

Risk-based public health impact assessment for drinking water contamination emergencies

Taler S. Bixler, M. Robin Collins, Weiwei Mo*

Department of Civil and Environmental Engineering, University of New Hampshire, Durham,
New Hampshire 03824, United States

*Corresponding Author: 35 Colovos Road, 334 Gregg Hall, Durham, New Hampshire 03824,
Ph: +1-603-862-2808, Email: weiwei.mo@unh.edu

Abstract:

Chemical spills in surface waters pose a significant threat to public health and the environment. This study investigates the public health impacts associated with organic chemical spill emergencies and explores timely countermeasures deployable by drinking water facilities. Using a dynamic model of a typical multi-sourced New England drinking water treatment facility and its distribution network, this study assesses the impacts of various countermeasure deployment scenarios, including source switching, enhanced coagulation via poly-aluminum chloride (PACl), addition of powdered activated carbon (PAC), and temporary system shutdown. This study reveals that the deployment of multiple countermeasures yields the most significant reduction in total public health impacts, regardless of the demand and supply availability. With the combination PAC deployed first with other countermeasures proving to be the most effective strategies, followed by the combination of facility shutdowns. By understanding the potential public health impacts and evaluating the effectiveness of countermeasures, authorities can develop proactive plans, secure additional funding, and enhance their capacity to mitigate the consequences of such events. These insights contribute to safeguarding public health and

24 improving the resilience of drinking water systems in the face of the ever-growing threat of
25 chemical spills.

26

27 **Key Words:** Drinking water treatment; Chemical spill; Emergency scenario; Disability adjusted
28 life years; Drinking water countermeasures; Public health assessment.

29

1. Introduction

The United States Environmental Protection Agency (USEPA) estimates that approximately 200 million pounds of toxic chemicals are released into surface waters through chemical spills each year (USEPA, 2022a), with roughly 15% of the spills occurring within the proximity of local drinking water facility intakes (Brett Walton, 2021). These spills can have detrimental environmental impacts and can lead to public health emergencies. To mitigate the impact associated with these emergencies, the Congress enacted the American Water Infrastructure Act in 2018 (H.R. 115, 2018), requiring all community drinking water facilities to undergo an extensive analysis of their municipality and identify all potential emergencies which may impact their ability to provide their community with safe drinking water and the countermeasures that they can deploy to mitigate the emergencies' effects. While this procedure does assist municipalities in understanding how to respond to potential threats, it does not require them to fully understand the sustainable tradeoffs associated with the countermeasures selected.

The quality of drinking water depends on the interplay of three main components: source water, treatment, and distribution. Although many studies have focused on the risks associated with source water contamination and its impact on public health (Azizullah et al., 2011; Currie et al., 2013; Fabro et al., 2015; Horzmann et al., 2017; Nordberg, 1990) and treatment technologies for addressing chronic pollutions (Glassmeyer et al., 2023; Zamri et al., 2021), little attention has been given to the actions that drinking water managers can take to prevent that contamination from reaching their customers in an acute setting. On the other side of the treatment process, most studies focus on the distribution system, which has been highlighted as being particularly vulnerable to contamination (Besner et al., 2011; Davis Michael J. AND Janke, 2016; Murray et

al., 2006; Xin et al., 2012). Many of these studies place particular emphasis on network monitors (Davis and Janke, 2009; Perelman and Ostfeld, 2010; Poulin et al., 2008; Yang et al., 2009) and isolation methods (Afshar and Najafi, 2013; Poulin et al., 2008) to better understand the movement of contamination through the network in the hopes of reducing the contaminant amount which reaches the customers. While such studies recognize the challenges posed by source water contamination and distribution network management, they overlook the role of treatment facilities and the timely measures that operators can take to mitigate the impact of contamination events. Although some studies have examined the entire drinking water system in the context of past events, such as the Elk River chemical spill (Thomasson et al., 2017; Whelton et al., 2015) or the Flint, Michigan water crisis (Hanna-Attisha et al., 2016), these investigations have limited applicability beyond those specific emergencies. Studies that have explored a multitude of drinking water systems have focused on implementing safety and risk management plans (Baum et al., 2015; Tang et al., 2013), which were shown to enhance a system's water quality, regulatory compliance, and public health protection. However, these studies have not fully explored the specific procedures embedded in the safety and risk management plans during contamination events.

To fill in these gaps, this study aims at investigating the public health impact associated with an organic chemical spill emergency under various emergency action scenarios, using a typical New England small-scale drinking water facility with multiple water sources as a test site. A dynamic model that mimics the water intake, treatment, and distribution processes was developed to estimate the carcinogenic and non-carcinogenic impacts associated with various response scenarios, including source switching, enhanced coagulation, powdered activated carbon, or

system shutdown. The results of this study will provide valuable insights for drinking water facility operators and policy makers to make timely and informed decisions about the tradeoffs associated with different response strategies in the event of an organic chemical spill emergency.

2. Surrogate Drinking Water System and Contamination Event Overview

The surrogate drinking water facility (DWF) is a typical small community water system in New England that serves a population of approximately 15,000 individuals, treating a daily average of 2,000 m³ of water through a four-step treatment process illustrated in Figure 1. The DWF's distribution system consists of 30 miles of pipelines, 3 storage tanks, and over 259 nodes representing buildings and neighborhoods. Water is drawn by DWF from three distinct sources: (1) Surface Water A, high-quality river water; (2) Surface Water B, relatively low-quality reservoir water independent of Surface Water A; and (3) Ground Water, high-quality groundwater. Surface Water A serves as the primary drinking water source; however, it is subject to withdrawal restrictions to ensure its downstream flow is maintained, necessitating blending with the other sources under low flow and/or high demand conditions. In this study, a contamination spill event was assumed to occur in Surface Water A to simulate the most severe impact on the DWF and its serving community.

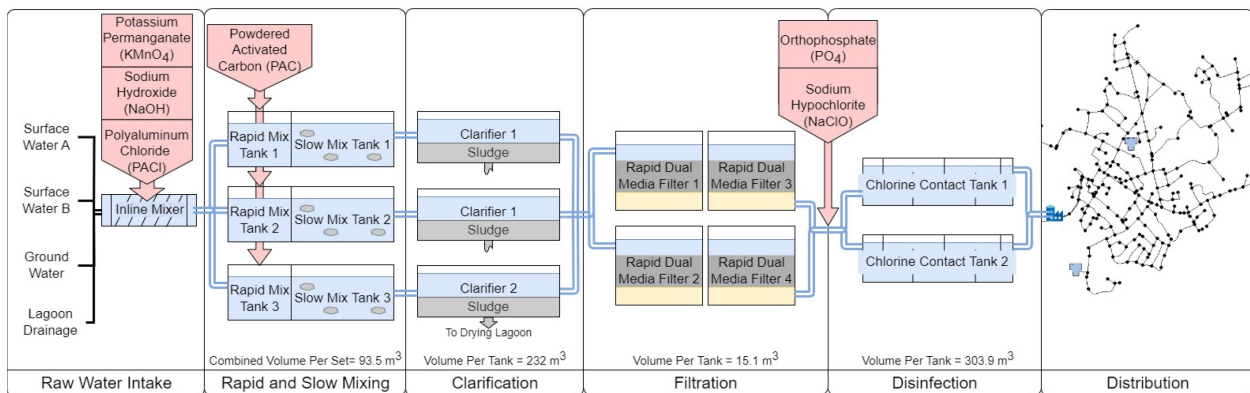


Figure 1: Process flow diagram outlining the treatment process in the modeled treatment facility with the water entering the facility, passing through the rapid and slow mixing flocculation tanks before being clarified and passing through the rapid dual media filters. This filtered water then enters the chlorine contact tanks before distribution to the local community.

3. Methods

Figure 2 outlines the modeling framework developed to assess the DWF's resiliency against chemical spill events. The framework is comprised of four sub-models, which are: (A) an intake sub-model that simulates the contaminant concentration at the intake of the DWF, (B) a treatment sub-model that simulates the treatment/removal of the contaminant throughout the treatment train under both normal operation and emergency (with countermeasure application) scenarios, (C) a distribution sub-model that characterizes the quantity and quality of water transported through the distribution network, leveraging the Water Network Tool For Resilience (WNTR) Python package (USEPA, 2017), and (D) a public health impact sub-model that estimates the contamination event's carcinogenic and non-carcinogenic effects from oral consumption of the polluted water on consumers. The model was developed in Python for a chemical spill event which occurred within a 7-day study period, with a timestep of 1-minute. After the 7-day period, we assumed that the DWF would take the action to flush out any remaining contaminant within the system.

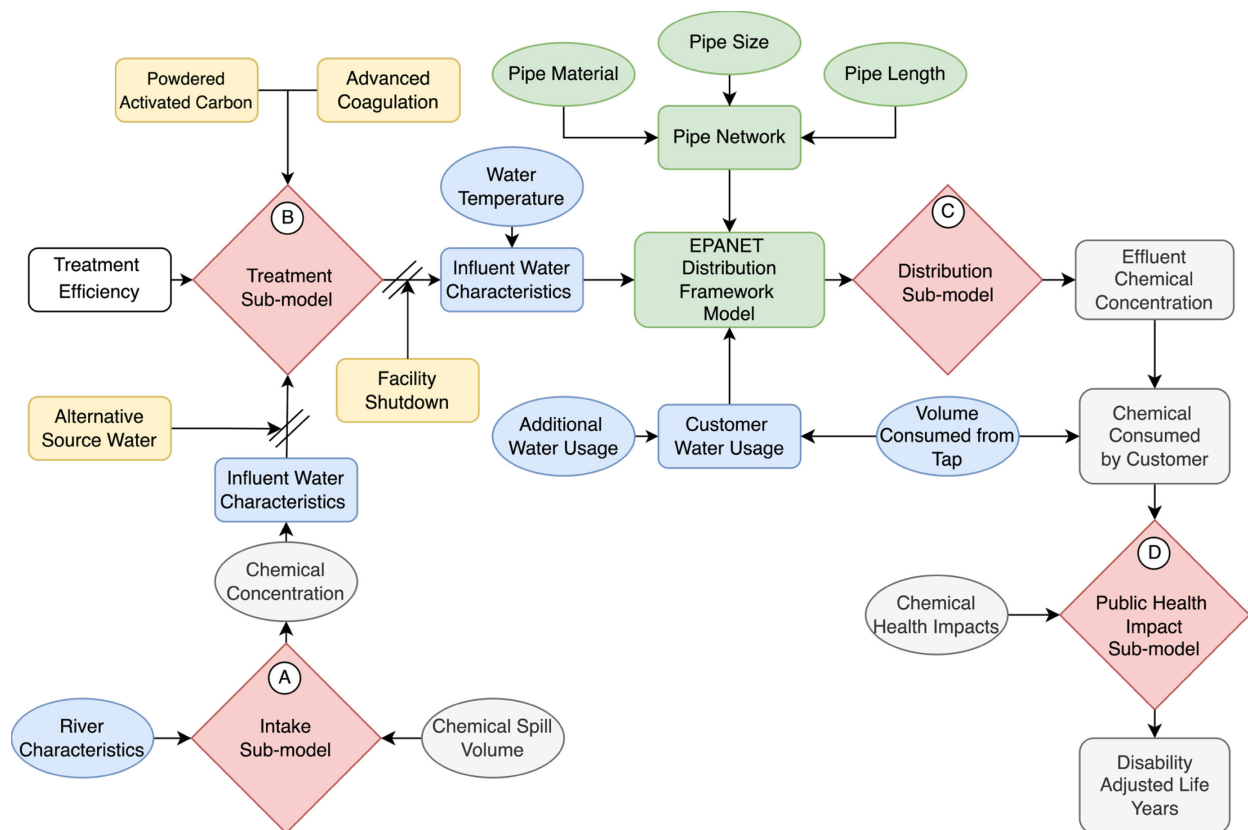


Figure 2: An outline of the modeling framework developed to assess the resiliency of a typical New England drinking water treatment plant against chemical spill events. Red shapes represent the sub-models of: (A) Intake, (B) Treatment, (C) Distribution, (D) Public Health Impacts. Blue shapes represent the movement of water, grey boxes represent chemical movement or treatment, yellow shapes represent different countermeasures which can be applied, and green represents the distribution network data.

3.1. Sub-model (A): Intake

The intake sub-model seeks to simulate the contaminant concentration at the intake of the water treatment plant under various seasonal and contaminant toxicity scenarios. To obtain the typical ranges of the carcinogenic and non-carcinogenic impacts of chemicals commonly found in chemical spill events, we first identified a list of 335 organic chemicals that have impacts associated with oral consumption in the USEPA's Integrated Risk Information System's (IRIS) database (USEPA, 2020a). This list was cross checked with the USEPA's Treatability Database (USEPA, 2020b) narrowing this initial list to 30 organic chemicals with known treatment processes. To identify the chemicals which would represent the upper and lower bounds of

public health effects, we ranked these chemicals by their carcinogenic slope factors and non-carcinogenic severity weights associated with oral consumption, normalized by each chemical's Freundlich treatability values. From this list we selected four chemicals representing the highest and lowest normalized carcinogenic and non-carcinogenic effects, respectively. Details regarding the selected chemicals and the selection process can be found in Table 1 in Section A.1 of the supporting information (SI).

Table 1: The four organic chemicals selected in this study to represent the higher and lower bounds of carcinogenic and non-carcinogenic impacts associated with oral consumption.

Chemical Category	Chemical Density (g/ml)	Freundlich adsorption isotherm (k_f) (Crittenden et al., 2012; USEPA, 2020b)	Freundlich adsorption isotherm ($1/n$) (Crittenden et al., 2012; USEPA, 2020b)	Carcinogenic slope factor (mg/kg-day) (USEPA, 2020a)	Non-carcinogenic severity weight (WHO, 2004)
High Carcinogenic Effect	1.387	7.326	0.613	30.000	0.200
High Non-Carcinogenic Effect	1.80	10.030	0.5369	0.070	0.591
Low Carcinogenic Effect	1.14	710.989	0.063	0.000	0.108
Low Non-Carcinogenic Effect	1.46	28.000	0.62	0.046	0.000

In our simulation, we assumed the emergency event occurred as a result of a 30-m³ truck transporting an organic chemical tipped over and spilled its entire contents 1.6-km upstream of the DWF's inlet pipe in Surface Water A. It was assumed that the chemical content was released all at once within the first 30 minutes of the facility's first operating window during the 7-day study period. The spill time was intentionally chosen to be close to the facility's operating window to mimic the highest impact on the community regardless of DWF's operational schedule.

Equation 1 (Rathbun, 2000) was used to determine the contaminant's concentration at DWF's inlet pipe using data related to the river's slope, depth, and velocity (USGS, 2022) (SI Section

A.2). It has to be noted that river depth and velocity change based on the scenarios specified in Section 3.2.

$$C_{(x,t)} = \left(\frac{\rho O}{d_t \times w \times \sqrt{4\pi t \frac{0.058 V_T \times d_T \times w}{S_w}}} \right)^{-\frac{(X-V_T t)^2}{4t \frac{0.058 V_T \times d_T \times w}{S_w}}} \quad (\text{Equation 1})$$

Where:

$C_{(x,t)}$ = Concentration of the spilled chemical at x distance downstream of the spill location, kg/m³;

ρ = Chemical density, kg/m³;

O = Volume of chemical spill (FMCSA, 2022), 30 m³;

d_T = River depth at the time of the year T (USGS, 2022), m (Figure 1 of the SI);

V_T = River velocity at the time of the year T (USGS, 2022), m/minute (Figure 1 of the SI);

w = Average river width (USGS, 2022), 30 m;

S = River slope, 0.06 (Fenoff, 2021);

T = Time of the year t , minute;

t = Time since spill, minute; and

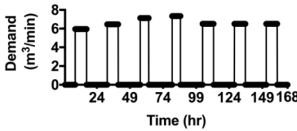
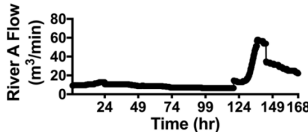
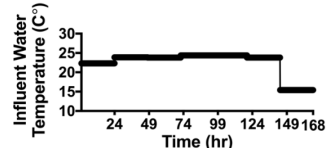
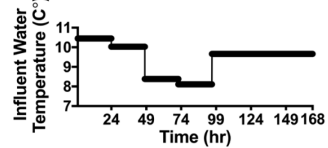
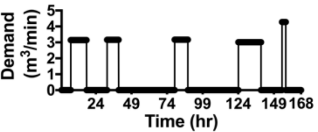
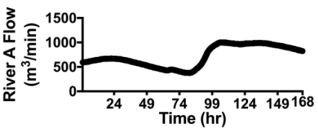
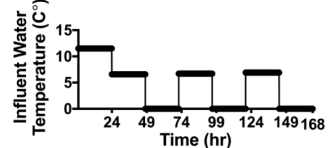
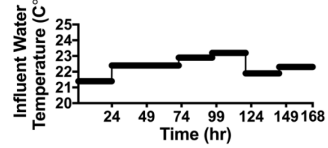
X = Distance from initial spill site to drinking water inlet, assumed to be 1,609 m.

3.2. Sub-model (B): Treatment

Historical water quality and quantity data from DWF and the simulated Surface Water A was evaluated to assess the influence of seasonality on the pollutant flow and treatment. From these datasets, two periods of surface water flow and facility demand data were selected, representing a high-water demand / low river flow scenario (HDLS) and a low water demand / high river flow

171 (LDHS) scenario. Each scenario is further split into a summer and a winter scenario based on the
172 DWF's historical data, which maintain water quality and flow patterns but alter the temperature
173 of the intake water (Table 2). The variable temperature scenarios influence the contaminant
174 removal efficiency and the amount of chemicals required to treat the water. Each scenario spans
175 7 days starting from midnight on the first day. Total Organic Carbon (TOC) was used as a
176 surrogate to calculate the contaminant removal efficiencies within each treatment step (Shetty
177 and Goyal, 2022; Wang et al., 2021).

178 **Table 2:** Identification of the facility demand, supply, and temperature scenarios which form the upper and lower bounds of chemical contamination impacts.

Scenarios		Facility Demand and Operating Windows (m ³ /day)		River Flow (m ³ /min) (USGS, 2022)		Temperature (C°)	
		Temporal	Average	Temporal	Average	Temporal	Average
High Demand Low Supply Scenario (HDLS)	Summer		6.6		14.8		22.6
	Winter						9.2
Low Demand High Supply Scenario (LDHS)	Summer		3.2		719.6		4.5
	Winter						22.3

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Once the water is withdrawn, it is first dosed with potassium permanganate (KMnO_4 ; oxidant), poly-aluminum chloride (PACl ; coagulant), and sodium hydroxide (NaOH ; pH adjustment) before entering the two operating rapid mix tanks, which were followed by the two operating slow mixing tanks. It was assumed that unless a countermeasure is activated, these chemical dosages follow the historical patterns under the HDLS and the LDHS scenarios.

While chemical reactions begin to occur during the rapid and slow mixing step, it was assumed that contaminants are removed during the clarification step. The effluent rates from the rapid and slow mixing tanks were modeled after a continually stirred batch reactor (Table 3) (Crittenden et al., 2012). After the rapid and slow mixing, the drinking water is combined in a central trough before being equally distributed to the two operating clarification tanks using plate settling. Each clarification tank has a volume of 232.9 m^3 and contains 114 inclined plates to better facilitate the flocculation and sedimentation process. The clarification tanks were modelled as plug flow reactors for estimating chemical removal (Crittenden et al., 2012). After clarification, water is combined into another trough before being evenly distributed to three rapid dual media filters (RDMFs). These filters are designed with 0.91 m of anthracite coal on top of 0.25 m of sand. As with the clarification tanks, the RDMFs operate as plug flow reactors (Crittenden et al., 2012).

To maintain TOC removals, the DWF has established three conditions that trigger backwashing of the RDMFs: (1) a continuous 20-minute head loss of greater than 1.52 m, (2) 20 consecutive minutes of breakthrough turbidity of greater than 0.2 NTU, or (3) a cumulative runtime of 96 hours. Detailed equations for calculating the terminal head loss and breakthrough can be found in the SI Section A.3 (Crittenden et al., 2012). When a filter backwash is triggered, the facility

diverts all flow away from the affected filter. Chlorinated water is pumped from the backwash storage tanks and is passed up through the spent media for roughly 26 minutes followed by a 5-minute filter to waste ripening period. This spent water is collected via the backwash troughs to the drying lagoons outside. Expended backwash water within the lagoons is reintroduced into the facility at no more than 10% of the raw water inflow.

When the backwash is complete, the filter inlet is opened once again. Immediately following the backwash activities, the flow from the rapid dual media filters is diverted away from the disinfection tanks, this diverted water is used to recharge the backwash supply tanks. After the filtration step, the treated water is collected in a central trough where sodium hypochlorite, measured as chlorine dosage, is added for disinfection before being transported to one of two serpentine chlorine contact tanks. Equations in Table 3 guide the calculation of the treatment performances and effluent rates in each treatment step.

Table 3: Breakdown of the treatment steps, the total number of tanks operating per step, treatment equations dictating the removal of TOC within each treatment step and the equations governing the effluent mass from each step.

Treatment Step [Number of tanks operating / number of tanks available]	Total Organic Carbon Removal	Reference	Effluent Mass Estimation
Rapid and Slow Mixing [2/3]	No Reduction	N/A	$E_M = \frac{C_{M,t}}{\frac{Q_t}{O}} \times \frac{Q_t}{O}$ <p>Where, $E_{M,t}$ = Effluent TOC mass from the tank, mg/min $C_{M,t}$ = Influent TOC concentration to tanks, mg/L-min; V = Tank volume, 93.5 L; Q_t = Flow through the facility, L/min; O = Number of tanks operating; and t = Current time step, min.</p>
Clarification [2/3]	$C_{R,C,t} = (C_{I,C,t} \times F_{DOC}) - C_{eq,t} + NDOC_t$ <p>Where,</p>	(Crittenden et al., 2012)	$E_{M,t} = (C_{I,(t-R_t)} - C_{R,t}) * V$

	$C_{R,C,t}$ = TOC concentration reduction from the coagulation and flocculation process, mg/L-min; $C_{I,C,t}$ = Influent TOC concentration, mg/L-min; F_{DOC} = Fraction of TOC which is dissolved organic carbon (DOC), assumed to be 0.9; $C_{eq,t}$ = Equilibrium aqueous phase DOC concentration, mg/L-min (SI Section A.3); $NDOC_t$ = Influent non-dissolvable organic carbon concentration, mg/L-min (SI Section A.4); and t = Current time step, min.		<p>Where,</p> $E_{M,t}$ = Effluent TOC mass from the tank, mg/min; t = Current time step, min; R_t = Retention time within the tank, min; C_t = Influent TOC concentration to treatment tank, mg/L-min; $C_{R,t}$ = Mass of organics removed during treatment process, mg/L-min; and V = Volume of tank, L.
Rapid Dual Media Filtration [3/4]	$C_{R,F,t} = C_{I,F,t} - C_{E,F,t}$ $C_{EF,t} = (0.76093 * C_{IF,t}) + 0.27689$ <p>Where, $C_{R,F,t}$ = TOC concentration reduction from the filtration step, mg/L-min; $C_{I,F,t}$ = Influent TOC concentration to the filter, mg/L-min; $C_{E,F,t}$ = Effluent TOC concentration from the filter, mg/L-min; and t = Current time step, min.</p>	Regression equation based on historical data (SI Section A.5)	$R_t = \frac{V}{Q_t}$ <p>R_t = Retention time within the tank, min; Q_t = Flow entering the facility, L/min; V = Volume of the tank, L; and t = Current time step, min.</p>
Disinfection [1/2]	$C_{R,D,t} = 0.06 \times C_{I,D,t}$ <p>Where, $C_{R,D,t}$ = TOC concentration reduction after the disinfection step, mg/L-min; $C_{I,D,t}$ = Influent TOC concentration entering the disinfection tanks, mg/L-min; and t = Current time step, min.</p>	Equation estimated using historic data	

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221 Beyond normal operation, DWF identified four effective countermeasures to combat source
222 water contamination. These include 1) the increased dosage of PACl for enhanced coagulation to
223 maintain pre-event TOC removal efficiencies; 2) the addition of PAC at the rapid and slow
224 mixing step to reach an average of 95% TOC removals (AWWA, 2021; Carroll, 2009). The mass
225 of PAC entering the RDMF was also estimated, which further informs the breakthrough and the
226 backwashing of the RDMF; 3) switching water source from Surface Water A to an equal mixture
227 of Surface Water B and Ground Water, which alters the PACl and orthophosphate dosage; and 4)
228 shutting down the treatment facility, in which the community still have access to the surplus
229 water stored in the distribution network and storage tanks before it runs out. Table 4 provides the
230 equations utilized for estimating the additional treatment chemical requirement when various

countermeasures are applied. Unlike the addition of PACl and PAC, orthophosphate does not directly influence the concentration of TOC within DWF.

Table 4: Equations governing the mass addition and corresponding equations for treatment chemicals within DWF as a result of the activation of various countermeasure actions.

Countermeasure	Source	Corresponding Equations
Poly-aluminum chloride (PACl) (Equations applicable for Countermeasures 1 and 3)	Regression analysis (SI Section A.7)	$M_{PA,t} = Q_{T,t} \times C_{PA,t} = Q_{T,t}(C_{P,t} - C_{PB,t})$ $C_{P,t} = 30.87 + 1.59 \times T - 6.01 \times P + 169.46 \times UV_{254} - 4.50 \times 10^{-5} \times Q_{SW,B,t} - 7.60 \times 10^{-5} \times Q_{SW,A,t} - 1.02 \times 10^{-4} \times Q_{GW,t} + 6.70 \times 10^{-5} \times Q_{T,t}$ <p>Where: $M_{PA,t}$ = Additional mass of PACl added to water in relation to the contaminate, mg/L-min; $Q_{T,t}$ = Total flow entering the facility, L/min; $C_{PA,t}$ = Additional concentration of PACl added to water in relation to the contaminant, mg/L-min; $C_{PB,t}$ = Baseline reported concentration of PACl added to water, mg/L-min; $C_{P,t}$ = Concentration of PACl added to water, mg/L-min; t = Current time step, min; T = Temperature, C°; P = Water pH; UV_{254} = Ultraviolet 254 reading, nm; $Q_{SW,B,t}$ = River B flow into facility, L/min; $Q_{SW,A,t}$ = River A flow into facility, L/min; $Q_{GW,t}$ = Groundwater flow into facility, L/min; and $Q_{T,t}$ = Total flow into facility, L/min.</p>
		$M_{PAC,t} = \frac{C_{IC,t} - (C_{IC,t} \times IR)}{k_f(C_{IC,t} \times IR)^{\frac{1}{n}}} Q_{T,t} t_{CR}$ <p>Where: $M_{PAC,t}$ = Mass of PAC applied, kg/min; $C_{IC,t}$ = Concentration of organic pollutant entering the clarification tanks, mg/L-min; IR = Ideal removal percentage to be achieved by countermeasure, 95%; k_f = Freundlich constants (Table 1), mg/kg; $1/n$ = Freundlich constants (Table 1), unitless; $Q_{T,t}$ = Total flow entering the facility, L/min; t_{CR} = Clarification tank retention time, min (Table 3); and t = Current time step, min.</p>
		$M_{PAC-RDMF,t} = M_{PAC,t} \times TSS_{R,t} = \frac{d}{L_p \cos \theta + d \sin \theta} = \frac{v_s}{v_{f\theta,t}}$ <p>Where: $M_{PAC-RDMF,t}$ = Mass of PAC entering the rapid dual media filters, kg/min; $M_{PAC,t}$ = Mass of powdered activated carbon applied, kg/min; $TSS_{R,t}$ = Remaining PAC post clarification, %; d = Distance between inclined plates within the clarifier, 0.05 m; L_p = Length of the inclined plates within the clarifier, 3.05 m; θ = Inclined plate angle within the clarifier, 55°; v_s = Settling velocity of the particles, 1.68 m/min (Crittenden et al., 2012); $v_{f\theta,t}$ = Water velocity, m/min; and t = Current time step, min.</p>
Orthophosphate (Equations applicable for Countermeasure 3)	Regression Analysis (SI-008)	$M_{PO_4} = Q_{T,t} \times C_{PO_4,t}$ $C_{PO_4,t} = 10.77 + 1.58 \times \frac{Q_{SW,B,t}}{Q_{T,t}} + 0.04 \times \frac{Q_{GW,t}}{Q_{T,t}} - 9.64 \times 10^{-7} \times Q_{T,t} - 0.04\sigma + 4.48 \times UV_{254} + 3.38 \times C_{Mn,t}$ <p>Where: $M_{PO_4,t}$ = Mass of Orthophosphate added, mg/min $Q_{T,t}$ = Total flow entering the facility, L/min;</p>

$C_{PO_4,t}$ = Concentration of Orthophosphate added, mg/L;
 $Q_{SW,B,t}$ = Flow entering facility from Surface Water B, L/min;
 $Q_{GW,t}$ = Flow entering facility from Ground Water source, L/min;
 σ = Specific conductance of the influent, $\mu\text{S/cm}$;
 UV_{254} = Ultraviolet 254 reading, nm;
 $C_{Mn,t}$ = Concentration of manganese in influent water, mg/L; and
 t = Current time step, min.

Each countermeasure can be utilized independently or in conjunction with one another. We designed 10 scenarios as per the DWF's recommendations (Table 5). During the contamination event, it was assumed that once each countermeasure is activated, it remains active for the duration of the event unless the facility is shut down or the source water is switched. We also assumed that only one countermeasure could be activated per 30-minute interval. However, countermeasures can be triggered at any of the 30-min intervals during the 7-day window. If DWF is offline during a countermeasure's activation, it is assumed that the countermeasure would be applied within the next available DWF operating window (Table 2).

Table 5: Countermeasure combinations can include the increase in poly-aluminum chloride (PACl) concentrations, addition of powdered activated carbon (PAC), total facility shutdown, or switch away from the polluted source water. The numbers under each countermeasure represent the order in which they are deployed.

Combination Number	PACl	PAC	Shutdown	Source Water Switch	Number of Runs	
					HDLS	LDHS
1	1	0	0	0	736 per combination	945 per combination
2	0	1	0	0		
3	0	0	1	0		
4	0	0	0	1		
5	1	2	0	0	33,488 per combination	53,360 per combination
6	1	0	2	0		
7	1	0	0	2		
8	2	1	0	0		
9	0	1	2	0		
10	0	1	0	2		

3.3. Sub-model (C): Distribution

Water flow through the distribution network was modeled using each pipeline's dimensions, material, and roughness as well as each node's specific demand intensities and patterns. A model

of this network has been built using EPANET, which calculates flow of water and contamination using pressure driven equations (Rossman, 1999). The EPANET distribution network model was combined with the treatment facility model via WNTR, a Python package (USEPA, 2017). It was assumed that all chemical propagation through the network follows zero order reaction kinetics with the residual chlorine in the water, biofilm, and pipe materials.

The node demand and use patterns utilized by EPANET represent the number of people living at each node and their daily water usage activities, respectively. The model multiplies the node intensity by the demand pattern to determine the amount of water demanded by each node at each time step. For simplicity, each node was assumed to have the same baseline use pattern which was adjusted to match the reported facility demand for the HDLS and LDHS scenarios (Table 2) using the methodology outlined in the Supplemental Information Section A.9.

3.4. Sub-model (D): Public Health Impact

Each scenario has been evaluated for its potential public health carcinogenic and non-carcinogenic impacts, considering both the direct contributions via the consumption of contaminated water by the public and the indirect contributions associated with the countermeasure strategies employed.

The public health impact of the contamination event was evaluated using the Disability Adjusted Life Years (DALY) metric (Equation 2) (Bixler et al., 2021; Seidel et al., 2014), which considers the direct impacts across the 7-day time horizon. These were determined by summing the mass

of pollutant consumed by all nodes in the network as calculated within the distribution sub-model.

$$DALY_{Total} = (DALY_C + DALY_{NC}) \quad (\text{Equation 2})$$

Where:

$DALY_{Total}$ = Total health impact resultant from both carcinogenic and non-carcinogenic effects, days;

$DALY_C$ = Carcinogenic disability adjusted life years lost resulted from direct consumption of contaminated water, years;

$DALY_{NC}$ = Non-carcinogenic disability adjusted life years lost direct consumption of contaminated water, years;

The total carcinogenic impact associated with the contamination event and countermeasure scenario is estimated using Equation 3 (Seidel et al., 2014), which utilizes the cancerous slope factors (USEPA, 2022b) reported for each spilled chemical (Table 1) and the weight-adjusted mass of chemical consumption per person. This calculation is performed for all nodes within the community which are summed to obtain the total carcinogenic impact associated with the direct consumption of contaminated water across the 7-day event horizon.

$$DALY_C = \sum_{n=0}^N F \times M_W \times L \times ED \times P_N \quad (\text{Equation 3})$$

Where:

$DALY_C$ = Carcinogenic disability adjusted life years lost resulted from direct consumption of contaminated water, years per event;

F = Cancerous slope factor (USEPA, 2022b), (mg/kg-day)⁻¹;

N = Total number of nodes within the distribution network; 259 nodes

n = Node index;

M_W = Weight adjusted mass of chemical consumption per event, mg/kg-event-person;

L_p = Mean loss of life due to cancer, 20 years/person which is the average mean loss of life across all carcinogenic ailments as reported by the World Health Organization (WHO, 2004);

ED = Percentage of event duration out of the expected lifetime, 0.0027 years; and

P_N = Residents per node, number of people;

The weight-adjusted mass of chemical consumption per person per event was calculated using Equation 4. The distribution network sub-model was used to determine the mass of chemical consumed per person, which was then added up across the event.

$$M_W = \sum_{t=0}^T \frac{C \times V}{W} \quad (\text{Equation 4})$$

Where:

M_W = Weight adjusted mass of chemical consumption, mg/kg-event-person;

T = Final timestep of contamination event, 10,080 min;

314 t = time, min;

315 C = Concentration of contamination at node, mg/m³-min;

316 V = Volume of water consumed, m³/min; and

317 W = The average weight of each person, 70 kg. (Seidel et al., 2014).

318

319 Equation 5 (Seidel et al., 2014) is used to estimate the non-carcinogenic impacts resulting from
320 the consumption of contaminated water. Like the carcinogenic impacts, the non-carcinogenic
321 impacts utilize the weight-adjusted mass of chemical consumption (Equation 4).

322

323
$$DALY_{NC} = \sum_{n=0}^N I_R \times \frac{M_W}{D \times U} \times S \times L_p \times P_N \quad (\text{Equation 5})$$

324

325 Where:

326 $DALY_{NC}$ = Non-carcinogenic disability adjusted life years lost resulted from direct
327 consumption of contaminated water, years per event.

328 N = Total number of nodes within the distribution network; 259 nodes

329 n = Node index;

330 I_R = Incidence rate for noncancerous diseases caused by direct ingestion of toxic
331 chemicals, assumed to be 1% according to (Dourson et al., 1996);

332 M_W = Weight adjusted mass of chemical consumption per event, mg/kg-event-person;

D = Reference dose (USEPA, 2022b), ng/kg-day;

U = Uncertainty factor (USEPA, 2022b), dimensionless;

S = Non-carcinogenic severity factor (USEPA, 2022b), dimensionless;

ED = Percentage of event duration out of the expected lifetime, 0.0027 years; and

P_N = Residents per node, number of people.

4. Results and Discussion

4.1. Health Impacts When No Action Is Taken During the Contamination Event

Figure 3 shows the temporal variation of the cumulative TOC masses in each treatment step within the DWF under both the HDLS and LDHS scenarios. A clear differentiation between the baseline TOC level with no contamination and the TOC level under the contamination event can be seen. This differentiation results in an average 4.6% and 15.3% higher organic load under the contamination scenario during HDLS and LDHS, respectively. A clear propagation of the pollutant through the facility can also be seen through the separation between the solid and dashed lines representing the contaminated and non-contaminated runs of the model. Times which see a larger spread between the two lines represent the periods in which the contamination is exiting that treatment stage. This is best seen during HDLS before and after the dotted vertical line which represents the first instance of contamination entering the facility. Before this moment the data in both the contaminated and non-contaminated runs are the same. However, following this time the two datasets exhibit a clear separation. This pre and post contamination trend is not as prevalent under LDHS because during HDLS the river flow is so low that it takes nearly 11

times longer for the spill front to reach the facilities intake. This highlights the importance of early detection of chemical spills and early implementation of countermeasures.

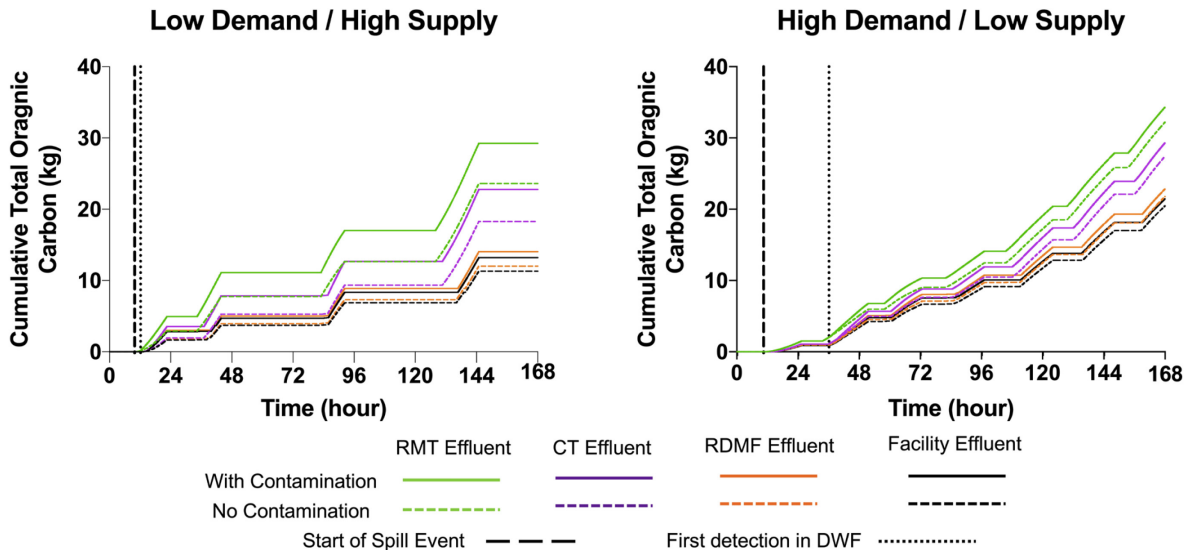


Figure 3: A comparison between the cumulative total organic carbon effluent mass from each treatment step (RMT: Rapid and Slow Mixing Tanks; CT: Clarification Tanks; RDMF: Rapid Dual Media Tanks) with and without contamination under low demand high supply and high demand low supply scenarios. The vertical dashed line indicates the time at which the spill occurs and the vertical dotted line represents when the contaminate first enters the facility.

Figure 4 shows the cumulative average DALY impacts associated with the chemical spill events under the LDHS and HDLS with no countermeasures deployed. Interestingly, under the LDHS scenario the community experiences over 2 times higher DALY impacts despite having 48% lower average demand as compared to the HDLS scenario. This can be attributed to the difference in the percentage of total water drawn from the polluted Source Water A. Under LDHS, all water drawn by the DWF comes from Source Water A, whereas this source represents only 7% of the average daily volume during HDLS. Such trends highlight the importance of not

only having multiple source waters, but also using a blend of them under normal operations as it can reduce the cumulative impact on the community if a pollution event goes unnoticed.

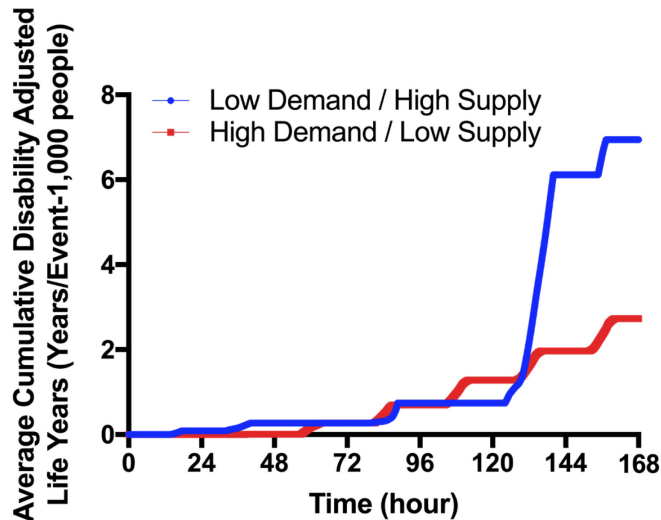


Figure 4: Graph showing the average cumulative disability adjusted life years experienced by the community across the 7-day event horizon under both the LDHS and HDLS scenarios.

4.2. Health Impacts Under Emergency Actions

Figure 5 presents the influence of countermeasures on the public health impacts (DALY) per 1,000 customers. Out of all countermeasures, PAC with facility shutdown has the highest effect in reducing the DALY experienced by the community. This is a result of both the high treatment efficiency associated with the PAC which can reduce the majority of the pollutant inflow as well as the facility shutdown which can prevent the pollutant peak from entering into the network. However, it should be noted that shutting down the facility can lead to broader public impacts resultant from water supply shortages, and hence its duration needs to be minimized.

Alternatively, increasing coagulant via PACl has the least impact to total DALY given its minimal treatment efficiency which is compounded with the marginal increase in the average TOC influent concentrations as compared to the no-contamination data, 13.3% and 4.5% under the LDHS and HDLS, respectively. Thus, under contamination the DWF will only slightly increase the levels of PACl added to maintain the pre-contamination TOC removal trends. Similarly, source switching follows as the second least effective countermeasure under both LDHS and HDLS. This is primarily driven by the fact that treatment chemicals within the facility are dosed in accordance with the influent water parameters. Thus, when switching from the polluted source to the other two sources, the average TOC influent concentration is significantly changed. This results in an overall change in the treatment parameters in the tanks, which can cause increased pollutant loads if the contamination is within the rapid and slow mixing and / or coagulation tanks.

If shutting down the facility is not feasible, the next best option is to combine the application of PAC with source switching. This approach avoids under-treating the contaminated water during source switching, as PAC is applied within the tanks rather than at the inlet like PACl, thus enabling this combination to capture any residual contaminate within the rapid and slow mixing tanks regardless of the alteration in source water treatments.

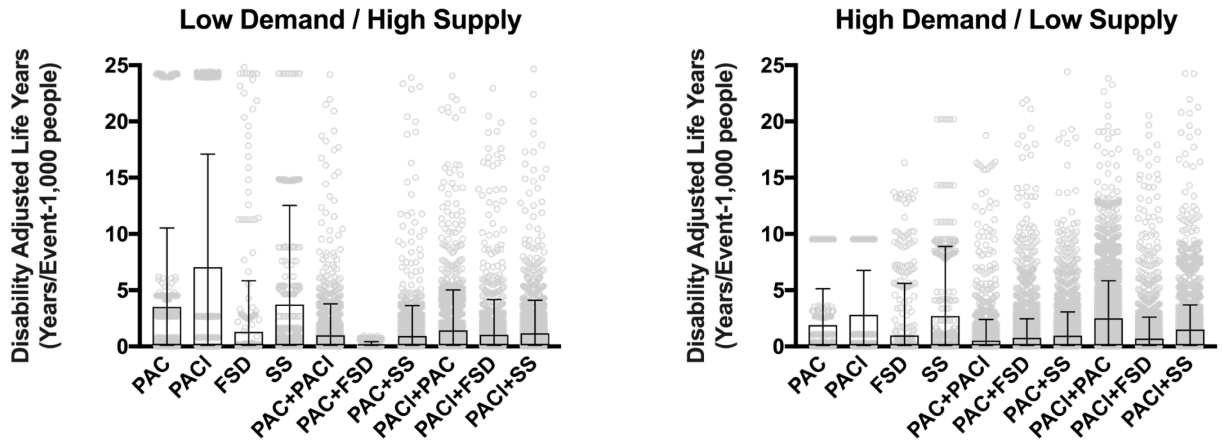


Figure 5: Comparison of the average disability adjusted life years resultant from the deployment of one or two countermeasures during the contamination event under both the LDHS and HDLS scenarios. Boxes and whiskers show the means and standard deviations of the DALY impacts. Countermeasures are denoted as following; PAC : Powdered Activated Carbon; PACI : Poly-Aluminum Chloride; FSD : Facility Shutdown; and SS : Source Switching.

Overall, combining countermeasures is generally more effective than applying individual countermeasures reducing the total DALY across all scenarios, 78% in LDHS scenario and 50% in the HDLS scenario. This highlights the importance of investing in diverse countermeasure options. Alternatively, if the DWF has the capacity to only implement one countermeasure, the most effective action is to shut down the system. This results in a 68% reduction in health impact as compared to taking no action in the HDLS scenario and an 84% average reduction in the LDHS scenarios. However, during HDLS this approach may result in a 32% unmet demand or 152 m³ of water loss experienced by the community during the 7-day time. Conversely, under LDHS there is no loss in service to the community as there is ample supply in the network to meet the lower demand.

4.3. The Impact of Temporal Variations in Countermeasure Applications

In Figure 6, the impact of deploying countermeasures across the contamination event is demonstrated. Across both scenarios the application of PACI represents the lowest sensitivity to timing actions, followed by facility shutdown and PAC. This is because PACI has a low effectiveness in pollutant reduction. Alternatively, the use of source switching is the most sensitive to the time of deployment with many times resulting in higher DALY impacts experienced by the community than when no countermeasure is applied, indicated by the horizontal dotted line. This high sensitivity to timing is a result of the alteration of source water treatment which changes the removal performances within the clarification tanks. This may result in a non-ideal system especially if the pollutant peak has already entered into those tanks.

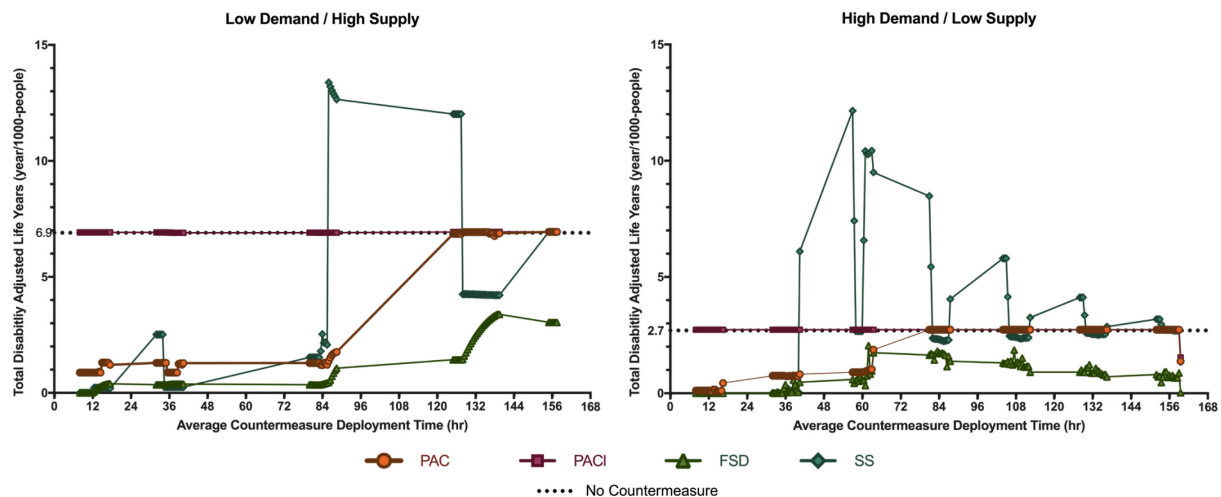


Figure 6: The cumulative total Disability Adjusted Life Years resultant from deploying a single countermeasure at various points across the contamination event horizon. Countermeasures are denoted as following; PAC : Powdered Activated Carbon; PACI : Poly-Aluminum Chloride; FSD : Facility Shutdown; and SS : Source Switching.

Figure 7 highlights the influence that timing has on the cumulative DALY experienced by the community when the facility deploys two countermeasures. Each point in the figure represents

the total DALY experienced by the community based on the average countermeasure deployment times. Like the use of a single countermeasure, the deployment of two countermeasures is sensitive to the timing of implementation, with the highest benefits being experienced with earlier activation, on average. Although sensitive to timing, under the LDHS scenario a combination of countermeasures greatly reduces the public health impact to the community, with only 1% of deployments resulting in a higher DALY than in the no-action scenario. Amongst the trendlines, the application of PACI and source switching has the highest sensitivity to timing followed by the application of both PACI and PAC, whereas the application of PACI with facility shutdown results in the lowest sensitivity to timing. This is primarily because PACI has a minimal effect on the reduction of the pollutant. The effect that PACI has on the reduction of sensitivity can also be seen under the PACI+PAC countermeasure.

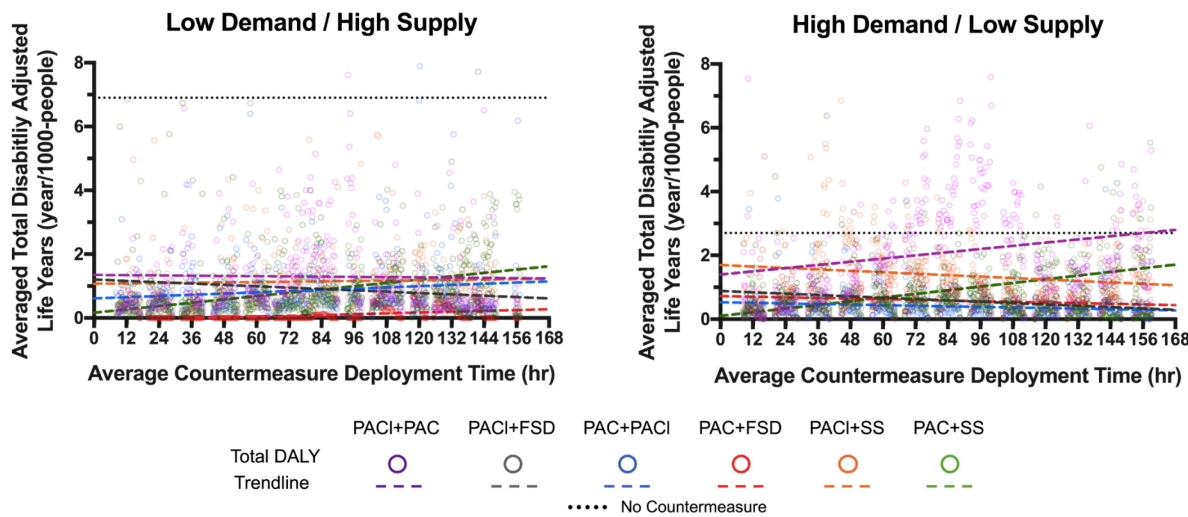


Figure 7: The cumulative total Disability Adjusted Life Years resultant from deploying 2 countermeasures at various points across the contamination event horizon for both the low demand high supply and high supply low demand scenarios. Dashed lines represent the average DALY experienced by the community if the DWF does not implement any countermeasures. Countermeasures are denoted as following; PAC: Powdered Activated Carbon; PACI: Poly-Aluminum Chloride; FSD: Facility Shutdown; and SS: Source Switching.

Alternatively, in the HDLS scenario 10% of the combinations result in a higher DALY impact than no countermeasure scenario, again represented by the dotted horizontal line. These combinations have a higher DALY value due to most of them utilizing PACl as their primary countermeasure, which as we discussed earlier is not as efficient as the others, even when combined. Amongst the trendlines, the application of PACl with PAC has the highest sensitivity to timing, followed by PAC with facility shutdown, while PACl with facility shutdown combination has the lowest sensitivity to timing for similar reasons as explained above.

As shown in these results the use of PAC in combination with other countermeasures increases the sensitivity of the action to timing across the contamination event. This is primarily due to the high treatment efficiency of PAC, as identified in Section 4.2, which is only applicable when the bulk of the contaminate is within the rapid and slow mix tanks. After which the use of PAC has little benefit as the contamination has already passed its operational window.

5. Concluding Remarks

Chemical spills are detrimental events, especially when occurring within the source water of drinking water treatment facilities. This study conducted a public health tradeoff analysis to investigate the benefits to the public health that result from the deployment of a variety of countermeasures under drinking water contamination. Our findings show that the deployment of powdered activated carbon either alone or with facility shutdowns resulting in the lowest direct impact to the community. The results have also underscored the importance of having a quick

response time as earlier countermeasure applications can significantly reduce the cumulative public health impact.

It is important to acknowledge several limitations of this study. While the investigation explored the range of impacts from organic chemical spills, further research examining spill durations and locations across different water sources - both surface and groundwater - could provide valuable insights. Furthermore, all chemicals investigated in this study were assumed to have a direct correlation to TOC trends, which may overestimate the actual pollutant removals. Although the study focused on countermeasures recommended by the drinking water facility (DWF), additional countermeasures exist and warrant further investigation to assess their public health tradeoffs comprehensively. Along with additional countermeasures, varying public responses and adjustments in water usage patterns could also provide valuable insights into optimizing emergency response strategies and minimizing public health risks effectively. The present study can also be expanded to include additional source water and community demand settings to understand how these parameters influence the efficacy of countermeasures in reducing impacts.

Despite these limitations, our findings highlight the importance of early detection and early action. If alerted promptly, the DWF can enact most countermeasures and effectively avoid the majority of public health impacts experienced by their community. However, if a significant delay occurs, it may be imperative that drinking water authorities prepare by implementing multiple countermeasures such as the use of PAC with either source switching or facility shutdown to reduce public health impacts.

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510

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