment disruptions, and have long been associated with spikes in waterborne contamination (**Curriero2001**). Historical evidence from the United States shows that over half of documented drinking water disease outbreaks between 1948 and 1994 were preceded by periods of unusually heavy rainfall. Such events facilitate the transport of pathogens and pollutants into water sources by washing contaminants from soils, agricultural fields, and urban surfaces into rivers and aquifers.

The climate in Kentucky has shown growing volatility in recent years, marked by intense precipitation episodes and flash floods that disrupt communities and critical infrastructure. The historic 2022 floods in eastern Kentucky exemplify these extremes, causing widespread damage, with water systems overwhelmed by sediment, debris, and bacterial contamination. The Kentucky Division of Water labeled the event a "1-in-1000-year flood" in certain localities, highlighting a gap between historical design standards and current weather realities.

This study leverages high-resolution meteorological and hydrological data to investigate the multifaceted impacts of weather on drinking water quality in Kentucky. We move beyond traditional daily metrics to incorporate sub-daily precipitation intensity and satellite-derived soil moisture, allowing for a more mechanistic understanding of contamination pathways. We ask three primary research questions:

1. How do different dimensions of weather (temperature, precipitation, and soil moisture) affect the concentrations of regulated contaminants, including nutrients (nitrate), disinfection byproducts (HAA5, TTHM), and microbial indicators (*E. coli*)?

2. Are high-frequency (sub-daily) weather metrics more predictive of water quality changes than daily or multi-day aggregates?

3. What are the distinct physical and chemical pathways through which weather in-

fluences different types of contaminants?

By addressing these questions, this paper contributes to a growing body of literature on the environmental economics of climate adaptation. We provide robust, panel-data evidence on the vulnerability of public water systems and offer insights to inform the design of more resilient infrastructure and adaptive regulatory frameworks.

2 Literature Review

This study builds on three distinct strands of literature: (1) public health research linking weather to waterborne disease, (2) economic analyses of climate impacts and drinking water compliance, and (3) emerging work using high-resolution data to model environmental systems.

Early public health research established a strong correlational link between extreme rainfall and waterborne disease outbreaks. **Curriero2001** found that over half of U.S. outbreaks were preceded by heavy precipitation. Case studies, such as the 1993 Milwaukee Cryptosporidium outbreak, confirmed that runoff and overwhelmed treatment systems are key mechanisms (**Jagai2015**). More recent work has affirmed these findings, linking extreme weather to microbial contamination and gastrointestinal illness across various regions (**Brunkard2011**; **Uejio2014**).

Economists have increasingly studied the costs of climate change and the efficacy of environmental regulation. **Allaire2018** provided a comprehensive analysis of U.S. drinking water violations, finding them to be widespread, persistent, and disproportionately concentrated in small, rural, and low-income communities. While their work did not focus on weather, it highlighted the systemic vulnerabilities that climate change is poised to exacerbate. Other research has examined how utilities respond to regulation, sometimes through strategic behavior like "sampling out" to avoid detecting contamination (**Bennear2009**), and how disparities exist in the time it takes systems to return to compliance after a violation (**Fedinick2019**).

Most recently, studies have begun to directly connect high-resolution climate data with water quality outcomes. A working paper by the U.S. EPA found that heavy rainfall and flooding led to significant increases in regulated contaminants, including a 14–26% higher detection likelihood for coliform bacteria (**Austin2024**). Other studies have demonstrated that droughts can concentrate pollutants (**Qiu2023**) and wildfires can increase nitrate and arsenic levels (**Pennino2022**). Our study contributes to this frontier by integrating sub-daily weather metrics and satellite-based soil moisture data, providing a more mechanistic analysis of contamination pathways across a diverse set of water systems and contaminants.

3 Data and Methodology

3.1 Data Sources

Our empirical analysis combines four main types of data for all community water systems in Kentucky from 2005 to 2022.

Water Quality Data. We compile water quality monitoring records from the Kentucky Division of Water's Drinking Water Watch database and the U.S. EPA's Safe Drinking Water Information System (SDWIS). Our primary dependent variables are the measured concentrations of three key contaminants: Nitrate, Total Haloacetic Acids (HAA5), Total Trihalomethanes (TTHM); and the detection of two: Total Coliform and *E. coli* (binary). We use the log-transformed concentration for the chemical contaminants to account for the skewed distribution of the raw data.

Weather Data. We use a rich set of meteorological variables to characterize weather conditions for each water system. High-resolution hourly precipitation data are sourced from NOAA's gridded products. Temperature data, including daily minimum and maximum, are also from NOAA. From these raw data, we construct a comprehensive set of metrics capturing different dimensions of weather, including average temperature, extreme heat and cold days (e.g., frost days, summer days), precipitation totals over various windows (1 to 7 days), and measures of precipitation intensity (e.g., maximum 1-hour rainfall).

Soil Moisture Data. To capture antecedent hydrological conditions, we incorporate satellite-derived soil moisture data from the NASA Soil Moisture Active Passive (SMAP) mission, accessed via the Crop Condition and Soil Moisture Analytics (CROP-CASMA) portal. This provides daily data at a 9-km resolution from 2015 onwards. We use three primary variables in our analysis: the daily mean soil moisture, and decomposed "drought" and "wet" anomalies, which measure deviations from the local long-term climatology.

Socio-demographic Data. To control for community characteristics, we include county-level data from the U.S. Census Bureau, including median household income, racial composition, median year built to capture the age of the infrastructure, and housing density.

3.2 Empirical Strategy

Our primary empirical approach is a panel fixed-effects model. This design allows us to control for any time-invariant unobserved characteristics of a water system (e.g., its infrastructure quality, primary water source, or management practices) as well as any common shocks affecting all systems in a given year (e.g., major policy changes or statewide economic trends). The baseline specification is:

$$\ln(Y_{it}) = \beta_1 \text{Weather}_{it} + \mathbf{X}'_{ct}\gamma + \alpha_i + \delta_t + \epsilon_{it} \tag{1}$$

where Y_{it} is the concentration of a contaminant in water system i at time t. Weather_{it} is the weather variable of interest (e.g., average temperature or precipitation intensity). $\mathbf{X}_{ct}$ is a vector of time-varying socio-demographic controls for the county c where the system is located. α_i represents the water system fixed effects, and δ_t represents year fixed effects. ϵ_{it} is the idiosyncratic error term. Standard errors are clustered at the water system level to account for serial correlation in the outcomes.

We run separate regressions for each weather metric and each contaminant to avoid issues with multicollinearity and to clearly identify the impact of each specific weather dimension.

4 Results

We present our findings in a series of tables that explore the impact of temperature, precipitation, and soil moisture on our four target contaminants.

4.1 Temperature Effects

Table 1 summarizes the contrasting effects of temperature. For disinfection byproducts (HAA5 and TTHM), the relationship is consistently positive and significant. A 1°C increase in average temperature is associated with a 1.1% increase in HAA5 and a 2.1% increase in TTHM. Extreme heat shows even larger effects; an additional "Summer Day" (maximum temperature greater than 25°C) raises HAA5 by 19% and TTHM by over 43%. This is consistent with chemical kinetics, as the reactions that form DBPs are accelerated by heat.

In contrast, temperature has a negative effect on nitrate. A 1°C increase in temperature is associated with a 2.4% decrease in nitrate concentrations. This may be due to increased rates of denitrification in warmer soils and water bodies, or changes in agricultural practices during hot periods.

For microbial contaminants, the effects of average temperature are small but statistically significant for Total Coliform, while for *E. coli*, the effects are not statistically significant.

4.2 Precipitation Effects

The effects of precipitation are highly dependent on both the contaminant and the nature of the rainfall event (Table 2).

For nitrate, intense, short-duration rainfall appears to be the primary driver of contamination. The maximum 1-hour precipitation intensity has a strong, positive effect, suggesting that flash runoff is effective at mobilizing nitrates from agricultural land into water sources.

For DBPs, the story is more complex. While some measures of precipitation intensity over longer windows are associated with slight increases in HAA5 and TTHM, many other metrics, particularly those related to heavy precipitation days (R10 and R20), show a significant negative relationship. This suggests a dual mechanism: while runoff can introduce more organic precursors for DBP formation, very heavy rainfall events may also lead to a dilution effect within the water system that ultimately lowers the final concentration.

4.3 Soil Moisture Effects

Our analysis of the 2015–2022 subsample reveals that soil moisture is an exceptionally strong predictor of water quality, often with dramatic effects (Table 3).

The most striking result is for nitrate. Higher daily mean soil moisture is associated with a massive increase in nitrate concentrations. This indicates that when the ground is saturated, additional rainfall is more likely to run off the surface, carrying nitrates with it, rather than infiltrating the soil. Both drought and wet anomalies also significantly increase nitrate levels, suggesting a U-shaped relationship where any deviation from normal conditions exacerbates contamination.

For DBPs, the effect of soil moisture is the opposite. Higher mean soil moisture is associated with large decreases in both HAA5 and TTHM. This is likely a dilution effect at the source; when soils are wet, the concentration of organic precursors in the water that eventually reaches the treatment plant is lower. However, wet anomalies (i.e., unusually wet conditions) lead to an increase in DBPs, consistent with the idea that sudden runoff events can wash a high load of organic matter into the system.

5 Discussion

Our results paint a complex picture of how climate change will challenge drinking water safety. The impacts are not monolithic; they are highly specific to the contaminant in question and the dimension of the weather event. Three key themes emerge from our findings.

First, temperature and precipitation drive distinct contamination pathways. Temperature primarily governs the internal chemistry of water treatment, especially the formation of disinfection byproducts. As temperatures rise, utilities will face a fundamental trade-off: using more disinfectant to control pathogens could lead to higher levels of carcinogenic DBPs. Precipitation, in contrast, primarily governs the external mobilization of contaminants into source waters. Intense, short-duration rainfall is particularly effective at flushing surface pollutants like nitrate into rivers and reservoirs.

Second, antecedent hydrological conditions, as measured by soil moisture, are a critical and previously under-appreciated factor. The impact of a rainstorm depends crucially on how wet the ground already is. Our finding that high soil moisture dramatically amplifies nitrate contamination while suppressing DBP formation highlights the need for more sophisticated, process-based models for predicting water quality risks. Satellite-based soil moisture data, like SMAP, offers a powerful new tool for water managers to develop such predictive systems.

Third, the varied and sometimes opposing responses of different contaminants to the same weather event pose a significant challenge for water system operators and regulators. A hot, dry period followed by an intense thunderstorm may be a worst-case scenario for nitrate contamination but might have a minimal effect on DBPs. Conversely, a prolonged period of warm, drizzly weather could create ideal conditions for DBP formation. A one-size-fits-all approach to climate adaptation will be insufficient.

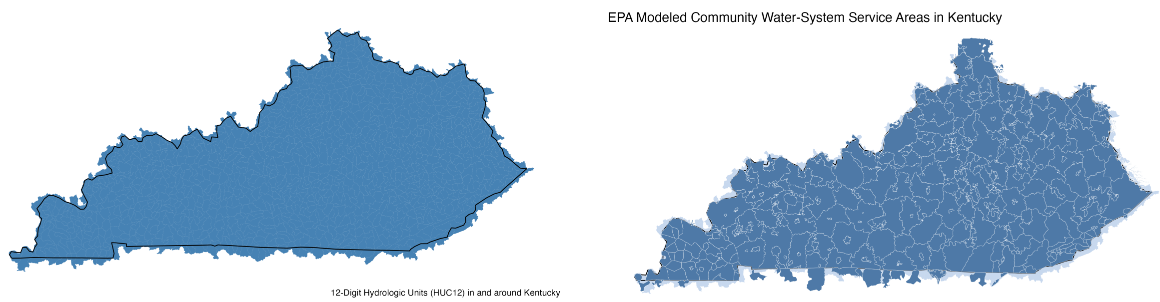
6 Conclusion

This paper provides an analysis of the impacts of extreme weather and soil moisture conditions on drinking water quality in Kentucky. By using high-resolution sub-daily weather data and fixed-effects estimations, we identify distinct pathways for different classes of contaminants. Our findings show that rising temperatures will likely increase the prevalence of disinfection byproducts, while changes in precipitation patterns will alter the risk profile for nutrient and microbial contamination.

The soil moisture data suggests a promising avenue for future research and for the development of operational early-warning systems for water utilities. As climate change continues to intensify weather extremes, a more granular, contaminant-specific, and data-driven approach to water quality management will be essential to protect public health. Future work should explore the heterogeneous impacts of these shocks across communities with different socioeconomic characteristics and levels of infrastructure resilience, and should quantify the economic costs associated with these climate-driven water quality challenges.

Figures

Figure 1: Maps of the Study Area

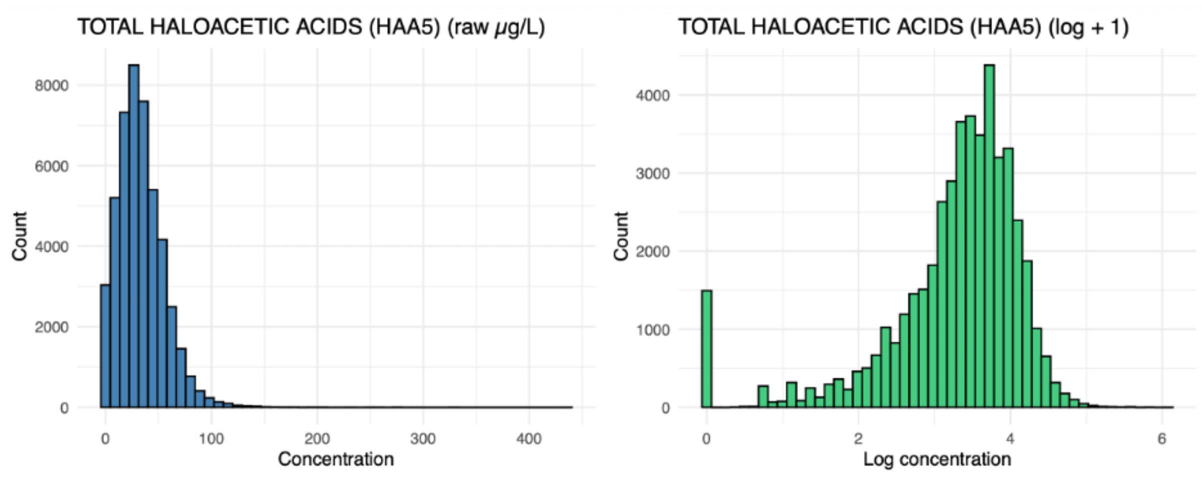


(a) 12-Digit Hydrologic Units (HUC-12) in Kentucky.

(b) Community Water System (CWS) Service Areas in Kentucky.

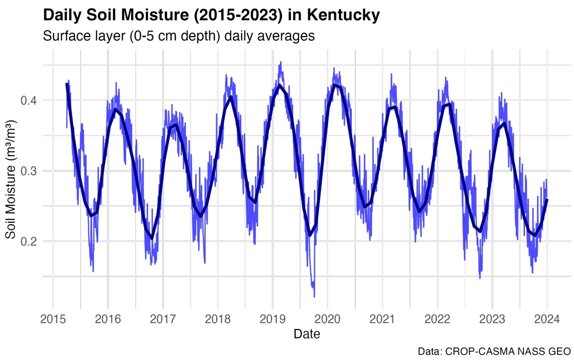
Notes: Panel (a) shows the 1,301 HUC-12 watersheds covering Kentucky. Panel (b) shows the modeled service area boundaries for the community water systems included in the study. Weather and soil moisture data are linked to water systems via an area-weighted overlay of these two geographies.

Figure 2: Distribution of Contaminant Concentrations

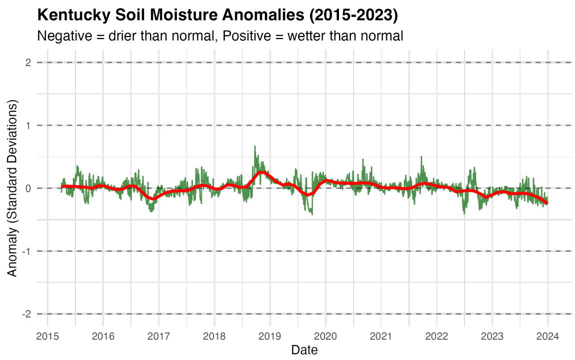


Notes: Histograms show the distribution of raw concentrations (left panels) and log-transformed concentrations (right panels) for Nitrate, HAA5, and TTHM. The log transformation helps to normalize the right-skewed data, but a significant mass at zero (non-detects) remains.

Figure 3: Soil Moisture Dynamics in Kentucky (2015-2023)



(a) Statewide Average Soil Moisture



(b) Statewide Average Soil Moisture Anomaly

Notes: Panel (a) shows the daily time series of average root-zone soil moisture across Kentucky. Panel (b) shows the standardized anomaly, highlighting periods of unusual wetness or dryness relative to the local climatology.

Tables

Table 1: Summary of Temperature Effects on Water Quality

	Percent Change (%) in Contaminant Concentration				
Metric	Nitrate	HAA5	TTHM	Total Coliform	E. coli
Average Temp. (+1°C)	−2.4***	1.1***	2.1***	0.02***	0.02
Extreme Day (Hot)					
Summer Day (above 25°C)	−37.1***	19.2***	43.3***	0.35***	1.18
Tropical Night (above 20°C)	−33.2***	19.4***	45.6***	0.36***	0.68
Extreme Day (Cold)					
Frost Day (below 0°C)	44.9***	−18.0***	−30.6***	−0.27***	−1.11
Ice Day (below 0°C)	25.0**	−20.3***	−35.2***	−0.28***	−1.84

Notes: Each entry represents the percentage change in the contaminant concentration from a separate regression. Full regression results are available in the Appendix. All models include controls for socio-demographics and precipitation, as well as PWSID and year fixed effects.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 2: Summary of Precipitation Effects on Water Quality

	Percent Change (%) in Contaminant Concentration				
Metric	Nitrate	HAA5	TTHM	Total Coliform	E. coli
Intensity					
Max 1-hr Precip.	0.53*	0.02	0.04	0.01*	−0.06
SDII (Wet Hour Avg)	1.93*	−0.01	−0.12	0.01*	−0.20
Amount					
1-Day Total Precip.	0.28**	−0.03	−0.05**	0.001	−0.02
7-Day Total Precip.	0.09**	0.03***	0.02***	0.0005*	0.002
Pattern					
Wet Day	6.61	−1.88***	−4.13***	0.06*	0.004
Heavy Precip. Day (R10)	8.12	−3.26***	−4.65***	0.07*	−0.18
V. Heavy Precip. Day (R20)	13.08*	−3.02**	−4.27***	0.06	0.17

Notes: Each entry represents the percentage change in the contaminant concentration from a separate regression. Full regression results are available in the Appendix. All models include controls for socio-demographics and temperature, as well as PWSID and year fixed effects.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 3: SMAP Decomposed Soil Moisture Effects on Water Quality (2015–2022)

Variable	(1) Nitrate log()	(2) HAA5 log()	(3) TTHM log()	(4) Total Coliform (binary)	(5) E. coli (binary)
Daily Mean Soil Moisture	3.636***	−0.965***	−2.423***	−0.004*	0.077
	(0.715)	(0.087)	(0.088)	(0.002)	(0.071)
Drought Anomaly	1.537***	−0.083*	−0.546***	0.003	0.078
	(0.394)	(0.044)	(0.043)	(0.002)	(0.049)
Wet Anomaly	0.706*	0.204***	0.381***	0.007***	0.012
	(0.319)	(0.043)	(0.042)	(0.002)	(0.051)
Observations	1,935	21,615	21,640	363,761	1,640

Notes: Results from a single regression per contaminant including all three SMAP variables. Standard errors (SE) clustered by PWSID are in parentheses. All models include weather and socio-economic controls, plus PWSID and Year fixed effects.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

A Appendix: Detailed Regression Results

A.1 Nitrate

Table 4: Temperature Effects on Nitrate Concentration (log)

	Dependent Variable: log(Nitrate)			
	(1) TAVG	(2) TMAX	(3) TMIN	(4) DTR
Temperature Variable	-0.024***	-0.022***	-0.025***	-0.007
	(0.004)	(0.003)	(0.004)	(0.004)
Observations	4,159	4,159	4,159	4,159
Pct. Change	-2.39	-2.22	-2.42	-0.66

Notes: Standard errors clustered at the PWSID level are in parentheses. All models include PWSID and year fixed effects, and controls for precipitation and socio-demographics.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 5: Temperature Extremes Effects on Nitrate Concentration (log)

	Dependent Variable: log(Nitrate)			
	(1) Summer Day	(2) Tropical Night	(3) Frost Day	(4) Ice Day
Temperature Extreme	-0.463***	-0.404***	0.371***	0.223**
	(0.080)	(0.099)	(0.058)	(0.075)
Observations	4,159	4,159	4,159	4,159
Pct. Change	-37.11	-33.20	+44.94	+25.02

Notes: Standard errors clustered at the PWSID level are in parentheses. All models include PWSID and year fixed effects, and controls for temperature, precipitation and socio-demographics.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 6: Precipitation Amount Effects on Nitrate Concentration (log)

	Dependent Variable: log(Nitrate)			
	(1) P_total_1day	(2) P_total_3day	(3) P_total_5day	(4) P_total_7day
Precipitation Variable	0.0028**	0.0011*	0.0010**	0.0009**
	(0.0010)	(0.0006)	(0.0003)	(0.0003)
Observations	4,159	4,159	4,159	4,159
Pct. Change	+0.28	+0.11	+0.10	+0.09

Notes: Standard errors clustered at the PWSID level are in parentheses. All models include PWSID and year fixed effects, and controls for temperature and socio-demographics.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 7: Precipitation Intensity Effects on Nitrate Concentration (log)

	Dependent Variable: log(Nitrate)			
	(1) SDII_hr	(2) P_Max_1hr	(3) P_Max_3hr	(4) P_Max_5hr
Precipitation Variable	0.0191*	0.0053*	0.0034*	0.0029*
	(0.008)	(0.002)	(0.001)	(0.001)
Observations	4,159	4,159	4,159	4,159
Pct. Change	+1.93	+0.53	+0.34	+0.29

Notes: Standard errors clustered at the PWSID level are in parentheses. All models include PWSID and year fixed effects, and controls for temperature and socio-demographics.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 8: Precipitation Patterns Effects on Nitrate Concentration (log)

	Dependent Variable: log(Nitrate)			
	(1) Wet Hours	(2) Wet Day	(3) R10 Day	(4) R20 Day
Precipitation Pattern	0.007*	0.064	0.078	0.123*
	(0.003)	(0.039)	(0.047)	(0.057)
Observations	4,159	4,159	4,159	4,159
Pct. Change	+0.70	+6.61	+8.12	+13.08

Notes: Standard errors clustered at the PWSID level are in parentheses. All models include PWSID and year fixed effects, and controls for temperature and socio-demographics.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

A.2 Haloacetic Acids (HAA5)

Table 9: Temperature Effects on HAA5 Concentration (log)

	Dependent Variable: log(HAA5)			
	(1) TAVG	(2) TMAX	(3) TMIN	(4) DTR
Temperature Variable	0.011^{***}	0.010^{***}	0.011^{***}	0.004^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	36,398	36,398	36,398	36,398
Pct. Change	+1.09	+1.04	+1.10	+0.35

Notes: Standard errors clustered at the PWSID level are in parentheses. All models include PWSID and year fixed effects, and controls for precipitation and socio-demographics.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 10: Temperature Extremes Effects on HAA5 Concentration (log)

	Dependent Variable: log(HAA5)			
	(1) Summer Day	(2) Tropical Night	(3) Frost Day	(4) Ice Day
Temperature Extreme	0.176^{***}	0.177^{***}	-0.198^{***}	-0.226^{***}
	(0.009)	(0.011)	(0.012)	(0.019)
Observations	36,398	36,398	36,398	36,398
Pct. Change	+19.20	+19.37	-17.98	-20.26

Notes: Standard errors clustered at the PWSID level are in parentheses. All models include PWSID and year fixed effects, and controls for temperature, precipitation and socio-demographics.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 11: Precipitation Amount Effects on HAA5 Concentration (log)

	Dependent Variable: log(HAA5)			
	(1) P_total_1day	(2) P_total_3day	(3) P_total_5day	(4) P_total_7day
Precipitation Variable	-0.0003	0.0001	0.0002^{***}	0.0003^{***}
	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Observations	36,398	36,398	36,398	36,398
Pct. Change	-0.03	+0.01	+0.02	+0.03

Notes: Standard errors clustered at the PWSID level are in parentheses. All models include PWSID and year fixed effects, and controls for temperature and socio-demographics.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 12: Precipitation Intensity Effects on HAA5 Concentration (log)

	Dependent Variable: log(HAA5)			
	(1) SDII_hr	(2) P_Max_1hr	(3) P_Max_3hr	(4) P_Max_5hr
Precipitation Variable	-0.0001	0.0002	-0.0001	-0.0001
	(0.001)	(0.0003)	(0.0002)	(0.0002)
Observations	36,398	36,398	36,398	36,398
Pct. Change	-0.01	+0.02	-0.01	-0.01

Notes: Standard errors clustered at the PWSID level are in parentheses. All models include PWSID and year fixed effects, and controls for temperature and socio-demographics.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 13: Precipitation Patterns Effects on HAA5 Concentration (log)

	Dependent Variable: log(HAA5)			
	(1) Wet Hours	(2) Wet Day	(3) R10 Day	(4) R20 Day
Precipitation Pattern	-0.002***	-0.019***	-0.033***	-0.031**
	(0.001)	(0.006)	(0.008)	(0.009)
Observations	36,398	36,398	36,398	36,398
Pct. Change	-0.22	-1.88	-3.26	-3.02

Notes: Standard errors clustered at the PWSID level are in parentheses. All models include PWSID and year fixed effects, and controls for temperature and socio-demographics.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

A.3 Total Trihalomethanes (TTHM)

Table 14: Temperature Effects on TTHM Concentration (log)

	Dependent Variable: log(TTHM)			
	(1) TAVG	(2) TMAX	(3) TMIN	(4) DTR
Temperature Variable	0.021***	0.020***	0.021***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	36,467	36,467	36,467	36,467
Pct. Change	+2.12	+2.02	+2.15	+0.70

Notes: Standard errors clustered at the PWSID level are in parentheses. All models include PWSID and year fixed effects, and controls for precipitation and socio-demographics.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 15: Temperature Extremes Effects on TTHM Concentration (log)

	Dependent Variable: log(TTHM)			
	(1) Summer Day	(2) Tropical Night	(3) Frost Day	(4) Ice Day
Temperature Extreme	0.360***	0.376***	-0.364***	-0.432***
	(0.010)	(0.012)	(0.011)	(0.019)
Observations	36,467	36,467	36,467	36,467
Pct. Change	+43.33	+45.56	-30.56	-35.20

Notes: Standard errors clustered at the PWSID level are in parentheses. All models include PWSID and year fixed effects, and controls for temperature, precipitation and socio-demographics.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 16: Precipitation Amount Effects on TTHM Concentration (log)

	Dependent Variable: log(TTHM)			
	(1) P_total_1day	(2) P_total_3day	(3) P_total_5day	(4) P_total_7day
Precipitation Variable	-0.0005**	0.0001	0.0003***	0.0002***
	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Observations	36,467	36,467	36,467	36,467
Pct. Change	-0.05	+0.01	+0.03	+0.02

Notes: Standard errors clustered at the PWSID level are in parentheses. All models include PWSID and year fixed effects, and controls for temperature and socio-demographics.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 17: Precipitation Intensity Effects on TTHM Concentration (log)

	Dependent Variable: log(TTHM)			
	(1) SDII_hr	(2) P_Max_1hr	(3) P_Max_12hr	(4) P_Max_24hr
Precipitation Variable	-0.001	0.0004	-0.0002	0.00002
	(0.001)	(0.0004)	(0.0002)	(0.0001)
Observations	36,467	36,467	36,467	36,467
Pct. Change	-0.12	+0.04	-0.02	+0.002

Notes: Standard errors clustered at the PWSID level are in parentheses. All models include PWSID and year fixed effects, and controls for temperature and socio-demographics.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 18: Precipitation Patterns Effects on TTHM Concentration (log)

	Dependent Variable: log(TTHM)			
	(1) Wet Hours	(2) Wet Day	(3) R10 Day	(4) R20 Day
Precipitation Pattern	-0.004***	-0.042***	-0.048***	-0.044***
	(0.001)	(0.006)	(0.007)	(0.009)
Observations	36,467	36,467	36,467	36,467
Pct. Change	-0.44	-4.13	-4.65	-4.27

Notes: Standard errors clustered at the PWSID level are in parentheses. All models include PWSID and year fixed effects, and controls for temperature and socio-demographics.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

A.4 *E. coli*

Table 19: Temperature Effects on *E. coli* Detection (LPM)

	Dependent Variable: E. coli Detected (0/1)			
	(1) TAVG	(2) TMAX	(3) TMIN	(4) DTR
Temperature Variable	0.0002 (0.0005)	0.0001 (0.0004)	0.0003 (0.0005)	-0.001 (0.001)
Observations	2,739	2,739	2,739	2,739

Notes: Standard errors clustered at the PWSID level are in parentheses. All models include PWSID and year fixed effects, and controls for precipitation and socio-demographics.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 20: Temperature Extremes Effects on *E. coli* Detection (LPM)

	Dependent Variable: E. coli Detected (0/1)			
	(1) Summer Day	(2) Tropical Night	(3) Frost Day	(4) Ice Day
Temperature Extreme	0.012 (0.009)	0.007 (0.010)	-0.011 (0.012)	-0.018 (0.010)
Observations	2,739	2,739	2,739	2,739

Notes: Standard errors clustered at the PWSID level are in parentheses. All models include PWSID and year fixed effects, and controls for temperature, precipitation and socio-demographics.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 21: Precipitation Amount Effects on *E. coli* Detection (LPM)

	Dependent Variable: E. coli Detected (0/1)			
	(1) P_total_1day	(2) P_total_3day	(3) P_total_5day	(4) P_total_7day
Precipitation Variable	-0.0002 (0.0002)	0.00005 (0.0001)	0.00003 (0.0001)	0.00002 (0.0001)
Observations	2,739	2,739	2,739	2,739

Notes: Standard errors clustered at the PWSID level are in parentheses. All models include PWSID and year fixed effects, and controls for temperature and socio-demographics.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 22: Precipitation Intensity Effects on *E. coli* Detection (LPM)

	Dependent Variable: E. coli Detected (0/1)			
	(1)	(2)	(3)	(4)
	SDII_hr	P_Max_1hr	P_Max_12hr	P_Max_24hr
Precipitation Variable	-0.002	-0.0006	-0.0001	-0.0001
	(0.001)	(0.0004)	(0.0002)	(0.0001)
Observations	2,739	2,739	2,739	2,739

Notes: Standard errors clustered at the PWSID level are in parentheses. All models include PWSID and year fixed effects, and controls for temperature and socio-demographics.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 23: Precipitation Patterns Effects on *E. coli* Detection (LPM)

	Dependent Variable: E. coli Detected (0/1)			
	(1)	(2)	(3)	(4)
	Wet Hours	Wet Day	R10 Day	R20 Day
Precipitation Pattern	0.0004	0.00004	-0.002	0.002
	(0.0006)	(0.008)	(0.008)	(0.010)
Observations	2,739	2,739	2,739	2,739

Notes: Standard errors clustered at the PWSID level are in parentheses. All models include PWSID and year fixed effects, and controls for temperature and socio-demographics.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

A.5 Total Coliform

Table 24: Temperature Effects on Total Coliform Detection (LPM)

	Dependent Variable: Total Coliform Detected (0/1)			
	(1) TAVG	(2) TMAX	(3) TMIN	(4) DTR
Temperature Variable	0.0002***	0.0002***	0.0002***	-0.00003
	(0.00002)	(0.00002)	(0.00002)	(0.00003)
Observations	666,048	666,048	666,048	666,048

Notes: Standard errors clustered at the PWSID level are in parentheses. All models include PWSID and year fixed effects, and controls for precipitation and socio-demographics.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 25: Temperature Extremes Effects on Total Coliform Detection (LPM)

	Dependent Variable: Total Coliform Detected (0/1)			
	(1) Summer Day	(2) Tropical Night	(3) Frost Day	(4) Ice Day
Temperature Extreme	0.003***	0.004***	-0.003***	-0.003***
	(0.0004)	(0.0004)	(0.0003)	(0.0003)
Observations	666,048	666,048	666,048	666,048

Notes: Standard errors clustered at the PWSID level are in parentheses. All models include PWSID and year fixed effects, and controls for temperature, precipitation and socio-demographics.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 26: Precipitation Amount Effects on Total Coliform Detection (LPM)

	Dependent Variable: Total Coliform Detected (0/1)			
	(1) P_total_1day	(2) P_total_3day	(3) P_total_5day	(4) P_total_7day
Precipitation Variable	0.00001	0.00001*	0.000007*	0.000005*
	(0.000007)	(0.000004)	(0.000003)	(0.000002)
Observations	666,048	666,048	666,048	666,048

Notes: Standard errors clustered at the PWSID level are in parentheses. All models include PWSID and year fixed effects, and controls for temperature and socio-demographics.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 27: Precipitation Intensity Effects on Total Coliform Detection (LPM)

	Dependent Variable: Total Coliform Detected (0/1)			
	(1) SDII_hr	(2) P_Max_5hr	(3) P_Max_12hr	(4) P_Max_24hr
Precipitation Variable	0.0001*	0.00003*	0.00002*	0.00001*
	(0.00005)	(0.00001)	(0.000009)	(0.000006)
Observations	666,048	666,048	666,048	666,048

Notes: Standard errors clustered at the PWSID level are in parentheses. All models include PWSID and year fixed effects, and controls for temperature and socio-demographics.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 28: Precipitation Patterns Effects on Total Coliform Detection (LPM)

	Dependent Variable: Total Coliform Detected (0/1)			
	(1) Wet Hours	(2) Wet Day	(3) R10 Day	(4) R20 Day
Precipitation Pattern	0.00005*	0.0006*	0.0007*	0.0006
	(0.00002)	(0.0002)	(0.0003)	(0.0004)
Observations	666,048	666,048	666,048	666,048

Notes: Standard errors clustered at the PWSID level are in parentheses. All models include PWSID and year fixed effects, and controls for temperature and socio-demographics.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.