When it Rains, it Pours: Severe Weather Events, Flooding, and Drinking Water Quality

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Abstract

Climate change will alter the spatial distribution and intensity of precipitation. While more extreme precipitation can be costly for many reasons, a relatively under-explored burden may come in the form of disruptions to drinking water quality. These disruptions are caused by changes to the physical and chemical properties of water, the mobilization of pollution through runoff, accidental spills of hazardous substances, and water infrastructure failure, all of which are impacted by heavy precipitation events and flooding. To test how extreme precipitation impacts drinking water quality, we developed a dataset of drinking water samples spanning two decades and covering a service population of 290 million across the United States. We combine these drinking water records with daily weather information and extreme weather event records. Our results suggest that heavier precipitation is associated with greater concentrations of disinfectant byproducts and increased detection of total coliform and E. Coli bacteria. We identify the disproportionate impacts of these drinking water quality disruptions across geographic regions, water system types, and socioeconomic groups. Finally, we estimate that monetary damages associated with extreme-precipitation-induced drinking water quality disruptions are over $1 billion annually based on altered bottled water purchases, cooking and dining practices, travel needs, work or school absences, and preterm birth newborns.

Keywords: Extreme Weather Events, Flooding, Water Pollution, Drinking Water Quality, Disinfection Byproducts, Climate Change

JEL: Q25 Water, Q28 Government Policy, Q53 Water Pollution, Q54 Climate

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1 Introduction

Global warming will increase the severity of extreme precipitation events because each degree of warming leads to a 6-7% increase in the concentration of atmospheric water vapor (Tabari, 2020).[1] More atmospheric water vapor leads to heavier rains which, in turn, increase the likelihood and severity of flooding. Coastal flooding events are also expected to increase in frequency primarily due to seawater rise (Kirezci et al., 2020). As such, prior work has projected higher flooding events globally (Arnell and Gosling, 2014; Alfieri et al., 2017). Severe storms, extreme precipitation, and associated flooding events can be extremely destructive, leading to property loss, displacement, and infrastructure damage (Desmet et al., 2021). From 2000 to 2019, flood and extreme precipitation rain events caused $208 billion in property damage across the United States (NOAA, 2021). Due to more intense and more frequent severe storms and flooding, Wing et al. (2022) estimate that the annual costs of these events in the US will rise from $32 billion in 2020 to $41 billion by 2050. According to the same study, coastal regions in the South and Eastern United States will see at least a 20% increased risk of flooding, although similar risks are expected in counties across nearly all states including more arid zones such as in New Mexico and Utah.

The more visible destruction caused by severe precipitation and flooding events often overshadows less obvious disruptions such as those to drinking water availability and quality, yet these impacts are well known to occur. For example, historic levels of precipitation caused a pump failure at the O.B. Curtis water treatment plant serving Jackson, Mississippi, leading to lengthy water disruptions and boil water advisories for over 150,000 people (Neuman, 2022). Drinking water contamination following Hurricane Harvey is also well documented (Landsman et al., 2019; Pieper et al., 2021). Studies have demonstrated elevated microbial growth in drinking water in other lesser-known instances of flooding (Phan and Sherchan, 2020), and prior work has shown that flooding can lower drinking water quality in both a developing- and developed-country context (Doocy et al., 2013). The causes of drinking

[1] This relationship is governed by the Clausius-Clapeyron equation.

water impairment following severe storms are manifold, as described in Section 2. However, fragmented drinking water quality data and relatively rare storm events have made it difficult to reliably estimate the relationship between heavy precipitation and drinking water quality over a large geographic area and time horizon.

In this paper, we assess how heavy precipitation and flooding relate to changes in drinking water quality across 47 states from 2000 to 2019. We identify heavy rain and flooding events from disaster records in the National Oceanic and Atmospheric Administration Storm Events Database, which defines "heavy rains" and "floods" as any such event that causes loss of property, injuries, or loss of life.[2] Due to the selective reporting of these events, we supplement the storm events records with daily precipitation information from the Oregon State Parameter-elevation Regressions on Independent Slopes Model (PRISM) weather data. For our dependent variables, we evaluate two bacteriological contaminants: total coliforms and Escherichia coli. We also investigate two classes of disinfection byproducts: total trihalomethanes (TTHM) and haloacetic acids (HAA5). As described further in section 2, we choose these drinking water quality parameters because of their potential health implications, frequency of Safe Drinking Water Act violations, relevance to extreme precipitation events, and importance to water system management decisions. We test for relationships between extreme precipitation events, flooding, and drinking water quality using a panel fixed-effects model at the drinking water system daily level. We flexibly model weather, seasonal, watershed, and water-system level factors using daily weather controls and high dimensional fixed effects. We also incorporate event studies of extreme weather events, asking how water quality indicators change over the weeks preceding and following precipitation.

We find that a recent flood or heavy rain event increases the likelihood of total coliform detection by 14% to 25%, and E. coli detection by 17% to 26%. A recent flood or heavy rain event increases the concentration of TTHM by 5% to 6%. Flooding increases the concentra-

[2] "Heavy rain" is a distinct type of disaster in the storm events database, while what we refer to as "flooding" is an aggregation of several flood types such as coastal floods and flash floods. We evaluate these disasters separately in all analyses.

tions of HAA5 by 6%, but we observe mixed results on the effect of heavy rains on HAA5. Both groundwater and surface water sourcing systems see increased risk of bacteriological contamination after precipitation events and flooding, suggesting these impacts at least partly relate to opportunistic microbial growth in the distribution system. While larger and surface water-sourcing systems have the largest increases in disinfectant byproducts (DBP) formation, smaller systems and groundwater systems bear higher risk of bacteriological contamination from extreme precipitation and flooding. We also find evidence that communities of color face greater risk of E. coli detection from flooding and increased concentrations of both TTHM and HAA5 following a flood or heavy rainfall. In back-of-the-envelope estimates of the damages of floods and heavy rains with respect to drinking water quality, we calculate the damages to be just over $1 billion each year.

Our study contributes to our understanding of the social costs of heavy precipitation and flooding. Many other studies have modeled local employment impacts, capital damages, insurance outlays, or the displacement costs of floods (Sarmiento and Miller, 2006; Davies, 2016; Allaire et al., 2018; Desmet et al., 2021). Here, we evaluate the effects of these disasters on drinking water quality and in turn public health. Further, the impacts of heavy precipitation and flooding events have been studied in the context of developing countries, but few studies evaluate drinking water quality with data from developed countries. Moreover, prior work often makes use of drinking water compliance monitoring data from a small geographic region or one state (Bennear et al., 2009; Schwetschenau et al., 2020; Ding et al., 2022; Hill and Ma, 2022). Our study is the first to evaluate the drinking water impacts of heavy precipitation and flooding over a nearly nationwide geographic region and two-decade time horizon. Broad data coverage is a key innovation as it allows us to better understand how water system characteristics affect risk across watershed regions, institutional environments, and topographic characteristics. A larger sample size also improves predictive power concerning rare storm events, as Safe Drinking Water Act compliance monitoring samples are collected relatively infrequently across water systems (Keiser et al., 2019). Understanding the relationship between extreme precipitation events and drinking water quality will help city planners and water resource managers optimally adapt to a changing climate and its many costs to society, particularly when drinking water disruptions pose a threat to public health (Michelozzi and Donato, 2014; Olmstead, 2014; Cushing et al., 2023).

Our study also contributes to a better understanding of the long-term costs of climate change and related natural disasters or extreme weather events, in particular with respect to water quality. Prior work has investigated the impacts of these events on ambient water quality, for example by investigating the impacts of droughts on surface water quality (Qiu et al., 2023). However, few studies have estimated the impacts of climate-related extreme weather events on "finished" drinking water quality over a large region.[3] Bryant-Sheth (2024) estimates the impacts of cyclones on coliform detections and fetal health outcomes in Florida, and we use this paper's findings to help quantify impacts of extreme weather events. Another related paper is Pennino et al. (2022), which investigates the impacts of wildfires on nitrate, arsenic, and disinfection byproduct violations and concentrations in drinking water systems across 28 states. The average retrospective relationships from natural disasters observed in Pennino et al. (2022) and extreme weather phenomena in this paper can be translated to prospective climate change damage functions, contributing to a more complete accounting of the social cost of greenhouse gases (USEPA, 2022).

Finally, our study contributes to a growing literature on environmental justice in drinking water and on the disparate impacts of climate change across groups with heightened socioeconomic vulnerability. In the context of drinking water, the environmental justice literature typically examines differences across demographic or income groups with regards to infrastructure quality (VanDerslice, 2011; Wakhungu et al., 2021), Safe Drinking Water Act (SDWA) violations (Marcillo et al., 2021; Statman-Weil et al., 2020), time to return to SDWA compliance (Pullen-Fedinick et al., 2019), water affordability (Goddard et al., 2021), con-

[3] Finished drinking water refers to potable water that has been treated to remove pathogens and other contaminants. Finished water contrasts to "raw" water, which is ambient water that has not yet been treated. "Raw" water can refer to surface waters in rivers and streams or groundwater.

taminant levels (Schaider et al., 2019; Pace et al., 2022), or a combination thereof. Our study is most closely related to prior work investigating multiple states and drinking indicators. For example, Mueller and Gasteyer (2021) investigates infrastructure and multiple drinking water quality metrics nationally. We are aware of few papers quantitatively estimating the disparate impacts of climate change on drinking water quality across demographic groups. A notable exception is Cushing et al. (2023), which shows how coastal flooding risk varies across neighborhoods in California with varying socioeconomic vulnerability and presence of toxic sites. In contrast to Cushing et al. (2023), our paper is retrospective in assessing risk across communities rather than prospective, and we do not assess differences in risk from the presence of toxic sites.

2 Background

In this section, we first fix terminology with a brief description of the drinking water treatment process and regulatory context. We then describe three mechanisms by which extreme precipitation events and associated flooding can impair drinking water quality, providing a strong basis for the research questions of this paper. We conclude with a discussion of the health impacts of the drinking water contaminants in this study.

Drinking Water Treatment: Public water systems (PWSs) acquire sourcewater (i.e., "raw water") from a designated supply of groundwater and/or surface water. Groundwater is typically not influenced by short-term fluctuations in precipitation or other weather phenomena.[4] Surface water supplies are bodies of water such as lakes, streams, and reservoirs that can be immediately impacted by precipitation. Some systems use many sources, such as for example multiple groundwater wells or a surface water source in combination with

[4]One exception is systems sourcing from groundwater under the influence of surface water. These systems source from relatively shallow wells that are connected to and influenced by nearby bodies of surface water through subsurface connections. For this paper, we designate these water systems as sourcing from surface water.

groundwater sources.[5] Drinking water systems treat raw water to varying extents depending on the type of sourcewater and its characteristics (EPA, 1991, 2002b, 2006a,b).[6] For example, water system treatment engineers may remove sediments, balance pH, or add anti-corrosive agents that reduce leaching from pipes (EPA, 2001; Shwetha et al., 2024). Treatment plant engineers also usually add disinfectant to eliminate pathogens and minimize microbial growth throughout the distribution network (Gibson and Bartrand, 2021). Surface-water sourcing systems tend to engage in more robust treatment processes and disinfectant use than groundwater systems due to the higher risk of pathogens or other contaminants in surface water compared to groundwater (EPA, 2009).

After treatment, "finished" water is sent to consumers through a distribution network.[7] The point at which water enters the distribution network is the "entry point." For most contaminants, the entry point is the location where finished water is sampled to determine compliance with SDWA. Conversely, microbial contamination and disinfection byproduct concerns often arise in the distribution system after water has passed the entry point, for which reason these parameters are sampled at representative locations in the distribution network.[8] Different nodes of the distribution network have varying potential for DBP formation depending primarily on water age, which is the time the water has spent in the distribution system prior to use (Pan et al., 2023; Lau et al., 2024). Higher water age profiles give more time for the disinfectant to interact with other materials, both depleting disinfectant residuals and increasing disinfection byproduct concentrations. Larger systems

[5] Public water systems that source from both groundwater and surface water are classified as surface-water sourcing systems in this paper.

[6] There are five Safe Drinking Water Act Rules that directly relate to best practices in treating raw source water. These include the Surface Water Treatment Rule, Interim Enhanced Surface Water Treatment Rule, the Long Term 1 and 2 Enhanced Surface Water Treatment Rules, and the Groundwater Rule.

[7] The distribution network is not necessarily located near the treatment plant or intake. Depending on local topographic characteristics and water system size, the distribution network may make use of sophisticating pumping and piping infrastructure to ensure adequate pressure at the tap for all homes.

[8] Water system practices related to DBP formation and microbial control are primarily regulated as part of three SDWA rules: the Revised Total Coliform Rule and the Stage 1 and 2 Disinfectants and Disinfectant Byproduct Rules. According to these rules, water systems and states coordinate on their selection of representative sampling points in the distribution system. For more information on the sampling requirements for DBPs, see EPA (2010).

tend to maintain greater disinfectant residual levels in their distribution system to ensure a detectable residual at the fringes of the distribution system (EPA, 2007, 2009). Potential for microbial contamination also varies across a distribution network and over time depending on many factors; depletion of disinfectant residual, aging infrastructure, leaks, water main breaks, and nitrification in system pipes can all contribute to microbial growth (EPA, 2007; NHDES, 2021; Hussein Farh et al., 2023). Aging infrastructure is a notable concern for water system managers as average water main pipes are often 75 - 100 years old; there were roughly 275,000 water main breaks each year from 2012 to 2018 (ASCE, 2021). Smaller leaks in older pipes are also problematic, with a typical system losing 10 percent of its water to leaks in the distribution network (Barfuss, 2023). These issues contribute to the substantial 20-year infrastructure investment need of $625 billion, most of which relates to upgrading distribution lines (EPA, 2023).

Extreme Precipitation and Ambient Water Quality Heavy precipitation alters the physical and chemical properties of surface water by increasing water flow, disturbing alluvia that are not typically exposed, and through atmospheric deposition of air pollutants. Increased flow and disturbed alluvia can affect select water parameters including temperature, pH, conductivity, dissolved oxygen, total hardness, redox potential, dissolved organic carbon, and nutrients such as nitrogen and phosphorus compounds (Puczko and Jekatierynczuk-Rudczyk, 2020). The direction of correlation between these mechanisms and water physical and chemical parameters can vary depending on the relative amount of rainfall and hence dilution, severity of flooding, and degree of urbanicity in a watershed among other factors (Miller and Hutchins, 2017; Omogbehin and Oluwatimilehin, 2022). Atmospheric deposition is a third mechanism by which precipitation can change the properties of surface water (Chen and Guo, 2022). Particularly extreme rainfall events, such as hurricanes and tropical storms in the Southeastern United States, have deposited large quantities of water soluble ions such as chloride, dissolved organic carbon, and nitrogen (Qiu and Felix, 2021), which in turn can overwhelm critical load thresholds for these parameters in a watershed and have an adverse impact on ecosystem health (Clark et al., 2018).

Extreme precipitation events also increase mobilisation of agricultural pollution, urban storm runoff, and legacy pollution. Agricultural runoff, which often carries fertilizer residuals and animal wastes, can elevate nutrient and pesticide levels in watersheds and increases the potential for bacteriological contamination (USEPA, 2003). Meanwhile, urban storm runoff collects grease from motor vehicles, pesticides from lawns, human and animal wastes, road salts, and heavy metals from various sources (EPA, 1983; Taebi and Droste, 2004; Mahbub et al., 2011; Ahmed et al., 2019). Publicly-owned treatment works (POTWs) also face challenges during heavy wet weather events. Due to lack of treatment capacity during peak flow events, POTWs may release partially treated sewage directly into surface waters (USEPA, 2014; Haley et al., 2024). In the United States, Abdul-Aziz and Ahmed (2017) found that agricultural runoff in Florida contributes a greater share of pollution in surface waters than urban runoff, although this likely varies regionally. Aside from agricultural and urban storm runoff, extreme precipitation events have the potential to re-mobilize legacy pollution deposited by historic industrial practices. Bank erosion and bathymetric changes can stir up such legacy pollutants and heavy metals in the sediments of waterbodies (Ciszewski and Matys Grygar, 2016). Mladenovic et al. (2019) found that a 2014 flood in Serbia increased the presence of toxic elements in flood-affected soils. Heavy metals or potentially toxic elements (PTEs) from historical mining and industrial activities may be mobilized by heavy rains or floods even after ground remediation efforts have taken place, in some cases reflecting contamination from centuries prior (Hutchinson and Rothwell, 2008; Žák et al., 2009; Foulds et al., 2014). Several independent processes contribute to the mobilization of toxic elements from flooding (Ponting et al., 2020), meaning that it can be difficult to predict water quality changes in one watershed in isolation. The release of legacy pollution during extreme storm events can be substantial and has been described as a "ticking time bomb" (Crawford et al., 2022).

Heavy precipitation and severe flooding can also damage current industrial or pollution storage sites, causing the inadvertent release of additional non-legacy pollution. For example, Hurricane Floyd caused the breach of at least 46 animal manure lagoons, releasing nutrients, bacteria, and veterinary drugs (Wing et al., 2002). Hurricane Florence caused damage to coal ash confinements and toxic chemical releases from Superfund sites in North Carolina (Aly et al., 2021). Hurricane Harvey caused the release of over 500 million gallons of hazardous chemicals across roughly 100 accidental spills in Houston (Thomas et al., 2018), and studies have shown that Harvey's floodwaters contained elevated levels of polycyclic aromatic hydrocarbons (Bacosa et al., 2020). Similar conclusions related to floodwater toxicity were also reported after Hurricane Katrina (Pardue et al., 2005). A 2002 flood of the Elbe River inundated industrial facilities in lower Saxony and increased contaminant levels in marine animal tissues downstream Einsporn et al. (2005). Flood risks from contaminated sites are not confined to industrial hotspots; prior work estimates that over 3 million people in the US live near a toxic site with a high risk of flooding (Marcantonio et al., 2020).

Extreme Precipitation and Drinking Water Quality: Sourcewater quality fluctuations have the potential to affect the drinking water treatment process even in the absence of flooding. For example, sourcewater disturbances from unconventional oil and gas well drilling have been associated with more volatile organic compounds and disinfectant byproducts in drinking water (Elliott et al., 2018; Abraham et al., 2023). DBPs are a wide class of chemicals that are formed when disinfectants, such as chlorine, chloramine, or ozone, interact with organic matter and other DBP precursors in sourcewater to create new chemicals in finished drinking water. Changes in source water characteristics affect formation of disinfection byproducts (DBPs) both during treatment and after treatment in the distribution network as disinfectants continue to react with elevated levels of DBP precursors (Xiao et al., 2024). For example, higher levels of dissolved solids in sourcewater can lower the efficacy of filtration systems, and the resulting post-filtration organic matter increases the formation of DBPs (Liu et al., 2012; Fakour et al., 2016). Elevated nutrients also contribute to DBP formation through impacts to algae growth (Aziz et al., 2023). Increases in halogens such as bromide in sourcewaters can increase the formation of brominated disinfection byproducts; for example, bromide can interact with ozone to form bromate (Good and VanBriesen, 2016; Wang et al., 2017).

A second major category of impacts to drinking water during extreme weather and flooding events relates to microbial contamination. Floodwaters in the US have elevated microbe levels (Yard et al., 2014). Wastewater treatment plant pollution, damaged sewer lines or septic tanks, and animal agricultural runoff can all contribute to elevated microbial pathogens in sourcewaters and microbial contamination of distribution systems (Liu et al., 2018). Microbial contamination of distribution systems is an especially difficult problem during severe precipitation events, as it can be hard to adequately monitor for and subsequently locate the source of the contamination (Palma et al., 2024). Phan and Sherchan (2020) found that flooding in Louisiana was associated with elevated levels of coliform bacteria in tapwater. Risk of microbial contamination is compounded when DBP levels are high, as DBP formation indicates that residual disinfectants intended to protect the water as it flows throughout the distribution network have been depleted, which permits the proliferation of opportunistic plumbing pathogens (EPA, 2002a; Isaac and Sherchan, 2019). Aside from disinfection byproducts and microbial contamination, sourcewater chloride increases the corrosivity of water and causes lead to leach from water pipes and fixtures (Stets et al., 2018). Collectively, these mechanisms are well known challenges for drinking water treatment engineers (Sun et al., 2016; Ahmed et al., 2020). Other natural disasters that impact source water quality, such as wildfires, pose related concerns for water system engineers (Hohner et al., 2017).

Damage to Drinking Water Infrastructure: Severe precipitation events can damage drinking water infrastructure and disrupt water supply. Many prior studies have described possible failures of water infrastructure during severe weather or flooding events (Arrighi et al., 2017; Allen et al., 2018). Possible accidents or supply disruption can relate to electricity loss, damage to pipes, facility or pipe inundation and leakage, pressure loss, and concerns with sourcewater contamination (CRC, 2005; Matthews, 2016). Buried infrastructure, such as water distribution and wastewater collection pipes, is also vulnerable to damage by above-ground inundation (Chisolm and Matthews, 2012). Recent flooding in Western Europe caused loss of water access for five days, and water had to be boiled for a month in other systems (Koks et al., 2022). Prior work has also characterized current resilience of drinking water treatment technologies to floods and super storms as medium to low, with many US counties at high risk of drinking water disruption due to severe weather events (Luh et al., 2015, 2017). Infrastructure damage is also much more likely when equipment is aging and already prone to failure, which is common across US water systems as previously discussed. Given heightened climate risks, WHO (2010) and Khan et al. (2015) advocate for for enhanced resiliency planning for drinking water systems.

Health Effects of Coliform Bacteria and Disinfection Byproducts: While extreme precipitation events may contribute to the detection of many contaminants in drinking water that may impact public health, we limit this analysis to two classes of drinking water contaminants that are frequently sampled across systems and strongly connected to heavy precipitation and flooding events. These are coliform bacteria and disinfection byproducts.

Coliforms are a large class of bacteria that are ubiquitous in the environment and present in the intestinal tracts of animals. Only a subset of coliform bacteria has the potential to cause illness or impact public health, but water systems sample for total coliforms because their presence serves as a proxy for the presence of more harmful pathogens in drinking water such as other bacteria, parasites, and viruses (EPA, 2012). Whenever coliform bacteria are detected, a water system is subsequently required to test for E. Coli, a coliform bacteria that causes illness.[9] Microbial growth in drinking water can lead to rapid and significant public

[9]E. Coli is not the only possible pathogen that can cause illness. (EPA, 2002a) provides a detailed

health concerns. As described in Hrudey et al. (2003), heavy rains for five days contributed to a waterborne illness in Ontario that killed seven people. From 2007 to 2008, 22 of 37 disease outbreaks associated with drinking water related to sourcewater, treatment plant, or distribution network contamination (Brunkard et al., 2011). Bacterial contamination in drinking water can lead to complications in pregnancy such as maternal sepsis that increases the odds of preterm birth threefold and the likelihood of infant mortality sixfold (Knowles et al., 2014; Page et al., 2019). Such contamination can also increase gastrointestinal illnesses for up to four weeks after a flooding event (Saulnier et al., 2017). Due to these risks, case studies have emphasized the importance of revising public notice requirements of the Safe Drinking Water Act during severe precipitation events (Exum et al., 2018). Infractions related to the total coliform rule are the most common type of health-based violation of the Safe Drinking Water Act, with over 35,000 such violations from 1982-2015 (Allaire et al., 2018).

Disinfectants such as chlorine are an effective means of limiting harmful microbial growth in drinking water, but disinfection byproducts can be harmful to public health, especially when a large share of the population is exposed to these substances. Prior studies have shown that DBPs are carcinogenic in lab animals, and epidemiological studies suggest an association between chlorinated drinking water and bladder, rectal, and colon cancer (EPA, 2005; Costet et al., 2011; Regli et al., 2015). A recent study estimated that DBP exposure at levels observed across US drinking water systems would lead to 45,000 excess lifetime cancer cases (Evans et al., 2019). Epidemiological research has also suggested associations between DBP exposure and reproductive or developmental effects (Padula et al., 2021), including heightened risk of miscarriage, that have also been shown in laboratory animals (Colman et al., 2011; Zhang et al., 2023).[10] Certain unregulated or less-understood disinfection byproducts are also highly toxic (Li et al., 2022). For these reasons, disinfection byproducts are reg-

description of the pathogens of health concern that may be present in drinking water distribution systems.

[10]The relationship between DBP exposure at levels commonly observed in US drinking water systems and developmental harm, especially risk of spontaneous miscarriage, has been questioned in the epidemiological literature (e.g., see Tardiff et al. (2006)).

ulated under the Stage 1 and Stage 2 Disinfectants and Disinfection Byproducts rules of the SDWA (EPA, 2005). The Stage 2 rule focuses on reducing concentrations of two classes of DBPs known as trihalomethanes (TTHM) and haloacetic acids (HAA5), which are considered "representative of many other DBPs that may also be present in the water" (EPA, 2006c). Violations of the disinfectant byproduct rules are the second-most common rule infraction of the Safe Drinking Water Act (Allaire et al., 2018).

3 Data

This paper uses information on drinking water systems, daily weather, and extreme storm events across the US from 2000 to 2019. The following sections detail data sources and construction of our analytic panel.

Safe Drinking Water Act compliance monitoring data and public water system information: We developed a large multi-state database of drinking water quality compliance monitoring samples across 47 US states.[11] The rationale for collating these samples across many states is to allow improved estimation when assessing the impacts of relatively rare and geographically-dispersed events such as natural disasters. It also permits more flexible controls for time-varying state and local characteristics, such as regulatory environment, that may ameliorate or worsen the effects of weather-driven drinking water disruption. Aside from permitting more flexible controls for local factors, our data allow us to assess which regions are most at risk and the factors underlying such risk (e.g., water source, system size, etc.).

While data sources vary, each observation of drinking water quality has a consistent format and provides similar information. In particular, the unit of observation is a drinking water quality sample of an analyte from a municipal water system on a particular date.

[11]The sample includes all US states except Alaska, California, and Michigan. Certain parameters may also be missing in particular states.

The samples are collected by a third party to determine compliance with the Safe Drinking Water Act (SDWA), and they are collected at a frequency determined by characteristics of the water system such as the population served. Appendix Table A1 shows the annual count of samples across drinking systems of varying size categories for each water quality analyte in this analysis. For 35 states, the water samples were assembled through a variety of means including requests, direct downloads, and web scraping of public sites containing the sampling data. For an additional 12 states, drinking water quality information was sourced from compliance monitoring data requested of states as part of the Six Year Review 3 and 4.[12] Appendix Table A8 lists these states, the annual range of their data, and the underlying source of the samples. For each chemical contaminant concentration used in this study, we standardize measuring units to micrograms per liter of water ($\mu g/L$). If the analyte was not detected in a specific sample, we assign a concentration value of zero.[13] For bacterial contaminants, we only observe a detected or not detected binary variable; we assign non-detects a value of 0 and detections a value of 100 so that point estimates are interpretable percentage point changes. We also drop all samples with an indicator or sample point location reflecting that they were collected from raw source water. We display summary statistics of mean detection rates and average concentrations in Table 2. We also summarize detection rates and concentrations on days with and without precipitation in Appendix Table A2.

We join SDWA compliance monitoring samples to information on water system characteristics and geographic location. The Safe Drinking Water Information System (SDWIS) is used to link basic characteristics on water systems such as population served, source water type, and regulatory category of system (EPA, 2024b).[14] SDWIS is EPA's primary dataset on all public drinking water systems, and it includes information on water system charac-

[12]See https://www.epa.gov/dwsixyearreview/six-year-review-3-compliance-monitoring-data-2006-2011 and https://www.epa.gov/dwsixyearreview/six-year-review-4-drinking-water-standards-information-collection-request

[13]While there are many ways to contend with non-detects, we choose to impute zero to limit the influence of differences in average detection limits over time and across systems. To the extent that imputing zero introduces measurement error, we expect this data convention could lead to attenuation bias.

[14]See: https://sdwis.epa.gov/ords/sfdw_pub/r/sfdw/sdwis_fed_reports_public/200

teristics and violation histories. Next, we assign the samples two geographic indicators for merging them to weather and natural disaster information. These include a county FIPS code indicator and a sub-watershed Hydrologic Unit Code 12 (HUC12) identifier.[15] The FIPS code indicator relates to the primary county served by the water system according to the Safe Drinking Water Information System. We use these county identifiers to join water systems to disaster records in the NOAA Storm Events Database, which are observed at the county-level. The HUC12 indicator relates to the location of the water system's intake location, where we source these HUC12 identifiers from the Drinking Water Mapping Application.[16] We use the HUC12 intake location to join water systems to PRISM precipitation and weather information where intake information is available. Since the PRISM data is raster-based, we extract precipitation records to more precise HUC12 intake watersheds. Since water systems may have intakes in multiple HUC12s, we select the mode HUC12 location across all intakes to represent the water system's intake location. We also classify water systems with at least one surface water intake as sourcing from surface water, even if all other intakes collect from groundwater.[17] Systems sourcing from groundwater under the influence of surface waters are also classified as surface water-sourcing systems.[18] The HUC12 intake information allows us to join water systems to weather and precipitation information that has been spatially aggregated to the HUC12 level, which provides greater precision with respect to the weather characteristics affecting a system's water source. For water systems where we lack HUC12 intake location, we assign weather information based on the county instead of the sub-watershed region.

National Oceanic and Atmospheric Association Storm Events Data: Information on natural disasters was acquired from the Storm Events Database, a product of the National

[15] On average, a HUC12 is 36 square miles, or less than a quarter of the size of a typical US county.

[16] See: https://www.epa.gov/sourcewaterprotection/drinking-water-mapping-application-protect-source-waters-dwmaps

[17] This classification scheme is consistent with recording practices in SDWIS.

[18] Groundwater under the influence of surface water describes a situation in which the water is shallow enough to be directly connected to a nearby surface water and influenced by fluctuations in water quality within that surface water.

Centers for Environmental Information in the National Oceanic and Atmospheric Association (NOAA).[19] The Storm Events Database includes all significant or abnormal weather and atmospheric phenomena that cause loss of property, injuries, or loss of life across the US. For this study, we isolate storm events labeled as "heavy rain" and several other events that we collectively refer to as "flooding."[20] Heavy rains and floods are distinct categories of storm events and hence variables in our estimating equations, although in some cases a heavy rain disaster coincides with a flood disaster in the data. Storm events are recorded at the county level, such that the same disaster may be represented multiple times in the dataset if it impacts multiple counties. Each unique disaster is identified by a disaster ID. The data list the type of natural disaster as well as the duration, property damage, and deaths associated with the disaster in each county. While the data include all disasters from 1950-2020, we limit it to the period from 2000-2019 to accord with our other information. Summary statistics of the natural disaster information are reported in Table 1.

We note that the storm events records are subject to important caveats. First, there is selection in reporting due to the inclusion criteria requiring loss of property, injuries, or loss of life. For example, severe flooding in an unpopulated area that does not cause injuries or loss of property is less likely to be recorded. Moreover, the intensity of a weather event is not consistent across different floods, and it likely systematically differs across geographic regions and ecosystem types. For example, a relatively light period of rainfall in an arid area prone to flash flooding may be recorded as a disaster, while minor flooding in an area of wetlands prone to frequent flooding might not be recorded. Due to these limitations, we also include precipitation levels as the independent variables, which allows us to draw firmer conclusions regarding the quantitative relationship between rainfall at various intensities and subsequent impacts on drinking water quality.

[19] Accessed online 3/1/2021 at https://www.ncdc.noaa.gov/stormevents/ftp.jsp

[20] The flood category includes coastal floods, flash floods, lakeshore floods, and "floods". The heavy rain category includes only heavy rains.

Daily Precipitation and Temperature: We source daily precipitation and temperature information from the Parameter-elevation Regressions on Independent Slopes Model (PRISM) created by the PRISM Climate Group at Oregon State University (PRISM, 2022). These data are a 800x800 meter raster surface that contains the outputs from the PRISM model (Hart and Bell, 2015). These values are extracted to polygons of hydrological units at the HUC12 (Hydrologic Unit Code of subwatersheds) level (EPA, 2022) using an area-weighted average of each raster cell's value. This procedure yields the average precipitation and average temperature in each HUC12 on every day of the sample.[21] The public water sample dataset that we construct includes information on the HUC12 locations of the source water intakes. We create a panel of daily weather for each water system by combining the HUC12 area-averaged precipitation and temperature information with water system intake HUC12 locations.[22] Where water systems make use of intakes in multiple HUC12 regions, we assign the mode HUC12 location across all intakes as the water system's geographic location. To limit the size of the dataset, we retain on a balanced window of weather for 14 days leading up to and following each drinking water sample for all systems. Summary statistics of weather variables are reported in Table 1.

Demographic Information of Drinking Water Systems: To determine the demographic characteristics of each community water system, we use the U.S. EPA Community Water System Service Area Boundary dataset version 3.0 (EPA, 2024a).[23] This data is a collation of service boundaries uploaded by state and local governments as well as modeled boundary locations where none are otherwise available. Modeled service area boundaries are produced using a machine learning approach to classify areas that are likely on public

[21]Replication data and code can be accessed in the public repository at https://github.com/bryanparthum/prism_weather_data

[22]Certain water systems lack information on the HUC12 of their intake. For these systems, we assign weather information associated with the primary county of the water system. Because we average temperature and precipitation over all grids within a HUC12 or county, our weather variables of interest are similar across either geographic assignment method.

[23]See: https://www.epa.gov/ground-water-and-drinking-water/community-water-system-service-area-boundaries?tab=faq for more information.

water and then to match these areas to nearby water system identifiers. The boundary data includes polygon locations for for 44,415 community water systems, or 98% of the population served by public water in the US. We join these service area boundary polygons to 2016-2020 American Community Survey sociodemographic data using the open-source package EJSCREENbatch, which areally apportion census block groups to each service boundary to determine average demographic characteristics over the region.[24] In heterogeneity analyses, we chose to examine the following demographic characteristics that correspond to the groups with heightened vulnerability specified in Executive Order 12898: share of population below the federal poverty line, percent Black, percent Hispanic, percent American Indian, percent Asian, and percent Pacific Islander.

4 Empirical Methods

Our objective is to test the relationship between extreme precipitation events and measures of drinking water quality. We test this relationship using three approaches that are summarized below.

Precipitation and Drinking Water Quality We start by assessing the relationship between precipitation levels and measures of drinking water quality in the same watershed region.[25] Let y_{idmst} represent the continuous concentration of DBPs or whether a sampling test detected a bacteriological contaminant in public water system i, day d, month m, state s, and year t.

$$y_{idmst} = \beta \sum_{d-3}^{d} Precipitation_{idmst} + X'_{idmst}\gamma + \eta_i + \eta_m + \eta_{st} + \nu_{idmst} \tag{1}$$

[24]Specifically, we run the land-based tool and employ the robust option. Link to the github repository: https://github.com/USEPA/EJSCREENBatch

[25]In some cases, we use precipitation in the county in the small number of cases where intake locational information is lacking.

In equation Equation 1, the term $\sum_{d-3}^{d} Precipitation_{idmst}$ is the total precipitation quantity across the three days prior to a sample collected in water system i on day d of month m in state s and year t.[26] The vector X includes controls for daily temperature and two daily lagged versions of this variable, as temperature contributes to microbial formation and is correlated with DBP concentrations.[27] We incorporate fixed effects for water system to control for time-constant heterogeneity across systems such as water system size, water source, or the degree of industrialization and urbanization around a water system.[28] We also include high-dimensional fixed effects for month and state-by-year to flexibly control for time-varying seasonal, regulatory, and institutional factors. We therefore control for local and state-level attributes that could be correlated with both weather and water quality over time. If a state changes regulations governing certain water quality indicators, the state-by-year fixed effects control for these regulatory constraints facing water systems. Changes to national regulations are also controlled for by the temporal fixed effects. Month controls allow for seasonal variation in water quality indicators, which is expected for bacterial contaminants and disinfectant byproducts. The parameter of interest is β, the marginal effect of an additional centimeter of precipitation in the three-day period immediately preceding a sample collection date. As such β suggests how rainfall events on average affect likelihood of bacterial detection or DBP formation rather than the effects of a severe precipitation event in particular. It therefore complements our analysis of less-frequent extreme weather events.

Extreme Precipitation, Flooding, and Drinking Water Quality Next, we consider how extreme precipitation and flooding events affect drinking water quality. As before, let y_{idmst} represent whether a sampling test detected a bacteriological contaminant or the

[26] Note the precipitation quantity is calculated as the average precipitation over the area of the HUC12 of a public water system's intake location when intake location HUC12s are available, and it is calculated as the average precipitation over the county of the water system when intake HUC12s are not available. Water quality sampling counts on days with and without recent precipitation are summarized in Table A2.

[27] Total coliform detection frequencies tend to increase with temperature in warmer months (Reitter et al., 2021; Blokker et al., 2016), and disinfectant byproducts also increase in warmer months.

[28] In sensitivity analyses, we also show results with fixed effects at the county level, sub-watershed HUC12 level, and watershed HUC8 level. These are presented in Appendix Table A4 to Table A7. In nearly all cases, results are qualitatively the same.

continuous level of disinfectant byproducts detected by the sample in public water system i, day d, month m, state s, and year t.

$$y_{idmst} = \beta Disaster_{idmst} + X'_{idmst}\gamma + \eta_i + \eta_m + \eta_{st} + \nu_{idmst} \tag{2}$$

In equation Equation 2, $disaster_{idmst}$ is an indicator equal to one if an extreme precipitation or a flooding event occurred in the same county as public water system i in the period immediately preceding collection of a sample on day d of month m in state s and year t.[29] We separately investigate a near-term $Disaster_{idmst}$ variable equal to one if an event occurred in the prior three days as well as a longer-term variable equal to one if the disaster occurred in the ten days prior to collection of the sample.[30] The vector X includes controls for daily temperature and two daily lagged versions of this variable. We do not include controls for precipitation, as these are correlated with extreme precipitation and flooding events and would therefore obscure our primary relationship of interest. We incorporate the same combination of fixed effects as before and for similar reasons. In particular, since severe weather events are not necessarily randomly geographically distributed, we note that our water system fixed effects control for any factors that are unique to areas experiencing frequent severe weather such as hurricane-prone regions. The parameter of interest is β, which represents the marginal relationship between a recent extreme precipitation event and measures of drinking water quality shortly after the disaster. To simplify the presentation, we consider periods of three and ten days after the disaster to capture the average effects of extreme precipitation events over a plausibly relevant time horizon. In what follows, we abstract from this assumption and break out daily impacts of precipitation over a 28-day period using an event study framework.

[29] Note that our NOAA storm events are geocoded to the county level only, and so we join these by the county of a water system rather than the HUC12 location of the intake.

[30] Sampling counts on days with and without recent severe weather events are summarized in Table A3.

Event Studies of Precipitation and Drinking Water Quality We also conduct event studies of the relationship between precipitation and drinking water quality. Consider the following regression:

$$y_{idmst} = \beta_d \sum_{d=-14}^{14} Precipitation_{inmst} + X'_{idmst}\gamma + \eta_i + \eta_m + \eta_{st} + \nu_{idmst} \tag{3}$$

In Equation 3, we replace the binary indicator for whether a disaster occurred on day d with a set of variables representing the continuous level of precipitation affecting a water system from day $d-14$ to day $d+14$. This specification tests whether precipitation before or after a sample is conducted impacts indicators drinking water quality, and it also tests the typical length of time over which heavy rain may continue to impact drinking water quality. For this specification, we do not investigate the impacts of binary disaster variables, as these events are sufficiently rare across systems to imply inferring from small sample sizes for each of the 29 daily coefficients.

5 Results

Extreme precipitation events increase the likelihood of detecting bacteria in drinking water as well as the concentration of two classes of disinfectant byproducts, TTHM and HAA5. To start, Table 3 and Table 4 display the relationship between precipitation events and bacteria detection in drinking water. The first two columns of Table 3 demonstrate the effect of having a flood within the prior 3 and 10 day period on the likelihood of total coliform detection. The point estimate of 0.28 from a flood in the prior 3 days suggests that one of these events increases the likelihood that a total coliform sample detects coliform bacteria by nearly 0.3 percentage points. Given the average detection rate for total coliform is 1.7, this is a 17% increase from the mean detection likelihood from a recent flood. The effect is slightly lower over a longer 10-day period at 0.23, suggesting that these effects may begin to subside over a longer time horizon but persist for over a week. The third and fourth columns of Table 3 show how heavy rain events, as reported to NOAA's Storm Events Database, affect the likelihood of detecting total coliform. The point estimates of 0.3 and 0.2 suggest that a heavy rain within the prior three days increases the detection likelihood of total coliform by 0.2 to 0.3 percentage points. These represent 11% and 17% increases from the mean detection rate, respectively. The fifth column of Table 3 reports the relationship between a centimeter of rainfall and the likelihood of detection of total coliforms, showing that each centimeter increases the likelihood of detection by 4% or 0.07 percentage points.

Next, we display the relationship between extreme precipitation and E. coli detection in drinking water in Table 4. As before, the outcome is a binary indicator for detection, and so the point estimates reflect percentage point changes. Flooding over the prior 3 or 10 day period increases the likelihood of an E. coli detection by 0.2 percentage points. This is roughly similar magnitude increase in likelihood of detection as for total coliform. Yet, because E. coli detections are rarer at a 0.4% detection rate, this represents a more dramatic percent increase in detection likelihood at 41%. Conversely, the relationship between heavy rains in the prior 3-day and 10-day period and E. coli detection is smaller in magnitude than observed for total coliform and only significant over a 10-day time horizon. Meanwhile, each centimeter of rainfall in the prior three days increases the likelihood of an E. coli detection by 0.04 percentage points, which again resembles the increased likelihood observed for total coliform detection likelihood. The increase of 0.004 percentage points is an 8% increase from the mean detection likelihood. Collectively, Table 3 and Table 4 demonstrate that flooding has the potential to dramatically increase the baseline risk of detecting bacteria in drinking water supplies, including disease-causing bacteria such as E. coli. Heavy rains demonstrate a weaker relationship to E. Coli detection, especially over shorter periods of time after a heavy rain. This discrepancy for E. Coli could be due to differences in sampling requirements for this bacteria, where sampling is first triggered by a total coliform detection.[31]

[31] In Appendix Table A3, we summarize sampling counts for all water quality parameters in the period just after severe weather events.

As discussed in section 2, flooding and extreme precipitation have the potential to increase disinfection byproduct levels because they increase organic matter and other DBP precursor levels in source water. Treatment engineers may also increase disinfectant dose to protect against bacterial contamination risk. The most frequently sampled classes of disinfectant byproducts are total trihalomethanes (TTHMs) and haloacetic acids (HAA5s), which are considered to represent DBP formation potential across all DBPs.[32] The relationship between extreme precipitation and TTHMs is displayed in Table 5, where TTHMs are measured in ($\mu g/L$) as a continuous variable. The first column of Table 5 demonstrates that a flood within the prior 3 or 10 day period increases the measured concentration of TTHMs by 1.4 to 1.6 ($\mu g/L$). Given the mean level of TTHMs is 32 ($\mu g/L$), this represents an increase in concentration of 4-5%. Meanwhile, a heavy rain over the prior 3 or 10 day period increases the concentration of TTHMs by a very similar magnitude of 1.3 to 2 ($\mu g/L$), or a 4-6% increase from the mean concentration. Finally, each additional centimeter of rainfall over the prior 3-day period increases the concentration of TTHMs by 0.2 ($\mu g/L$), or less than a 1% change from the mean per centimeter of rainfall. For context, the maximum contaminant level (MCL) for TTHMs is a locational running annual average of 80 ($\mu g/L$), so these changes would generally not be sufficient to push a water system into non-compliance with SDWA. Nevertheless, these changes have the potential to be relevant to public health, as the maximum contaminant level goal for certain trihalomethane compounds, such as bromoform and bromodichloromethane, is zero.

Table 6 shows the relationship between extreme precipitation events and HAA5 concentrations. For each flood over the prior 3 or 10 day period, the concentration of haloacetic acids increases by 1.2 to 1.4 ($\mu g/L$), an increase of 6-7%. We do not observe statistically significant increases in the concentration of HAA5 from heavy rain events observed in the NOAA Storm Events Database. However, we find that, on average, a centimeter of rainfall over the prior 3-day period increases the concentration of haloacetic acids by 0.12 ($\mu g/L$).

[32] These are the most frequently sampled DBPs because these are SDWA federally regulated DBPs. Unregulated DBPs, such as haloacetonitriles and other groups, are not typically measured.

For context on the magnitude of these shifts, the MCL for haloacetic acids is a locational running annual average of 60 ($\mu g/L$). Therefore, the impact from flooding is likely not sufficient to push typical water systems into noncompliance given average concentrations of 19 ($\mu g/L$) across water systems.

To understand how precipitation's timing impacts bacteria detection and disinfectant byproduct concentrations, we also conduct event studies around the time of the sample. In particular, we plot the coefficients β estimated in Equation 3—the impact of precipitation on different days within a 29-day window surrounding the date that a sample is taken—in Figure 1, Figure 2, Figure 3 and Figure 4. These plot results with respect to total coliforms, E. Coli, TTHM, and HAA5, respectively. Figure 1 and Figure 2 show a clear uptick in the relationship between precipitation and detection of either E. Coli or total coliform bacteria. This relationship is stronger for ground-water sourcing systems with respect to total coliform bacteria, but it is similar for both groundwater and surface water sourcing systems with respect to E. Coli. We take these impacts to groundwater systems, which generally source from deep groundwater that is not affected by short-term swings in precipitation, to indicate that infrastructure damage, leaks, and other concerns within the distribution network are a significant contributing factor to bacterial contamination risk from severe weather events and flooding.

Figure 3 and Figure 4 show the relationship over time between precipitation and TTHM and HAA5 concentrations. In both cases, systems sourcing from surface waters are far more impacted by precipitation than groundwater systems. This likely reflects an increase in DBP precursors in source waters used by these systems, whereas groundwater is unlikely to see immediate changes to DBP precursors following precipitation. Surface water systems may also differentially adjust their chlorination point during periods with actual or anticipated higher precipitation,[33] but we are unable to separately test these two possible mechanisms. We also note that these event studies suggest slight increases in DBP concentrations from

[33]In some cases, groundwater systems only use minimal chlorine sufficient to ensure disinfection throughout the distribution network (EPA, 2009).

rainfall that occurs after the sample is collected. In a typical event study, this finding could suggest issues with a causal interpretation of the results. However, in this case, we interpret these small but significant results as a plausible impact of future rainfall on current DBP levels, as water system engineers may engage in anticipatory adjustment of the chlorination point when they expect extreme precipitation events in the near future. This anticipatory adjustment would help to minimize risk of microbial growth risk in advance of any possible leaks or other concerns throughout the distribution system.

6 Supplemental Analysis

Our primary results reflect national average impacts of precipitation and flooding events on water quality. However, the effects of precipitation likely varies depending on the specific hydrologic, climatic, infrastructural, economic, or other conditions of public water systems. This section details heterogeneity analyses across water systems with different characteristics, including demographics of the population served, water system size, and underlying water source. The purpose of these heterogeneity analyses is to shed light on possible mechanisms and differential vulnerability to climatic stressors. Robustness tests are also described in this section.

Water System Demographics To examine disparate impacts of extreme precipitation and flooding on drinking water quality across demographic groups, we create water system sub-samples based on whether the system serves a relatively high proportion of a given demographic group. To ensure consistent sample sizes across demographic groups, we use a simple percentile threshold-based statistic to identify higher proportions. For example, if the community served by a water system is in at least the 75^{th} percentile with respect to share below the federal poverty line, we classify the system as serving a greater share of this demographic group. We then employ the same estimation procedure described in Equation 1 and Equation 2 over the sub-sample of water systems satisfying this condition. We note that these sub-samples entail conducting inference over smaller sample sizes, and so to an extent we should expect greater statistical noise with these results. To provide a comparison for the estimated coefficients, we include results over all systems as well.

The results of this demographic analysis are displayed in a set of coefficient plots for bacterial contaminants in Figure 5, while the same is plotted for disinfectant byproducts in Figure 6. In comparison to the average effect of interest across all water systems, we generally do not see higher adverse impacts with respect to precipitation for bacterial contaminants. One exception is systems serving higher shares of individuals in poverty, where we note slightly higher impacts on E. Coli detection. With respect to flooding, water systems serving a greater share of Black, Hispanic, and Pacific Islander communities see somewhat larger impacts of flooding on either total coliform detection or E. Coli detection than the average system. In particular, the increased risk is closer to 0.4 percentage points for these systems as opposed to 0.25 for all systems. Regarding DBPs, systems that serve the greatest shares of Black, Hispanic, American Indian, and Asian individuals experience larger impacts on TTHM concentrations from floods than a typical system. The average impact of recent precipitation on TTHM is also higher for systems serving higher shares of Hispanic, American Indian, and Asian populations. Recent precipitation is associated with larger impacts on HAA5 for water systems serving the greatest shares of Hispanic, American Indian, and Asian populations. Flood events appear to greatly impact HAA5 levels for systems serving higher shares of Black and American Indian populations, with effects that are 28-40% higher for these systems. The same is true for flood events and HAA5, although we note that water systems serving a greater share of Black individuals are also much more impacted by floods than the typical system along with the aforementioned groups affected by precipitation.

Water System Source The source of a water system refers to whether the water system uses surface waters for its drinking water, such as lakes and rivers, or groundwater, which is typically extracted from hundreds of feet below the earth's surface. Given the differential vulnerability of these water sources to short-term fluctuations in precipitation, we investigate our primary results for systems that primarily draw their water across each type of source. Figure 7 demonstrates how the effect of weather on bacterial detection differs by the source type of the water system. Water systems with groundwater sources are more susceptible to an increase in total coliform detection following precipitation or flooding events. For groundwater systems, the impact of a flood over the prior ten day period is nearly four times larger than for surface-water sourcing systems. The same pattern is true for E. Coli detection, with groundwater sourcing systems seeing larger effects, as shown in Figure 7(b). We show similar coefficient plots for disinfectant byproducts in Figure 8. In contrast to the results for bacterial contamination, we see much larger effects for water systems sourcing from surface waters than groundwater for all disaster types and DBPs analyzed. For haloacetic acids and groundwater sourcing systems, we observe no statistically significant relationship between natural disaster variables and the observed concentrations, although we observe some statistically significant impacts of flooding on TTHM for these systems.

Water System Size Categories Size categories refer to the population served by a given water system. These size categories are regulatory distinctions as well as practical categories of system, as larger systems are generally required to engage in more sampling or have other restrictions on their operating practices. Given the larger size of their distribution network, larger water systems may also face unique infrastructural challenges. Smaller systems, in contrast, often face more resource constraints because they are less able to spread the capital costs of water treatment across a large number of customers. Therefore, systems of different sizes face unique constraints that could impact our relationship of interest. Figure 9 shows the impact of flooding events, heavy rains, and precipitation on the likelihood of detecting coliforms across water systems of different size categories. In general, severe weather events impact smallest systems the most, with the largest systems not experiencing statistically significant changes in detection rates in the ten days after a flood. The smallest systems see a threefold greater risk from flooding than the average population-wide effect, and they also experience over four times the impact from rainfall alone as the largest systems. Interestingly, we observe that heavy rain events in the storm events database do not statistically significantly affect total coliform detection rates across all system sizes, however rainfall alone significantly predicts detection rate increases across all size categories. We observe similar patterns for E. Coli detection in Figure 10, where the smallest systems generally see the largest impacts. For E. Coli, however, these impacts are not always monotonically changing over the size categories, with the smallest systems representing clear outliers from the other size groups.

As for DBPs, Figures 11 and 12 show how risk from severe weather differs across water system sizes. For TTHM, we observe that the largest systems see the greatest increase in DBP concentration from severe weather events as well as rainfall in isolation. These impacts are generally monotonically increasing with larger population served, where very large systems see 2-3 times the impact from rainfall and flooding as the smallest systems. Figure 12 tends to show similar patterns for flooding and rainfall, although we often do not see statistically significant impacts from heavy rain events on HAA5. In particular, the largest systems experience the greatest increase in HAA5 after flooding and rainfall, with the smallest systems experiencing half or less the increase in concentrations. This heterogeneity in effects could be due to several causes. For one, larger systems are more likely to source from surface water and hence are more likely to have greater levels of DBP precursors; larger systems may also require more disinfectant use to control microbial growth across a larger distribution network (EPA, 2009). Size of the distribution network is also correlated with greater water age profiles, so precipitation-induced surges in natural organic matter have more time to interact with residual chlorine and form DBPs in larger systems (Blokker et al., 2016). Finally, larger systems may exhibit greater responsiveness to precipitation events by adjusting the chlorination point. We are unable to disentangle these mechanisms.

Overall, both large and small systems experience greater adverse impacts from flooding and extreme precipitation, with smaller systems facing a heightened bacterial contamination risk while larger systems see the largest spikes in DBP concentrations.

County and Regional Variation We test how our relationships of interest vary geospatially by running an altered statistical model that interacts the disaster or precipitation variable of interest with water system level fixed effects. The coefficients of these interaction terms capture the differential slopes of the weather variable across water systems and hence the differential impact of weather on water quality. We save these fixed effects and collapse them to the county-level to facilitate national mapping. Figures 13, 14, 15, and 16 show the heterogeneous impacts flooding, heavy rain events, and precipitation over the prior 3-day period on our outcomes of interest. The maps reflecting bacterial contamination risk generally suggest widespread but mostly small increases in risk from flooding events across nearly all states. This pattern implies that flooding can pose a risk to nearly all systems and geographies if sufficiently destructive. However, there are a few hot spots of larger impacts in coastal regions of South Carolina and the Chesapeake Bay, as well as large swathes of Alabama. Regarding DBP changes, we observe several hotspots from flooding and severe weather events across much of the Ohio river watershed and midwestern tributaries of the Mississippi. Oklahoma, Iowa, and Kentucky appear to have some of the greatest increases to DBP concentrations of any region. Certain coastal areas also have greater impacts than non-coastal regions, although much of the western coast appears minimally impacted.

7 Social Costs of Heavy Rains and Flooding Effects on Drinking Water

We estimate two cost categories with respect to extreme precipitation and flooding effects on drinking water quality. First, we transfer novel estimates of the developmental health costs of storm-induced bacterial detection in drinking water systems provided by Bryant-Sheth

(2024). This study estimates the relationship between Florida cyclones and drinking water system detections of total coliform. It then provides estimates of the impact of cyclone-induced water quality disruptions on the probability of preterm births and low birthweight newborns. Exploiting identifying variation in the location of water system intakes, the study finds that in-utero exposure to cyclone-contaminated water increased the incidence of preterm birth by 0.64 percentage points and the incidence of low birthweight of 0.5 percentage points. To transfer benefits from this study, we compute the ratio of the effect of a flood or heavy rain on total coliform detection to the effect of a cyclone on total coliform detection in Bryant-Sheth (2024); we then scale the relationship between cyclones and fetal health by this ratio and multiply it by the effect of cyclones on preterm birth.[34] Intuitively, this procedure estimates the likely relationship between floods and heavy rains on fetal health if these storm events had the same effect on coliform detections as Florida cyclones. We then scale the estimated effects of heavy rains and floods by the average annual frequency of these events across all community systems, their population served, and the share of pregnant women in the overall population.[35] This procedure yields a total of $1,241$ excess preterm births per year,[36] which we value at $760,000 per case as in Bryant-Sheth (2024).[37] This suggests annual social costs of preterm births at $943.2 million annually.

Second, we calculate the cost of water disruption using the estimated per person per day cost of water loss in Heflin et al. (2014). These cost figures relate to consumer purchases of bottled water or alternative water sources, adjusted cooking and eating decisions, altered

[34]For example, the effect of a flood on preterm births could be expressed as $\beta_{ptb} = \beta'_{ptb} * \frac{\gamma_{flood}}{\gamma_{cyclone}}$, or $0.0064 * (0.23/0.82) = 0.18$ percentage points. We use the 10-day post flood or heavy rain coefficients in this estimate.

[35]We use the SDWIS 2021 vintage to compute the number of active community water systems $(49,421)$ and average population served $(6,487)$. On average, community water systems have 0.09 floods and 0.04 heavy rains in the same county each year. While non-community water systems may also be affected, we limit to community systems to avoid double counting affecting populations. Next, based on Iezzoni et al. (2013), we assume that 3.5% of women, or 1.75% of the population, are pregnant at any given time.

[36]49,421 community water systems * 0.09 annual floods * 0.0018 point estimate * $6,487$ average service population * 0.0175 population share pregnant= 909 preterm births from flooding and 49,421 * 0.04 * 0.00148 * 6,487 *0.0175 = 332 from heavy rains.

[37]For context, this is a relatively small share of the roughly 370,000 preterm births annually (Barreto et al., 2024).

work and school schedules, and additional travel or commuting costs. Based on survey responses of individuals affected by water supply disruptions, Heflin et al. (2014) estimate costs of $94 per person per day.[38] To transfer this value to the frequency of water disruptions based on flooding and heavy rains, we make a simplifying and conservative assumption that only E. Coli detections result in a water service disruption.[39] We also assume that each service disruption lasts an average of five days based on the existing boil water advisory literature (Vedachalam et al., 2016; Alzahrani and Tawfik, 2024). These assumptions result in lower-bound cost estimates, as supply disruptions sometimes last much longer than five days, and they can also be caused by various contamination issues without an E. Coli detection. Given the point estimates in Table 4, we calculate the annual costs of all flood or heavy rain-induced E. Coli detections to be $58.8 million annually with respect to drinking water disruptions.[40]

For disinfectant byproduct exposures, available risk characterization numbers relate to lifetime rather than short-term exposures to these chemicals. Prior analyses such as Regli et al. (2015) and Weisman et al. (2022) employ a risk estimate suggesting that additional ($\mu g/L$) of TTHM concentrations in drinking water over a lifetime is associated with an odds ratio of bladder cancer of 1.004. Similarly, Evans et al. (2019) present drinking water concentrations of DBPs associated with a one-in-a-million cancer risk. These concentrations are 0.06 ($\mu g/L$) for bromodichloromethane, 0.4 ($\mu g/L$) for chloroform, 0.1 ($\mu g/L$) for dibromochloromethane, 0.5 ($\mu g/L$) for trichloracetic acid, 0.7 ($\mu g/L$) for dichloracetic acid, 0.5 ($\mu g/L$) for bromoform, and 0.1 ($\mu g/L$) for bromate. These estimated risk thresholds are below our estimated shifts in DBP concentrations after heavy precipitation events as presented in Table 5. However, since extreme precipitation events lead to short-term shifts in DBP exposures, we do not attempt to extrapolate lifetime risk from short-term fluctuations

[38]This value is close to the Federal Emergency Management Agency estimated cost of $97.

[39]These assumptions are based on the features of the Total Coliform Rule (see USEPA (2013)). A detection of E. Coli triggers a maximum contaminant level violation of the Revised Total Coliform Rule and requires a water system to conduct public notification as well as rapid assessment and corrective action.

[40]49421 water systems * 0.09 annual floods * 0.0034 point estimate * $94 per person *6487 service population * 5 days = $46.1 million and 49,421 *0.04*0.0021*94*6487*5 = $12.7 million.

in DBP concentrations.

Overall, the estimated external damages calculated from Heflin et al. (2014) and Bryant-Sheth (2024) suggest annual costs of at $1.002 billion from drinking water disruptions after extreme precipitation and flooding events.[41] We note several limitations of these estimated damages. To start, these cost estimates do not include damages from clinic visits and medication purchases, as could also be expected to occur based on Marcus (2022). Second, we do not estimate costs of water supply disruption to businesses, which can also be immense (Sjöstrand et al., 2021). Similarly, we do not quantify costs of disinfectant byproduct exposures, as risk estimates associated with acute exposures to DBPs are not available. Further, to the extent that illnesses from microbial growth contribute to mortality or other health effects not captured, these costs are not included in our estimates. Finally, these cost figures only include individuals served by public water. Users of private domestic wells, which are not regulated by the Safe Drinking Water Act, may also be affected.

8 Conclusion

Climate change has led to significant increases in severe weather events. This paper analyzes the costs of extreme precipitation and flooding by constructing a large multi-state drinking water quality database and investigating the relationship between extreme precipitation and disruption to drinking water quality. Our results advance our understanding of the multifaceted impacts of climate change. We explore the water system characteristics that are associated with heterogeneity in the impact of precipitation on drinking water quality. We also connect demographic characteristics of public water systems to assess heterogeneous impacts of precipitation on communities with greater social vulnerability, helping to shed light on the environmental justice dimensions of climate change. In addition, our back-of-the-envelope estimation of the costs of drinking water disruption from precipitation helps to establish this category of social costs from the emissions of greenhouse gases.

[41] $943.2 million + $58.8 million

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Tables

Table 1: Summary Statistics: County Mean Temperature (°C), Precipitation (%), Flood (days in a year), and Heavy Rain (days in a year)

	Mean	Std.Dev.	Min	Max
Temperature	12.87	4.61	-0.20	25.45
2002-2009	12.69	4.55	-0.20	24.70
2010-2019	12.93	4.66	-0.16	25.45
Precipitation	2.80	1.15	0.00	11.34
2002-2009	2.83	1.12	0.06	9.85
2010-2019	2.77	1.11	0.13	11.34
Flood	1.962	7.801	0	238
2002-2009	1.901	6.744	0	227
2010-2019	2.218	9.048	0	238
Heavy Rain	0.455	3.722	0	122
2002-2009	0.582	4.899	0	122
2010-2019	0.374	2.248	0	87
Observations	58998			

Notes: Table summarizes county-by-year weather variables and severe weather events from 2000-2019.

Table 2: Summary Statistics of Compliance Monitoring Samples by Water System Size and Source Type

	Mean	St. Dev.	Min.	Max.	Sample Count
Total Coliform (% Detection)	1.67	12.80	0.00	100.00	59986470
Ground Water	2.59	15.89	0.00	100.00	32026565
Surface Water	0.51	7.13	0.00	100.00	26982771
Very Large	0.50	7.04	0.00	100.00	7962444
Large	0.45	6.72	0.00	100.00	19273667
Medium	0.72	8.48	0.00	100.00	7754798
Small	1.48	12.09	0.00	100.00	8413233
Very Small	4.23	20.12	0.00	100.00	15606555
E. Coli (% Detection)	0.41	6.38	0.00	100.00	16674526
Ground Water	0.35	5.93	0.00	100.00	9199964
Surface Water	0.48	6.92	0.00	100.00	7084622
Very Large	0.20	4.50	0.00	100.00	1969285
Large	0.21	4.57	0.00	100.00	4507240
Medium	0.32	5.63	0.00	100.00	2216859
Small	0.50	7.03	0.00	100.00	2576083
Very Small	0.66	8.12	0.00	100.00	5015132
Haloacetic Acids ($\mu g/L$)	19.60	22.36	0.00	1000.00	2750020
Ground Water	8.50	18.07	0.00	1000.00	844737
Surface Water	24.63	22.23	0.00	961.90	1867963
Very Large	21.31	20.17	0.00	890.70	282852
Large	19.41	19.17	0.00	930.00	968198
Medium	22.40	21.43	0.00	759.00	408376
Small	20.23	23.92	0.00	992.60	630789
Very Small	15.27	27.46	0.00	1000.00	422474
Total Trihalomethanes ($\mu g/L$)	31.50	35.87	0.00	1000.00	3350492
Ground Water	16.44	31.22	0.00	1000.00	1206983
Surface Water	40.18	35.45	0.00	998.00	2098552
Very Large	28.83	34.98	0.00	997.27	401958
Large	31.55	31.52	0.00	957.90	1138270
Medium	36.69	32.71	0.00	950.00	460169
Small	35.99	39.21	0.00	998.00	717182
Very Small	23.75	40.48	0.00	1000.00	587948
Observations	82,761,508				

Notes: Table summarizes drinking water quality measures at the sample level by source of water and public water system size.

Table 3: Floods, Rainfall, and Total Coliform Detection

	Floods		Heavy Rains		Rainfall (cm)
	3-day	10-day	3-day	10-day	3-day
Precipitation Event	0.275***	0.231***	0.288***	0.189***	0.0657***
	(0.0411)	(0.0252)	(0.101)	(0.0434)	(0.00261)
Dep Var Mean	1.66	1.66	1.66	1.66	1.66
Pct. Change	16.51	13.88	17.31	11.34	3.95
Water System FEs	✓	✓	✓	✓	✓
Year and Month FEs	✓	✓	✓	✓	✓
Observations	57,187,558	57,187,558	57,187,558	57,187,558	57,187,558

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Notes: Standard errors clustered at the water system level in parentheses. Controls include daily temperature and two lags of daily temperature, water system fixed effects, year fixed effects, and month fixed effects. 3-day and 10-day precipitation events refer to the presence of precipitation or a severe weather event in the prior 3 or 10 day period.

Table 4: Floods, Rainfall, and E. coli Detection

	Floods		Heavy Rains		Rainfall (cm)
	3-day	10-day	3-day	10-day	3-day
Precipitation Event	0.189***	0.180***	0.0597	0.0727*	0.0363***
	(0.0398)	(0.0222)	(0.101)	(0.0408)	(0.00234)
Dep Var Mean	0.46	0.46	0.46	0.46	0.46
Pct. Change	41.07	39.13	12.95	15.76	7.88
Water System FEs	✓	✓	✓	✓	✓
Year and Month FEs	✓	✓	✓	✓	✓
Observations	12,714,203	12,714,203	12,714,203	12,714,203	12,714,203

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Notes: Standard errors clustered at the water system level in parentheses. Controls include daily temperature and two lags of daily temperature, water system fixed effects, year fixed effects, and month fixed effects. 3-day and 10-day precipitation events refer to the presence of precipitation or a severe weather event in the prior 3 or 10 day period.

Table 5: Floods, Rainfall, and Total Trihalomethanes ($\mu g/L$)

	Floods		Heavy Rains		Rainfall (cm)
	3-day	10-day	3-day	10-day	3-day
Precipitation Event	1.396***	1.620***	1.974***	1.343***	0.239***
	(0.366)	(0.199)	(0.544)	(0.263)	(0.0198)
Dep Var Mean	31.65	31.65	31.65	31.65	31.65
Pct. Change	4.41	5.12	6.24	4.24	0.76
Water System FEs	✓	✓	✓	✓	✓
Year and Month FEs	✓	✓	✓	✓	✓
Observations	3,204,609	3,204,609	3,204,609	3,204,609	3,204,609

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Notes: Standard errors clustered at the water system level in parentheses. Controls include daily temperature and two lags of daily temperature, water system fixed effects, year fixed effects, and month fixed effects. 3-day and 10-day precipitation events refer to the presence of precipitation or a severe weather event in the prior 3 or 10 day period.

Table 6: Floods, Rainfall, and Haloacetic Acids ($\mu g/L$)

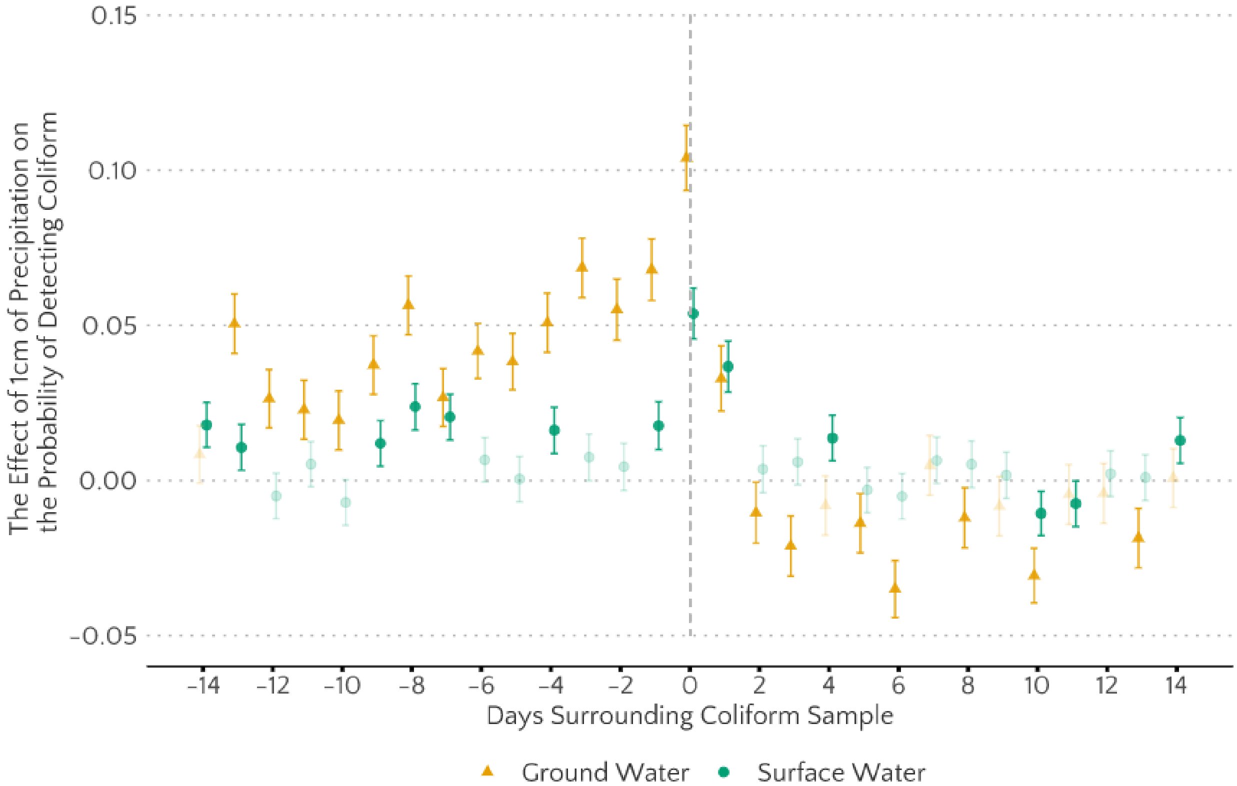
	Floods		Heavy Rains		Rainfall (cm)
	3-day	10-day	3-day	10-day	3-day
Precipitation Event	1.380***	1.217***	0.316	0.212	0.118***
	(0.296)	(0.135)	(0.423)	(0.164)	(0.0143)
Dep Var Mean	19.57	19.57	19.57	19.57	19.57
Pct. Change	7.05	6.22	1.61	1.08	0.60
Water System FEs	✓	✓	✓	✓	✓
Year and Month FEs	✓	✓	✓	✓	✓
Observations	2,663,215	2,663,215	2,663,215	2,663,215	2,663,215

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Notes: Standard errors clustered at the water system level in parentheses. Controls include daily temperature and two lags of daily temperature, water system fixed effects, year fixed effects, and month fixed effects. 3-day and 10-day precipitation events refer to the presence of precipitation or a severe weather event in the prior 3 or 10 day period.

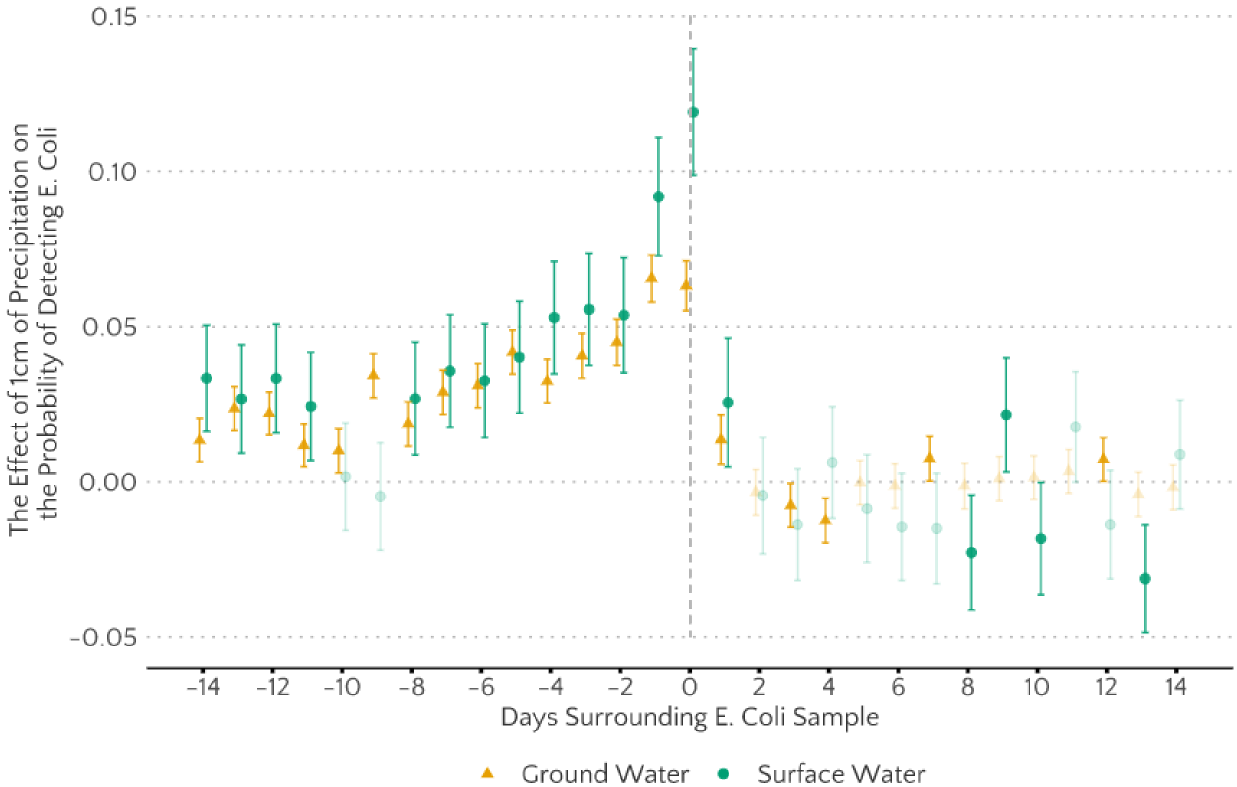
Figures

Figure 1: Centimeters of Rainfall and Total Coliform Detection Event Study



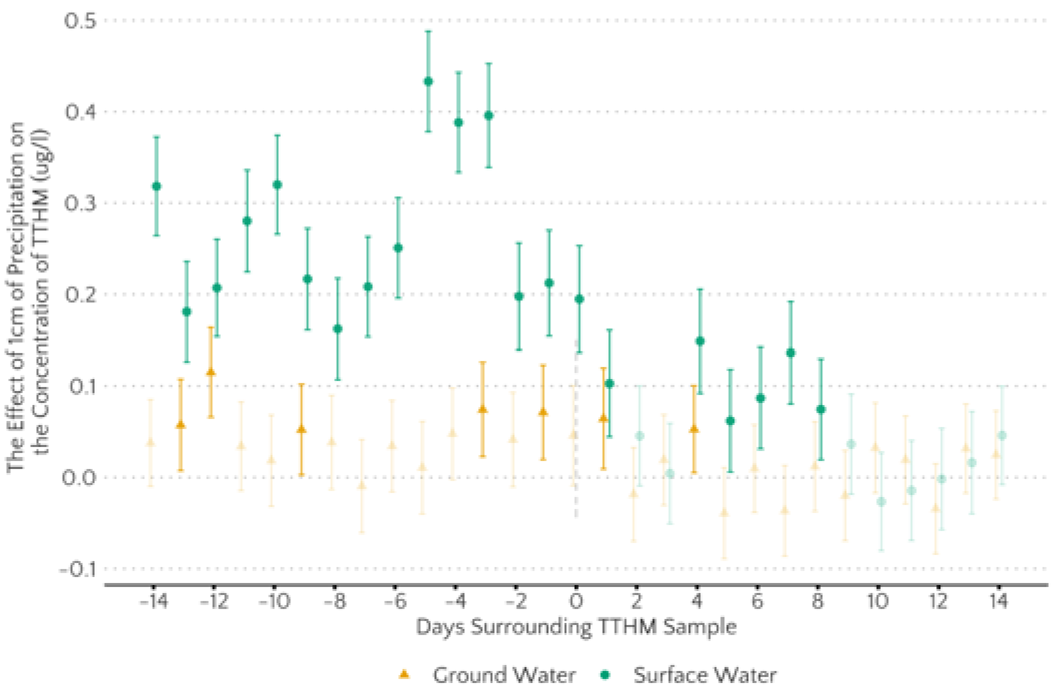
Notes: Effect sizes represent marginal percentage point changes in the likelihood of detection. Coefficients that are statistically significant at the 5% level of confidence shaded a darker color.

Figure 2: Centimeters of Rainfall and E. coli Detection Event Study



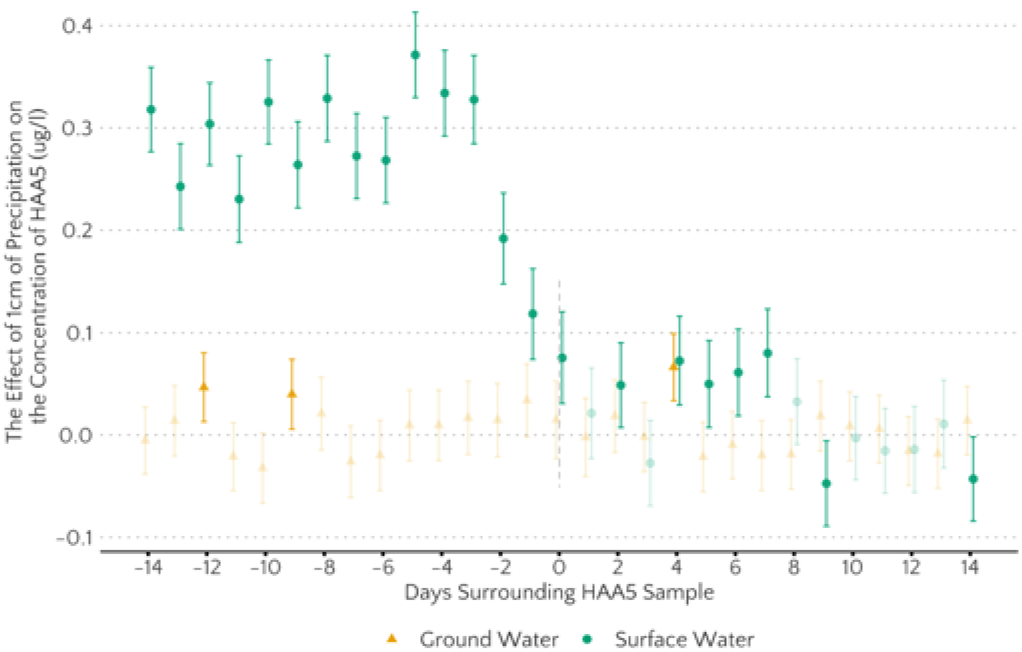
Notes: Effect sizes represent marginal percentage point changes in the likelihood of detection. Coefficients that are statistically significant at the 5% level of confidence shaded a darker color.

Figure 3: Centimeters of Rainfall and Total Trihalomethane (TTHM) Concentration (ug/l) Event Study



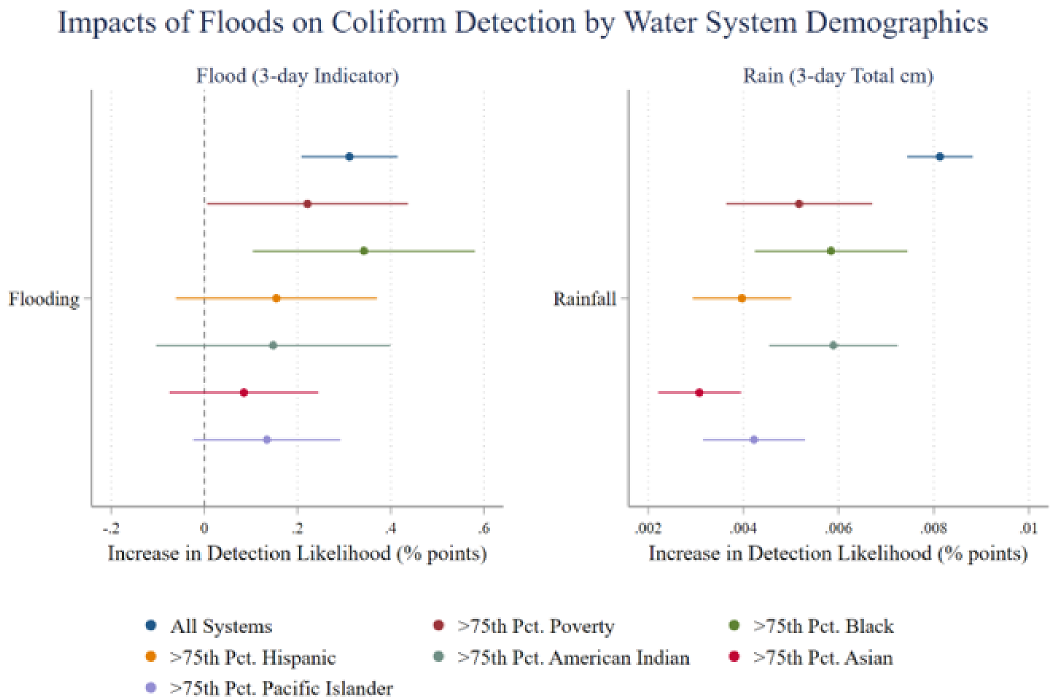
Notes: Effect sizes represent marginal changes in the concentration of total trihalomethanes. Coefficients that are statistically significant at the 5% level of confidence shaded a darker color.

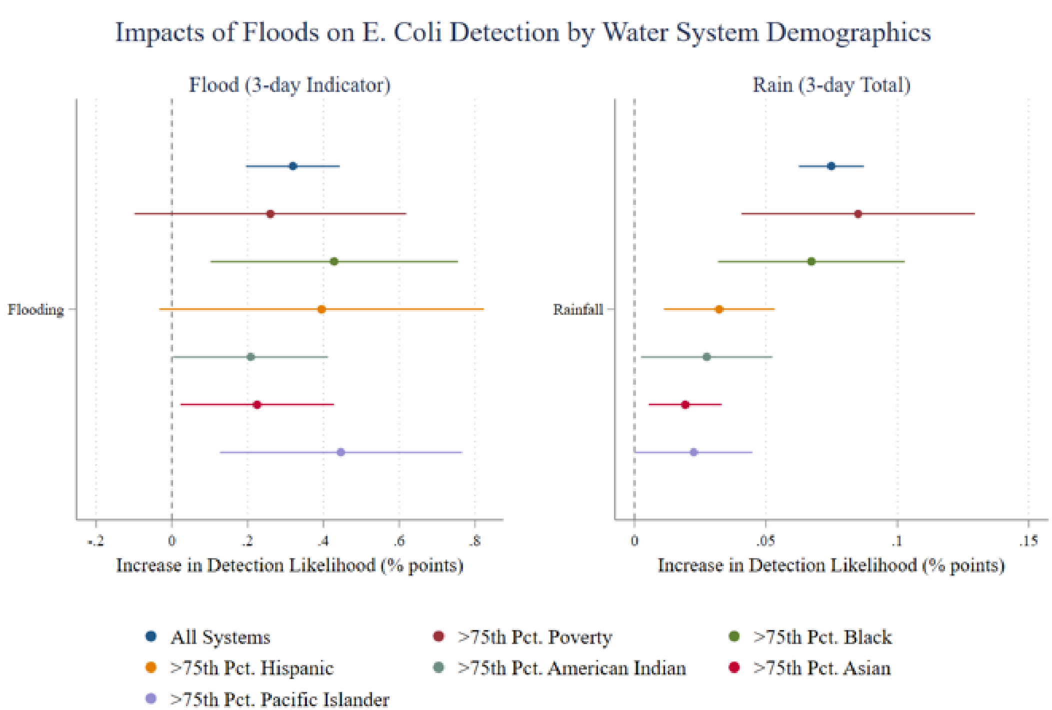
Figure 4: Centimeters of Rainfall and Haloacetic Acid (HAA5) Concentration (ug/l) Event Study



Notes: Effect sizes represent marginal changes in the concentration of the five major haloacetic acids. Coefficients that are statistically significant at the 5% level of confidence shaded a darker color.

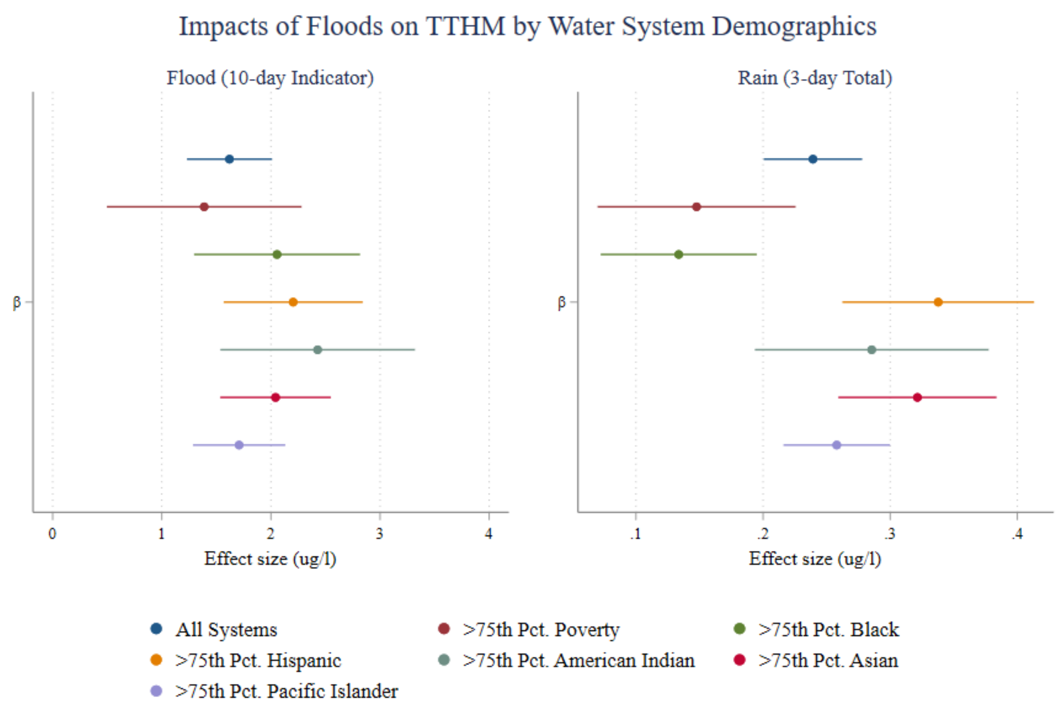
Figure 5: Effect of Weather on Bacteria Detection, by Water System Demographics

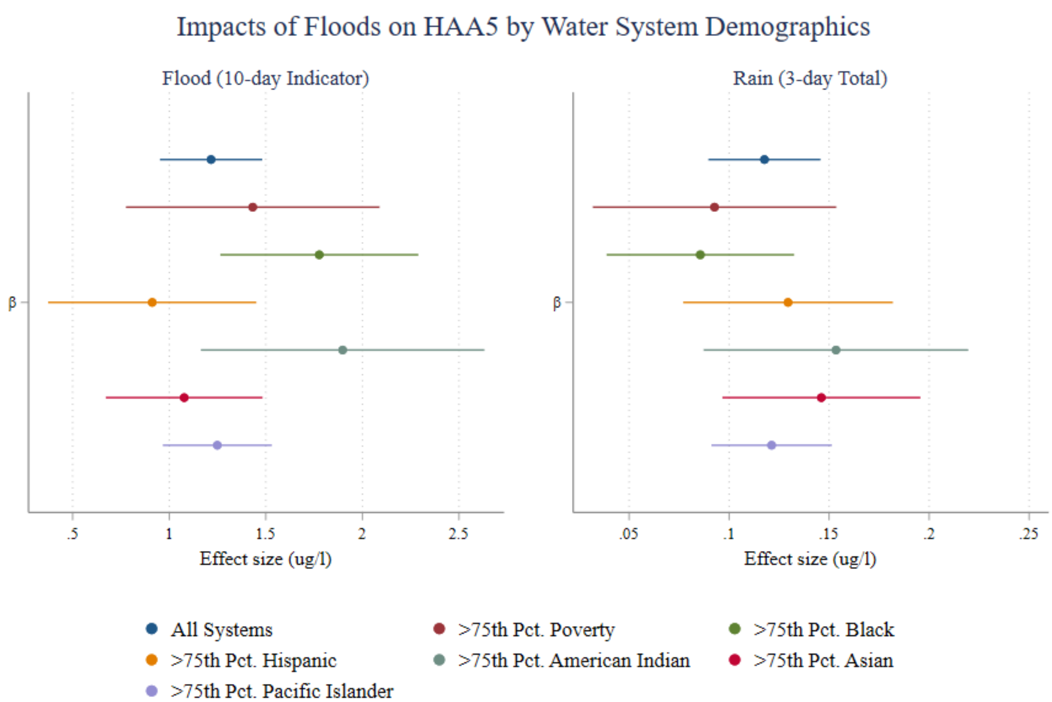




Notes: Each confidence interval represents the average effect of interest for sub-samples of water systems in at least the 75th percentile with respect to share of population of the listed demographic group.

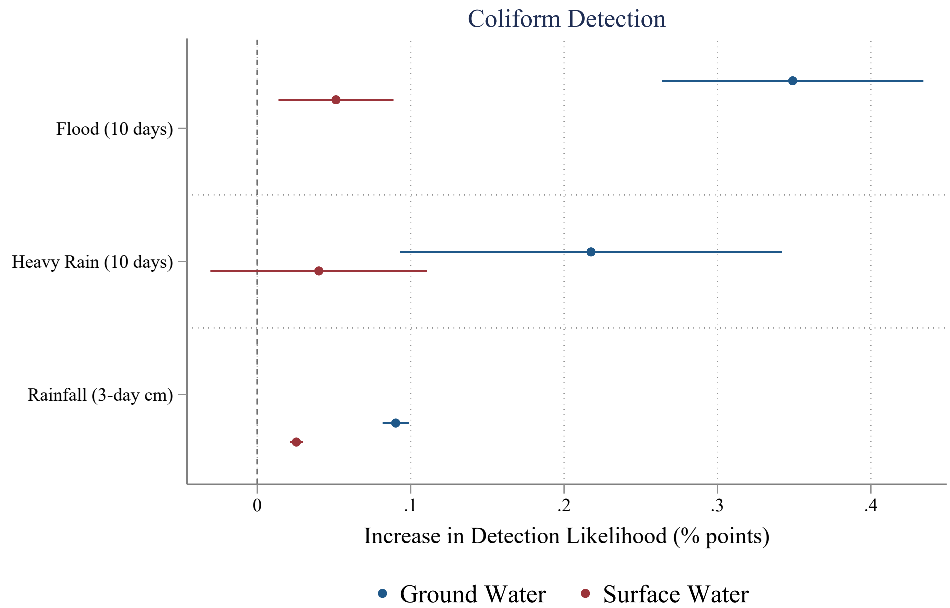
Figure 6: Effect of Weather on Disinfectant Byproduct Concentration, by Water System Demographics

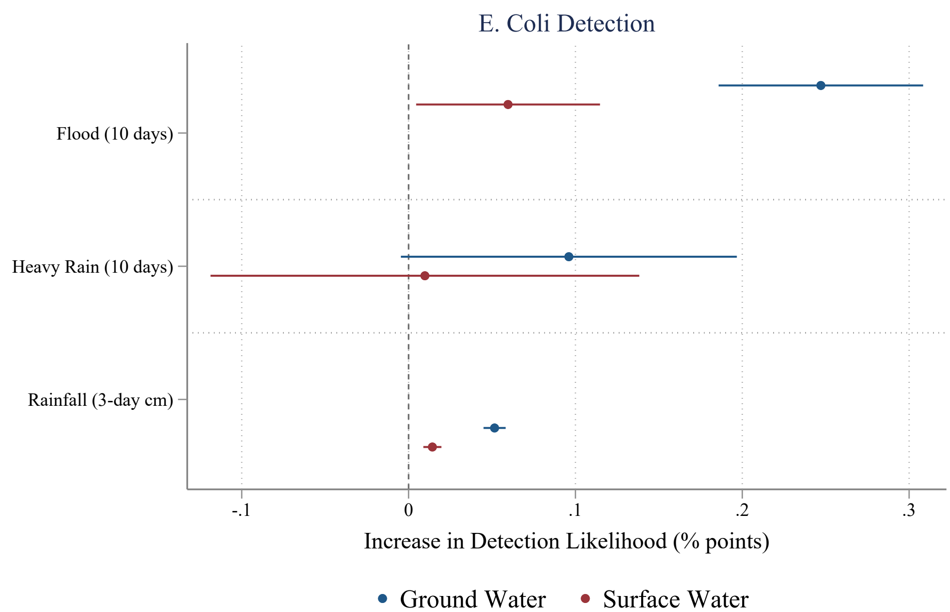




Notes: Each confidence interval represents the average effect of interest for sub-samples of water systems in at least the 75th percentile with respect to share of population of the listed demographic group.

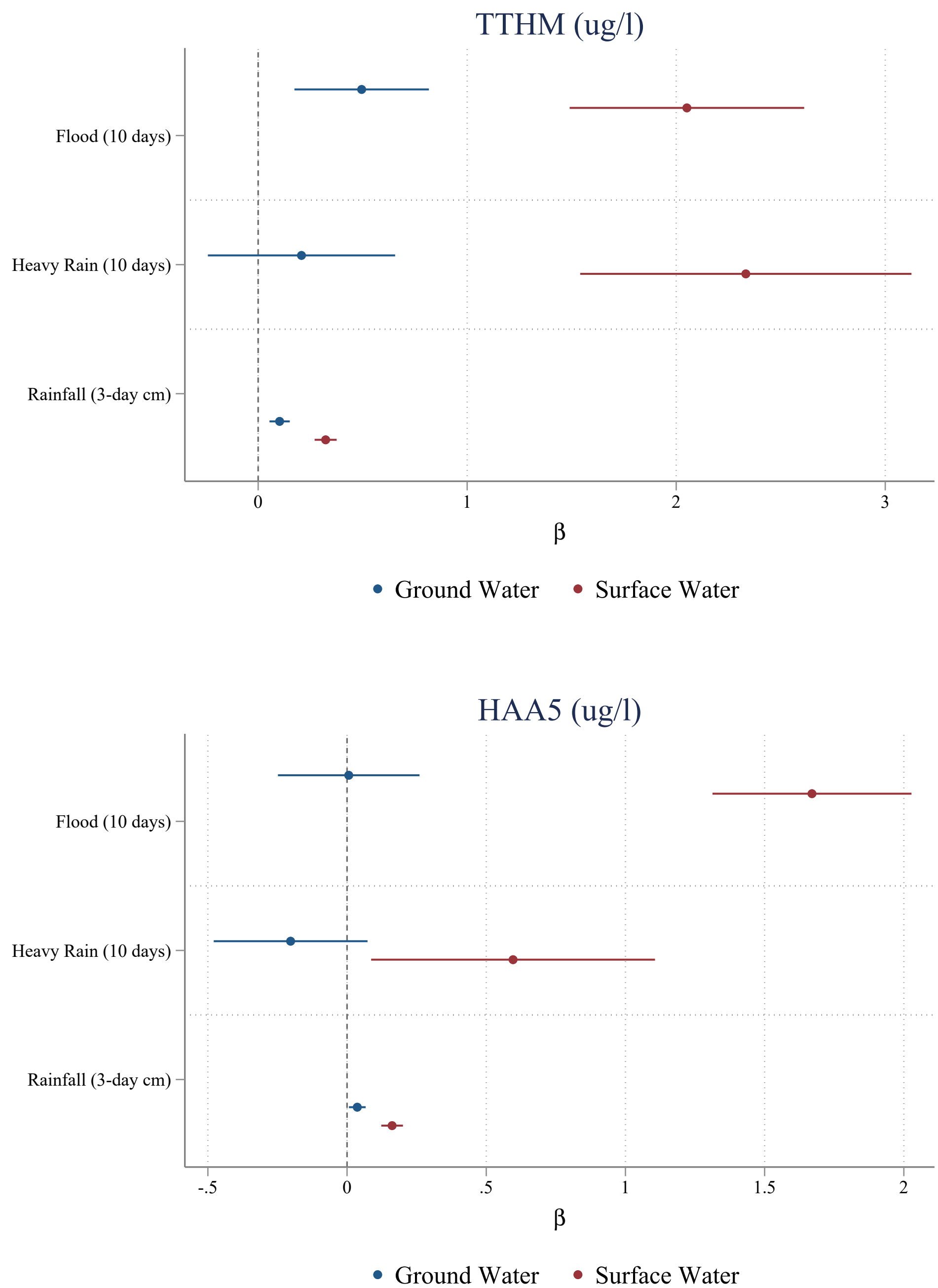
Figure 7: Effect of Weather on Bacteria Detection by Water System Source





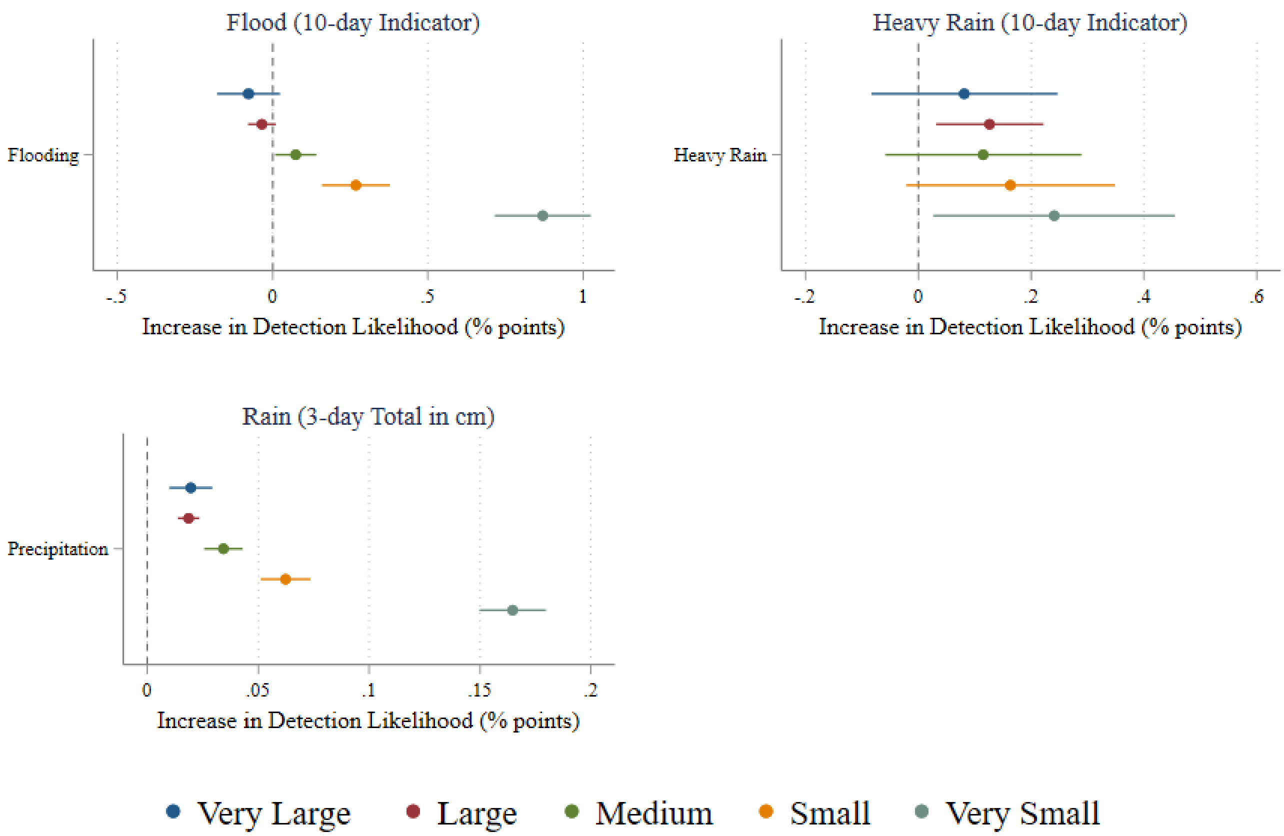
Notes: Figures display coefficient estimates for recent floods, heavy rains, and rainfall for systems that source drinking water from groundwater and surface water supplies. In some cases, we define systems that make use of a combination of groundwater and surface water as surface water systems.

Figure 8: Effect of Weather on DBP Concentrations by Water System Source



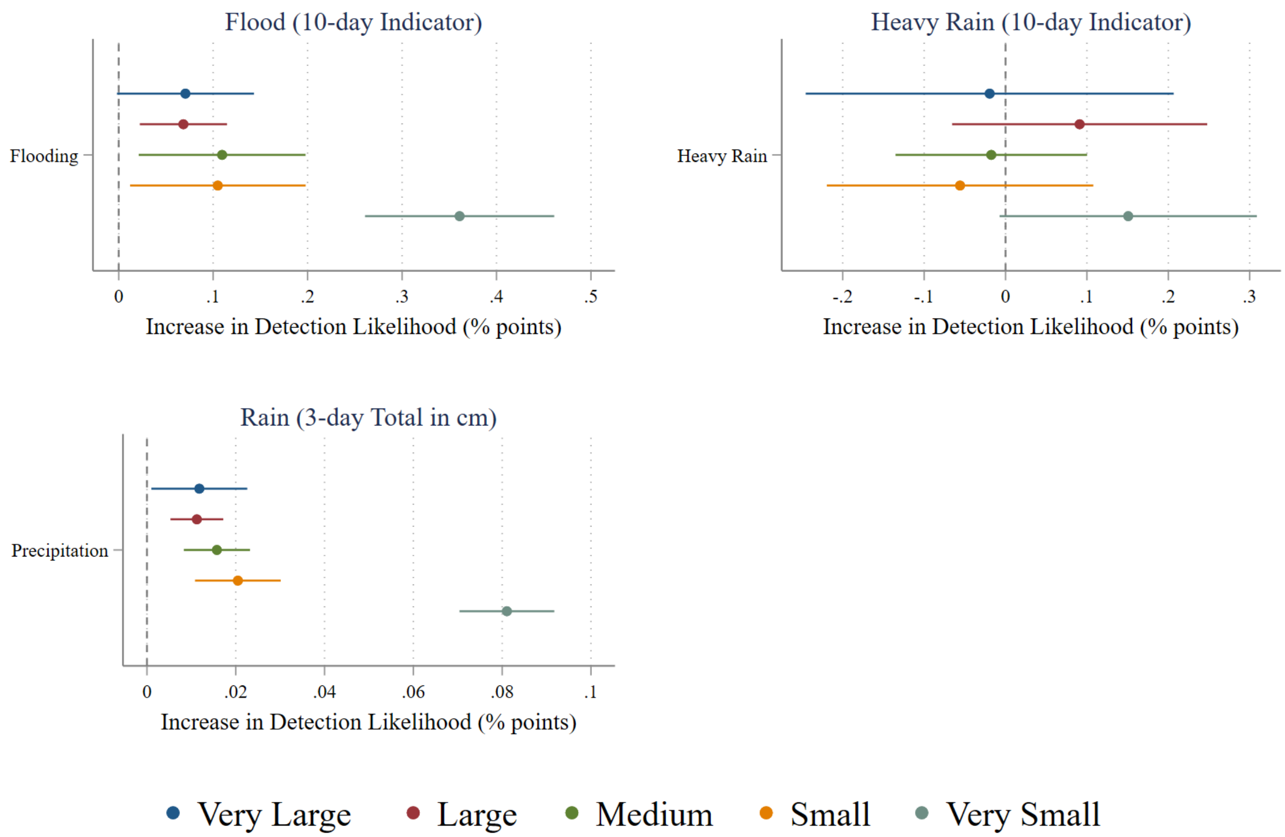
Notes: Figures display coefficient estimates for recent floods, heavy rains, and rainfall for systems that source drinking water from groundwater and surface water supplies. In some cases, we define systems that make use of a combination of groundwater and surface water as surface water systems.

Figure 9: Effect of Weather on Coliform Detections by Water System Size



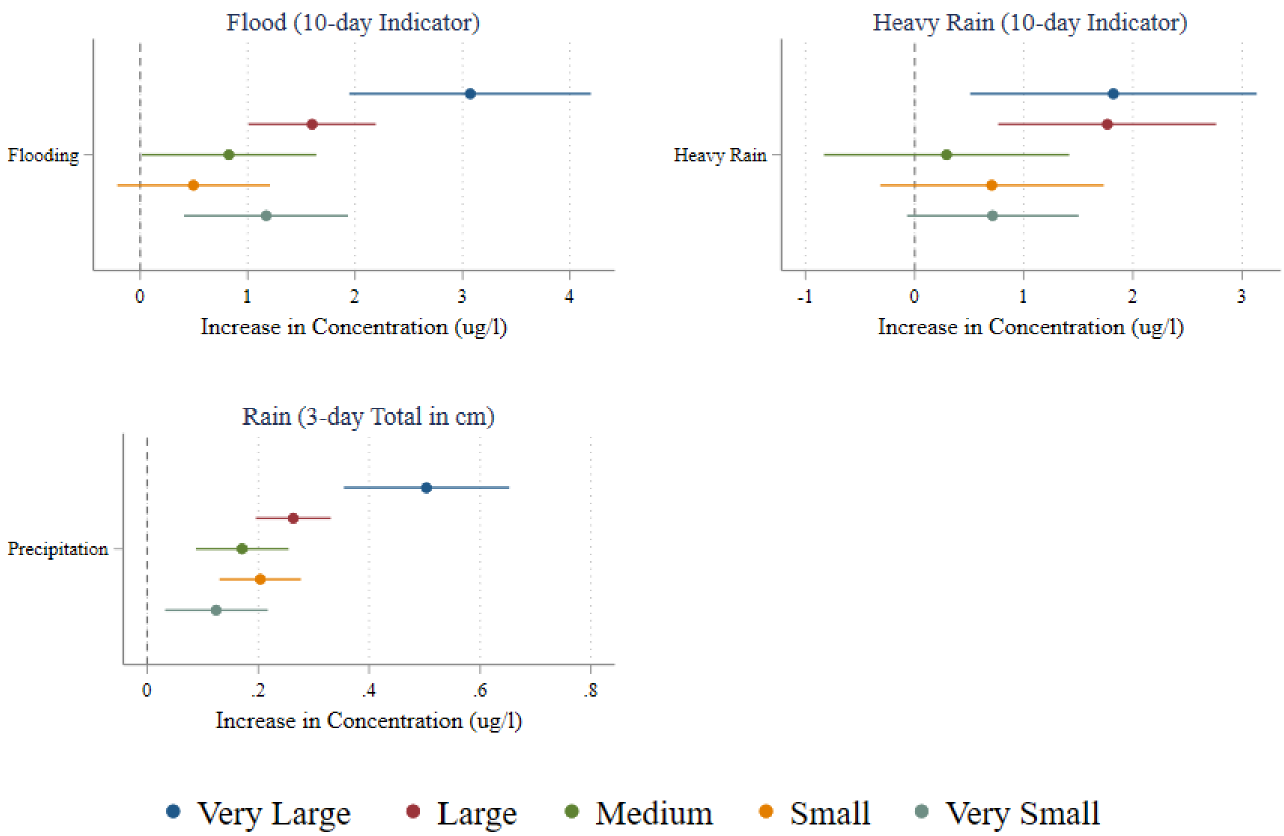
Notes: The size categories are service population categories where very small systems serve 500 individuals or less, small systems serve 501 to 3,300 individuals, medium systems serve 3,301 to 10,000 individuals, large systems serve 10,001 to 100,000 individuals, and very large systems serve over 100,000 people.

Figure 10: Effect of Weather on E. Coli Detections by Water System Size



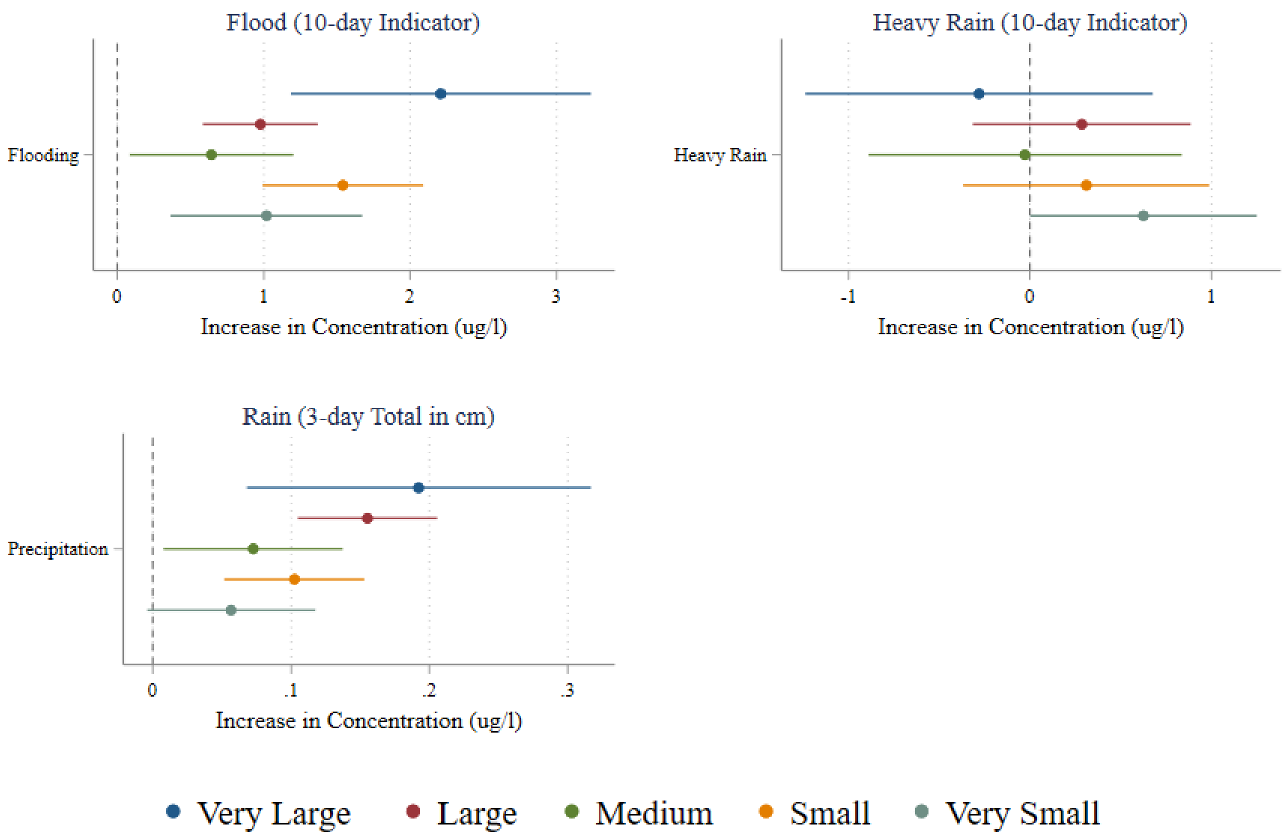
Notes: The size categories are service population categories where very small systems serve 500 individuals or less, small systems serve 501 to 3,300 individuals, medium systems serve 3,301 to 10,000 individuals, large systems serve 10,001 to 100,000 individuals, and very large systems serve over 100,000 people.

Figure 11: Effect of Weather on TTHM Concentrations by Water System Size



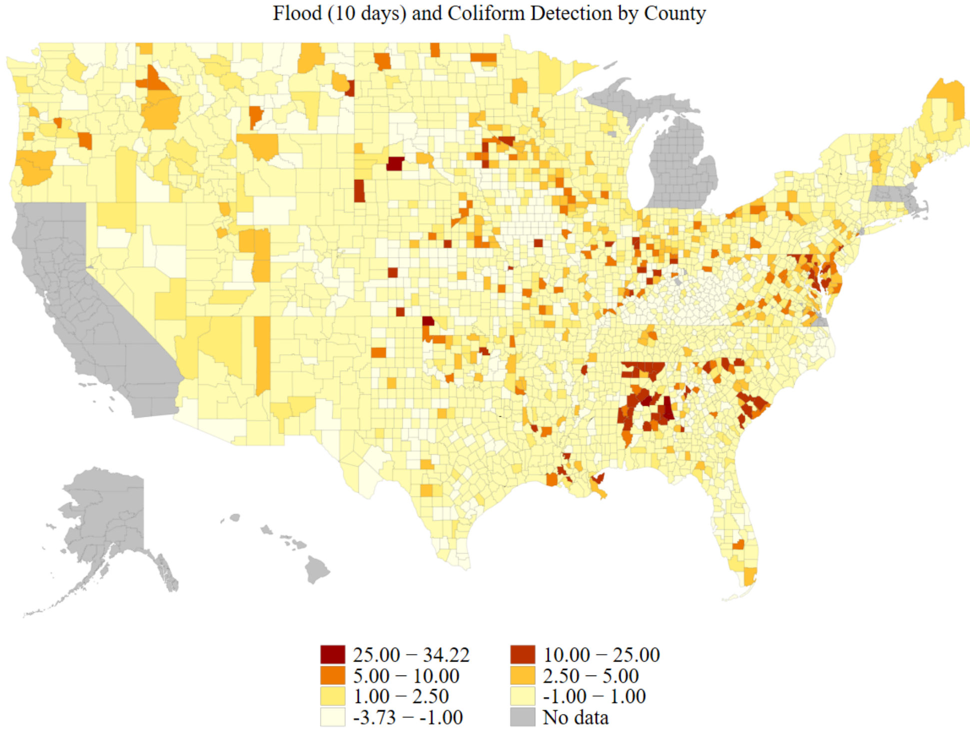
Notes: The size categories are service population categories where very small systems serve 500 individuals or less, small systems serve 501 to 3,300 individuals, medium systems serve 3,301 to 10,000 individuals, large systems serve 10,001 to 100,000 individuals, and very large systems serve over 100,000 people.

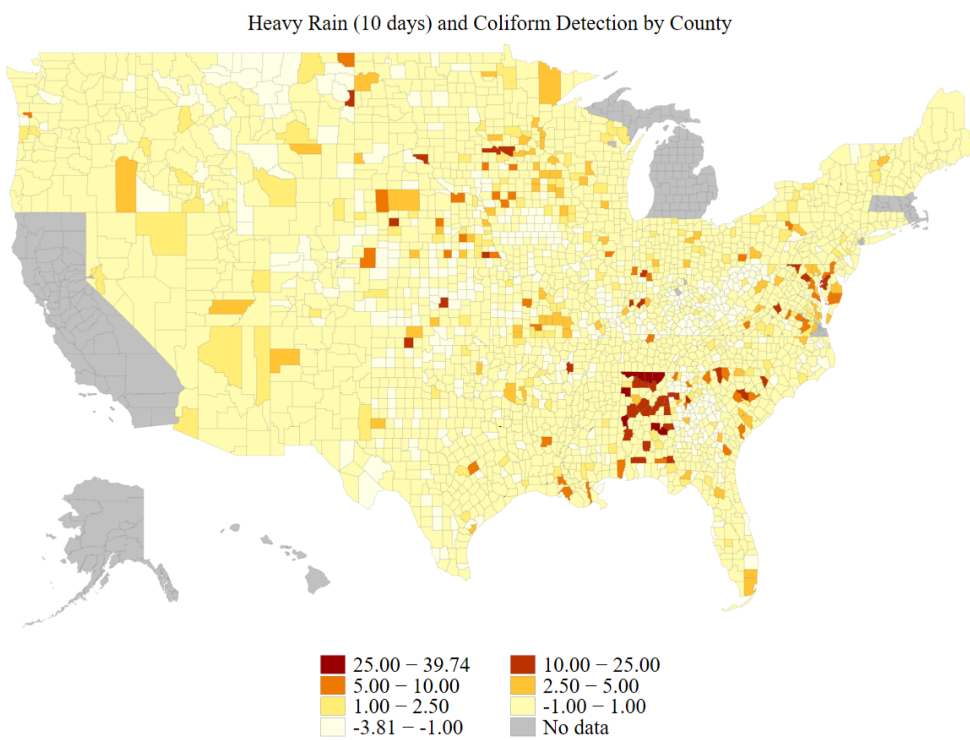
Figure 12: Effect of Weather on HAA5 Concentrations by Water System Size



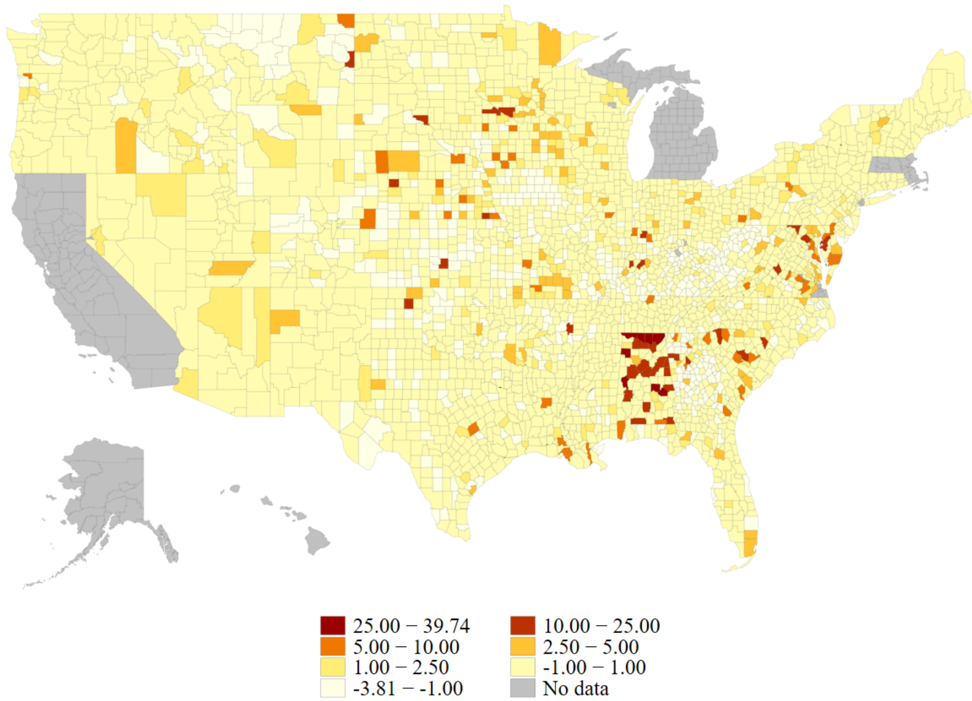
Notes: The size categories are service population levels where very small systems serve 500 individuals or less, small systems serve 501 to 3,300 individuals, medium systems serve 3,301 to 10,000 individuals, large systems serve 10,001 to 100,000 individuals, and very large systems serve over 100,000 people.

Figure 13: Impact of Weather on Coliform Detection Likelihood (% Point Change) by County



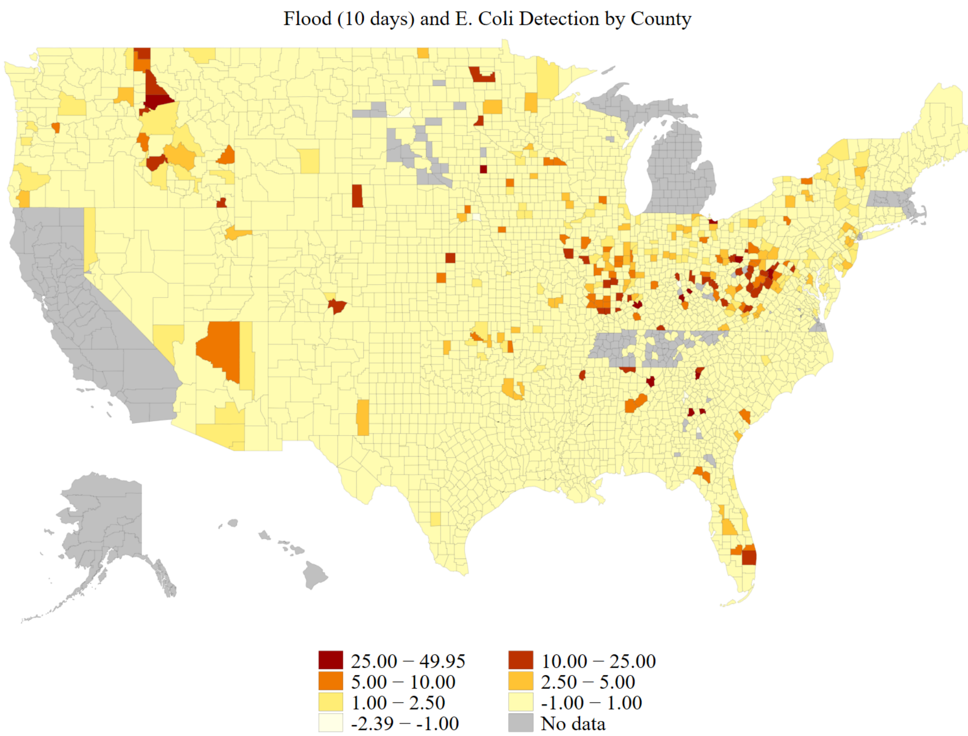


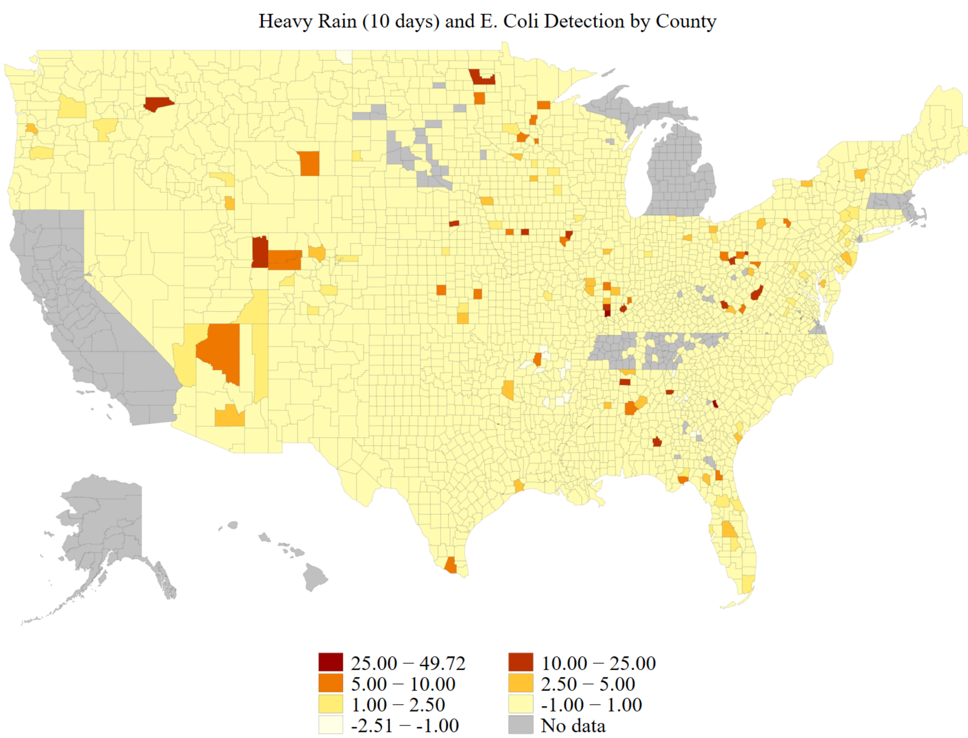
Rainfall (3 days) and Coliform Detection by County

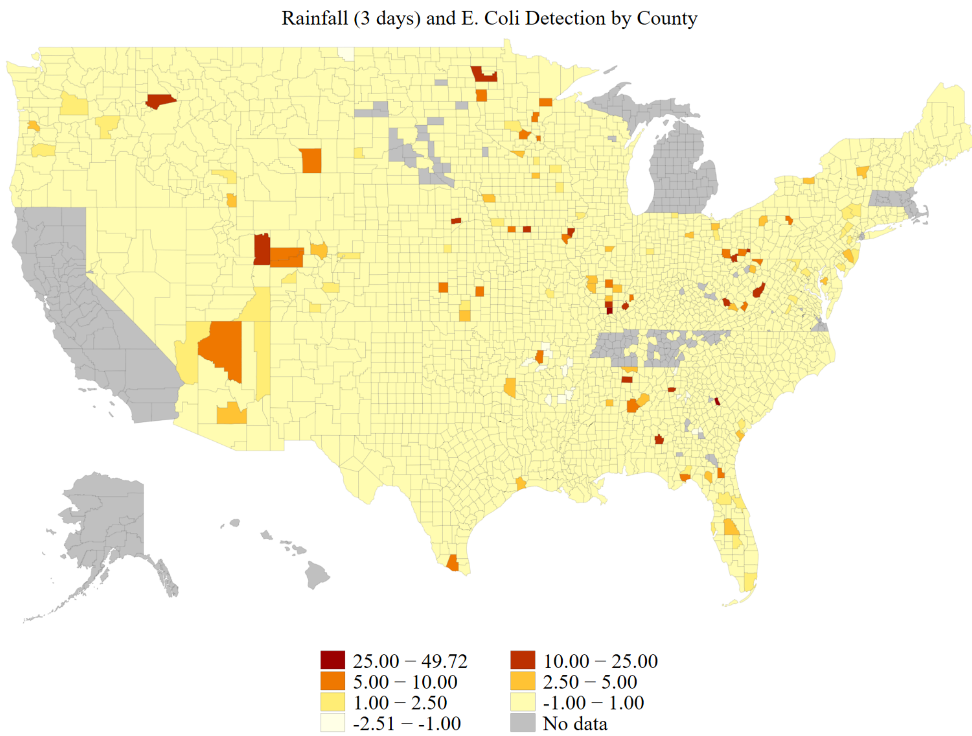


Notes: Maps display water-system level coefficients with respect to weather variables. These coefficients are averaged to the county level to facilitate visualization.

Figure 14: Impact of Weather on E. Coli Detection Likelihood (% Point Change) by County

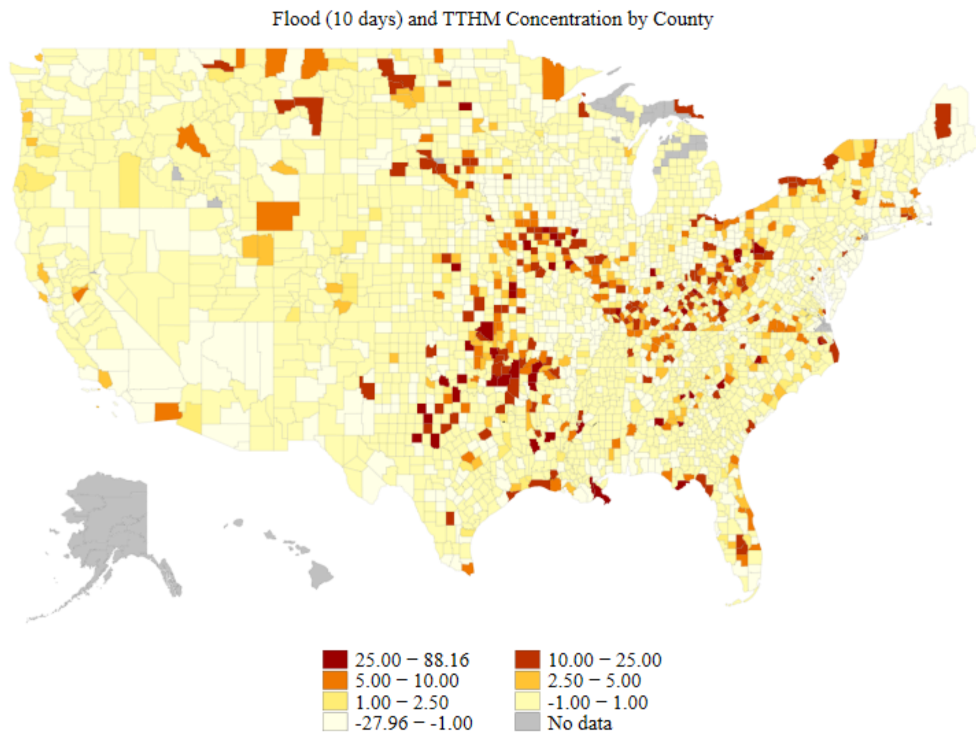


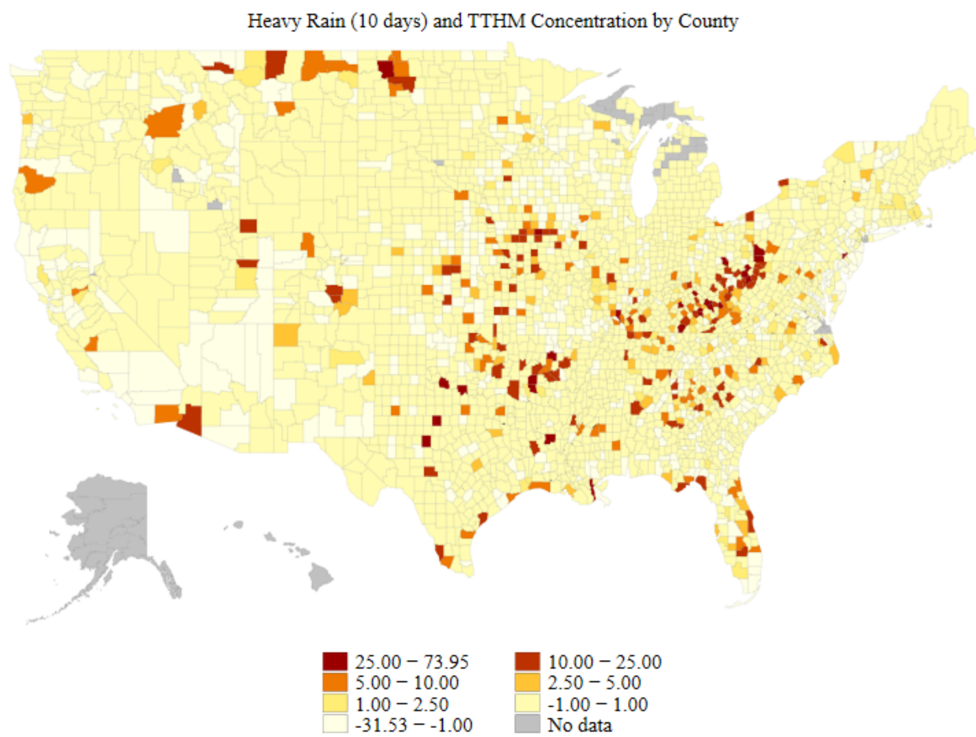




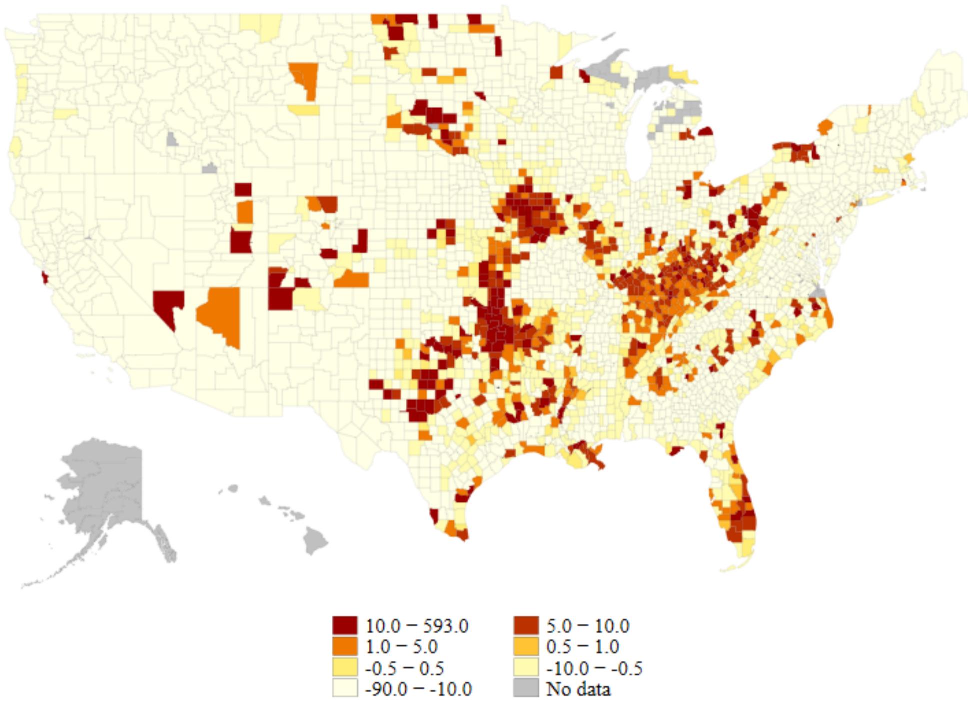
Notes: Maps display water-system level coefficients with respect to weather variables. These coefficients are averaged to the county level to facilitate visualization.

Figure 15: Impact of Weather on TTHM Concentration (ug/l) by County



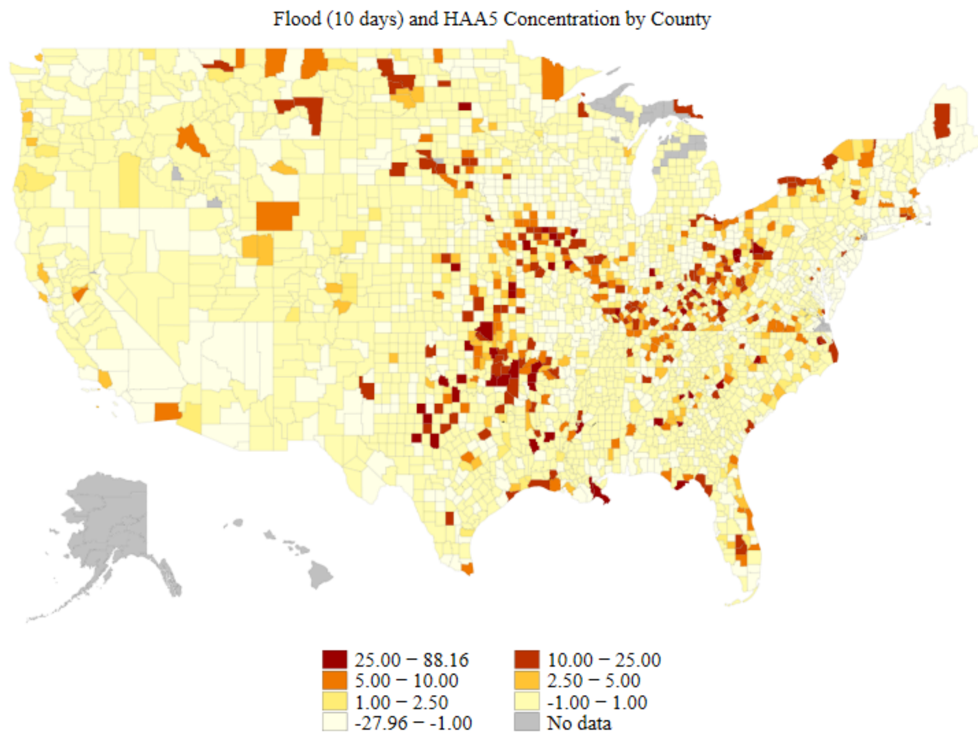


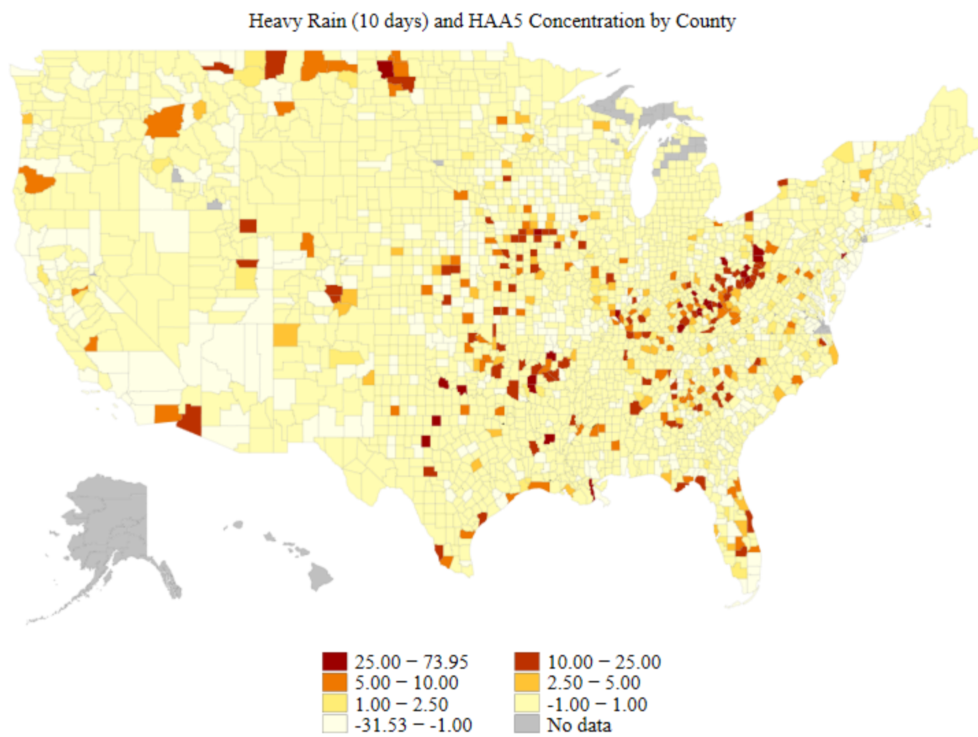
Rainfall (3 days) and TTHM Concentration by County

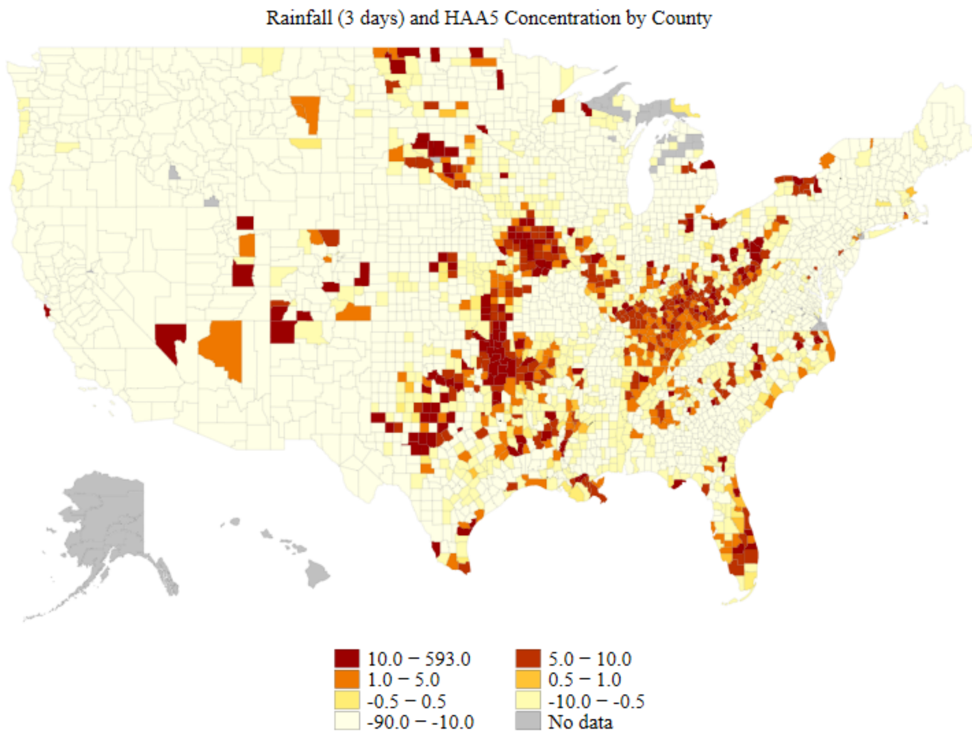


Notes: Maps display water-system level coefficients with respect to weather variables. These coefficients are averaged to the county level to facilitate visualization.

Figure 16: Impact of Weather on HAA5 Concentration (ug/l) by County

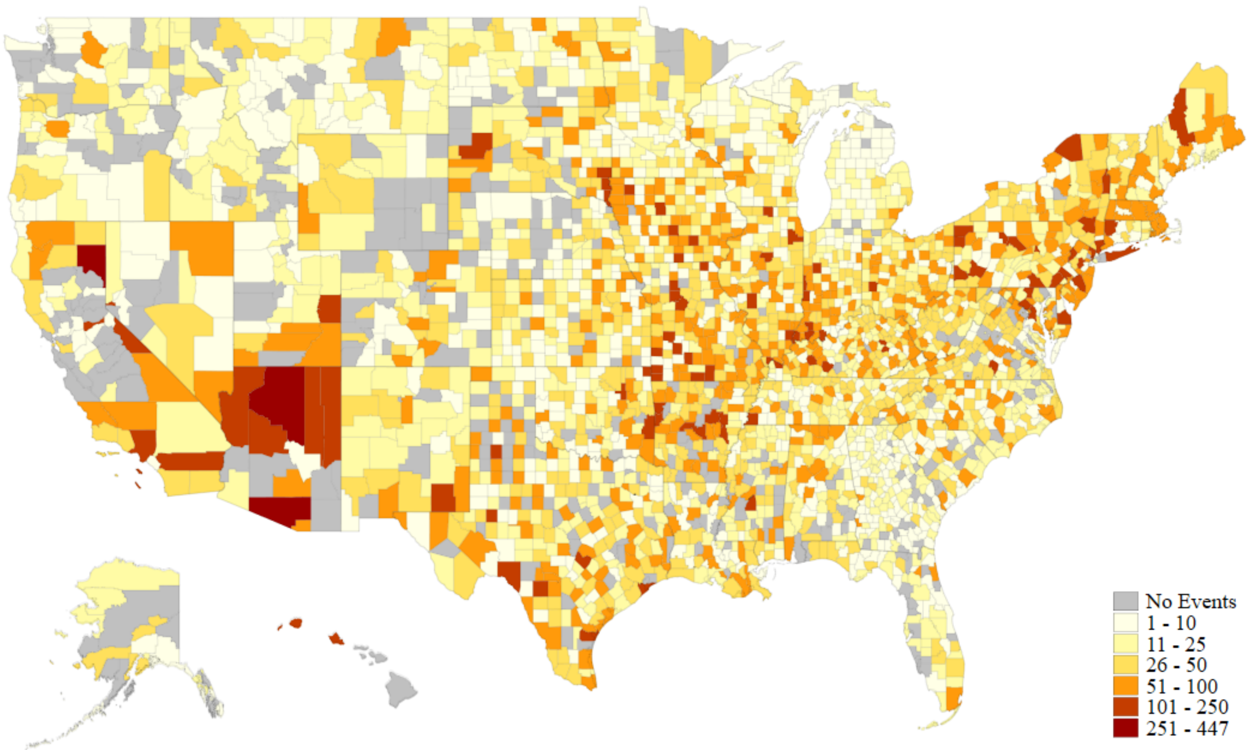






Notes: Maps display water-system level coefficients with respect to weather variables. These coefficients are averaged to the county level to facilitate visualization.

Figure 17: Number of NOAA Floods by County (2000 - 2019)



Notes: Includes all flood types.

Appendix

Table A1: Annual Sampling Frequency by Water System Size

	Mean	Std.Dev.	Min	Max	System Count
Total Coliform	29.24	144.6	1	13273.43	153,954
Very Large	1708.40	1720.93	1	13273.43	346
Large	416.15	419.82	1	3622	3,306
Medium	114.87	69.31	1	1125	5,076
Small	32.86	25.29	1	398.6	19,006
Very Small	10.52	15.36	1	2235	126,220
E. Coli	17.39	82.95	1	6014.67	111,323
Very Large	583.84	1021.25	1	6014.66	324
Large	152.45	265.43	1	3376.85	2,998
Medium	61.74	69.46	1	1125	4,374
Small	21.34	22.83	1	332.85	15,016
Very Small	7.90	12.40	1	2110.60	88,611
Haloacetic Acids	4.71	8.25	1	267.95	52,468
Very Large	47.49	35.76	1	267.95	437
Large	18.89	13.03	1	132.14	3,807
Medium	6.64	6.14	1	116	5,239
Small	3.95	3.78	1	82	14,802
Very Small	2.18	2.56	1	213.12	28,183
Total Trihalomethanes	4.40	10.57	1	1,226.38	64,721
Very Large	56.06	63.29	1	908.09	447
Large	19.95	24.68	1	1226.38	3,855
Medium	7.00	6.25	1	116	5,351
Small	4.04	3.76	1	84.5	15,951
Very Small	2.08	2.68	1	269.92	39,117

Notes: The size categories are service population categories where very small systems serve 500 individuals or less, small systems serve 501 to 3,300 individuals, medium systems serve 3,301 to 10,000 individuals, large systems serve 10,001 to 100,000 individuals, and very large systems serve over 100,000 people.

Table A2: Water Quality and Sample Count on Days with and Without Precipitation

	Recent Precipitation		No Recent Precipitation	
	Mean	Sample Count	Mean	Sample Count
Total Coliform	1.61	3062790	1.67	56923680
Ground Water	2.76	1183769	2.58	30842796
Surface Water	0.74	1299562	0.50	25683209
Very Large	0.46	445757	0.50	7516687
Large	0.55	787950	0.45	18485717
Medium	1.00	302245	0.71	7452553
Small	2.02	358790	1.46	8054443
Very Small	4.35	589923	4.22	15016632
E. Coli	0.33	1046018	0.41	15628508
Ground Water	0.22	369889	0.36	8830075
Surface Water	0.67	357978	0.47	6726644
Very Large	0.03	110237	0.21	1859048
Large	0.23	214535	0.21	4292705
Medium	0.30	105545	0.32	2111314
Small	0.80	104355	0.48	2471728
Very Small	0.80	193251	0.66	4821881
Haloacetic Acids ($\mu g/L$)	19.40	95119	19.61	2654901
Ground Water	7.27	21041	8.54	823696
Surface Water	24.43	54592	24.63	1813371
Very Large	21.58	10341	21.30	272511
Large	19.12	28989	19.42	939209
Medium	20.31	9470	22.45	398906
Small	18.79	14988	20.27	615801
Very Small	19.85	11866	15.14	410608
Total Trihalomethanes ($\mu g/L$)	25.78	155384	31.78	3195108
Ground Water	12.40	41860	16.58	1165123
Surface Water	30.86	91090	40.60	2007462
Very Large	16.86	29863	29.79	372095
Large	26.46	51728	31.79	1086542
Medium	29.50	13423	36.90	446746
Small	31.15	19088	36.12	698094
Very Small	24.76	18872	23.71	569076
Observations	4,359,311		78,402,197	

Notes: The size categories are service population categories where very small systems serve 500 individuals or less, small systems serve 501 to 3,300 individuals, medium systems serve 3,301 to 10,000 individuals, large systems serve 10,001 to 100,000 individuals, and very large systems serve over 100,000 people.

Table A3: Water Quality and Sample Count on Days with and Without Floods or Extreme Precipitation Events

	Recent Disaster		No Recent Disaster	
	Mean	Sample Count	Mean	Sample Count
Total Coliform	1.61	3062790	1.67	56923680
Ground Water	2.76	1183769	2.58	30842796
Surface Water	0.74	1299562	0.50	25683209
Very Large	0.46	445757	0.50	7516687
Large	0.55	787950	0.45	18485717
Medium	1.00	302245	0.71	7452553
Small	2.02	358790	1.46	8054443
Very Small	4.35	589923	4.22	15016632
E. Coli	0.33	1046018	0.41	15628508
Ground Water	0.22	369889	0.36	8830075
Surface Water	0.67	357978	0.47	6726644
Very Large	0.03	110237	0.21	1859048
Large	0.23	214535	0.21	4292705
Medium	0.30	105545	0.32	2111314
Small	0.80	104355	0.48	2471728
Very Small	0.80	193251	0.66	4821881
Haloacetic Acids ($\mu g/L$)	19.40	95119	19.61	2654901
Ground Water	7.27	21041	8.54	823696
Surface Water	24.43	54592	24.63	1813371
Very Large	21.58	10341	21.30	272511
Large	19.12	28989	19.42	939209
Medium	20.31	9470	22.45	398906
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Total Trihalomethanes ($\mu g/L$)	25.78	155384	31.78	3195108
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Very Large	16.86	29863	29.79	372095
Large	26.46	51728	31.79	1086542
Medium	29.50	13423	36.90	446746
Small	31.15	19088	36.12	698094
Very Small	24.76	18872	23.71	569076
Observations	4359311		78402197	

Notes: The size categories are service population categories where very small systems serve 500 individuals or less, small systems serve 501 to 3,300 individuals, medium systems serve 3,301 to 10,000 individuals, large systems serve 10,001 to 100,000 individuals, and very large systems serve over 100,000 people.

Table A4: Sensitivity Tests to Alternative Fixed Effects and Clustering - TTHM

	(1)	(2)	(3)	(4)
Precipitation (3-day)	0.239***	0.152***	0.171***	0.227***
	(0.0198)	(0.0294)	(0.0334)	(0.0242)
Dep Var Mean	31.65	31.62	28.05	28.05
Pct. Change	0.76	0.48	0.61	0.81
Flood (10 days)	1.620***	1.368**	1.500***	1.967***
	(0.199)	(0.534)	(0.379)	(0.247)
Dep Var Mean	31.65	31.62	28.05	28.05
Pct. Change	5.12	4.33	5.35	7.01
Heavy Rain (10 days)	1.343***	0.842**	0.182	1.310***
	(0.263)	(0.411)	(0.486)	(0.313)
Dep Var Mean	31.65	31.62	28.05	28.05
Pct. Change	4.24	2.66	0.65	4.67
Water System FEs	✓			
County FEs		✓		
HUC8 FEs			✓	
HUC12 FEs				✓
Year and Month FEs	✓	✓	✓	✓
Observations	3,204,609	3,208,313	2,440,579	2,440,220

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered at the water system, county, HUC8, or HUC12 level depending on the level of the fixed effects are displayed in parentheses. Controls include daily temperature and two lags of daily temperature.

Table A5: Sensitivity Tests to Alternative Fixed Effects and Clustering - HAA5

	(1)	(2)	(3)	(4)
Precipitation (3-day)	0.118***	0.0885***	0.0997***	0.117***
	(0.0143)	(0.0191)	(0.0237)	(0.0181)
Dep Var Mean	19.57	19.57	17.91	17.92
Pct. Change	0.60	0.45	0.56	0.65
Flood (10 days)	1.217***	1.198***	1.137***	1.397***
	(0.135)	(0.207)	(0.244)	(0.188)
Dep Var Mean	19.57	19.57	17.91	17.92
Pct. Change	6.22	6.13	6.35	7.80
Heavy Rain (10 days)	0.212	0.351	-0.204	0.300
	(0.164)	(0.278)	(0.338)	(0.214)
Dep Var Mean	19.57	19.57	17.91	17.92
Pct. Change	1.08	1.79	-1.14	1.67
Water System FEs	✓			
County FEs		✓		
HUC8 FEs			✓	
HUC12 FEs				✓
Year and Month FEs	✓	✓	✓	✓
Observations	2,663,215	2,664,590	1,935,468	1,935,334

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered at the water system, county, HUC8, or HUC12 level depending on the level of the fixed effects are displayed in parentheses. Controls include daily temperature and two lags of daily temperature.

Table A6: Sensitivity Tests to Alternative Fixed Effects and Clustering - Total Coliform

	(1)	(2)	(3)	(4)
Precipitation (3-day)	0.0657***	0.0687***	0.0631***	0.0672***
	(0.00261)	(0.00543)	(0.00603)	(0.00347)
Dep Var Mean	1.67	1.67	1.66	1.66
Pct. Change	3.95	4.12	3.80	4.05
Flood (10 days)	0.231***	0.267***	0.253***	0.241***
	(0.0252)	(0.0547)	(0.0797)	(0.0361)
Dep Var Mean	1.67	1.67	1.66	1.66
Pct. Change	13.88	16.04	15.27	14.53
Heavy Rain (10 days)	0.189***	0.196***	0.258***	0.217***
	(0.0434)	(0.0745)	(0.0713)	(0.0555)
Dep Var Mean	1.67	1.67	1.66	1.66
Pct. Change	11.34	11.77	15.57	13.09
Water System FEs	✓			
County FEs		✓		
HUC8 FEs			✓	
HUC12 FEs				✓
Year and Month FEs	✓	✓	✓	✓
Observations	2,663,215	2,664,590	1,935,468	1,935,334

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered at the water system, county, HUC8, or HUC12 level depending on the level of the fixed effects are displayed in parentheses. Controls include daily temperature and two lags of daily temperature.

Table A7: Sensitivity Tests to Alternative Fixed Effects and Clustering - E. Coli

	(1)	(2)	(3)	(4)
Precipitation (3-day)	0.0326***	0.0369***	0.0333***	0.0332***
	(0.00215)	(0.00391)	(0.00371)	(0.00273)
Dep Var Mean	0.41	0.41	0.42	0.42
Pct. Change	7.99	8.99	7.96	7.93
Flood (10 days)	0.166***	0.221***	0.208***	0.181***
	(0.0217)	(0.0345)	(0.0369)	(0.0287)
Dep Var Mean	0.41	0.41	0.42	0.42
Pct. Change	40.77	53.87	49.59	43.29
Heavy Rain (10 days)	0.0618	0.0757	0.0788	0.0351
	(0.0455)	(0.0556)	(0.0688)	(0.0503)
Dep Var Mean	0.41	0.41	0.42	0.42
Pct. Change	15.14	18.44	18.83	8.38
Water System FEs	✓			
County FEs		✓		
HUC8 FEs			✓	
HUC12 FEs				✓
Year and Month FEs	✓	✓	✓	✓
Observations	2,663,215	2,664,590	1,935,468	1,935,334

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered at the water system, county, HUC8, or HUC12 level depending on the level of the fixed effects are displayed in parentheses. Controls include daily temperature and two lags of daily temperature.

Table A8: Sources of Drinking Water Quality Information

State	Years	Source
Alabama	1988-2018	Request from the Alabama Department of Environmental Management.
Alaska	1980-2021	Webscrape. https://dec.alaska.gov/dww/
Arizona	1980-2021	Webscrape. https://azsdwis.azdeq.gov/DWW$_{E}XT$/
Arkansas	2006-2019	Six Year Review 3 & Six Year Review 4
California	1974-2020	Direct download. https://www.waterboards.ca.gov/drinking_water/certlic/ drinkingwater/EDTlibrary.htmldatabase
Colorado	2000-2020	Direct download. https://cdphe.colorado.gov/dwinfo
Connecticut	2006-2019	Six Year Review 3 & Six Year Review 4
Delaware	1999-2020	Webscrape. https://drinkingwater.dhss.delaware.gov/
Florida	2003-2019	Direct download. https://floridadep.gov/Water/Source-Drinking-Water
Georgia	2000-2018	Request from the Georgia Environmental Protection Division.
Hawaii	NA	NA
Idaho	1980-2022	Webscrape. http://dww.deq.idaho.gov/IDPDWW/
Illinois	1980-2020	Webscrape. https://www2.illinois.gov/services/IEPA/drinking-water-watch
Indiana	1997-2022	Webscrape. https://myweb.in.gov/IDEM/DWW/
Iowa	1990-2022	Webscrape. https://www.iowadnr.gov/Environmental-Protection/Water-Quality/Drinking-Water-Compliance
Kansas	2006-2019	Six Year Review 3 & Six Year Review 4
Kentucky	1992-2022	Webscrape. https://dep.gateway.ky.gov/DWW/
Louisiana	1991-2022	Webscrape. https://sdw.ldh.la.gov/DWW/
Maine	2006-2019	Six Year Review 3 & Six Year Review 4
Maryland	1985-2022	Webscrape. https://mde.maryland.gov/programs/Water/water_supply Pages/index.aspx
Massachusetts	1984-2023	Webscrape. https://eeaonline.eea.state.ma.us/Portal/!/search/drinking-water
Michigan	2006-2019	Six Year Review 3 & Six Year Review 4
Minnesota	2006-2019	Six Year Review 3 & Six Year Review 4
Mississippi	1990-2020	Webscrape. https://msdh.ms.gov/msdhsite/_static/30,0,76,793.html
Missouri	2005-2023	Webscrape. https://dnr.mo.gov/DWW/indexSearchDNR.jsp
Montana	1980-2021	Webscrape. http://sdwisdww.mt.gov:8080/DWW/
Nebraska	1980-2020	Webscrape. https://sdwis-dhhs.ne.gov
Nevada	1982-2022	Webscrape. https://ndwis.ndep.nv.gov/DWW/
New Hampshire	2006-2019	Six Year Review 3 & Six Year Review 4
New Jersey	1981-2022	Webscrape. https://www9.state.nj.us/DEP_WaterWatch_public/
New Mexico	1989-2021	Webscrape. https://dww.water.net.env.nm.gov/DWW/
New York	2006-2019	Six Year Review 3 & Six Year Review 4
North Carolina	2003-2018	Request from the North Carolina Department of Environmental Quality.
North Dakota	2006-2019	Six Year Review 3 & Six Year Review 4
Ohio	1980-2021	Webscrape. http://dww.epa.ohio.gov
Oklahoma	1981-2022	Webscrape. http://sdwis.deq.state.ok.us/DWW/
Oregon	1990-2022	Webscrape. https://yourwater.oregon.gov
Pennsylvania	2003-2021	Webscrape. http://www.drinkingwater.state.pa.us/dwrs/HTM/ Selection-Criteria.html
Rhode Island		Webscrape. https://dwq.health.ri.gov
South Carolina	2003-2018	S.C. Department of Health and Environmental Control (DHEC).
South Dakota	2006-2019	Six Year Review 3 & Six Year Review 4
Tennessee*	2006-2019	Six Year Review 3 & Six Year Review 4
Texas	1992-2021	Webscrape. https://dww2.tceq.texas.gov/DWW/
Utah	2006-2019	Six Year Review 3 & Six Year Review 4
Vermont	1999-2020	Webscrape. https://anrnode.anr.state.vt.us/DWW/
Virginia	2000-2019	Request from the Virginia Department of Environmental Quality.
Washington	1975-2021	Webscrape. https://fortress.wa.gov/doh/eh/portal/odw/si/downloadsreports.aspx
West Virginia	1993-2020	Webscrape. https://dww.wvdhhr.org/DWWpublic/
Wisconsin	1990-2021	webscrape. https://dnr.wi.gov/dwsviewer/DS/Search
Wyoming	1979-2021	Webscrape. https://sdwisr8.epa.gov/Region8DWWPUB/

We note that Tennessee has a Drinking Water Watch Website that was webscraped for this project, but the website contains very few samples. The Six Year Review dataset was used for this state instead.