Quantitative microbial risk assessment for drinking water intake threat prioritization

A comparison of vulnerability and threat assessment according to source water protection regulations of two Canadian provinces

Taghipour, Milad; Sylvestre, Émile; Shakibaeinia, Ahmad; Tolouei, Samira; Kammoun, Raja; Prévost, Michèle; Dorner, Sarah

DOI
10.1016/j.envc.2025.101193

Publication date
2025

Document Version
Final published version

Published in
Environmental Challenges

Environmental Challenges 20 (2025) 101193

Contents lists available at ScienceDirect

Environmental Challenges

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

Quantitative microbial risk assessment for drinking water intake threat prioritization: a comparison of vulnerability and threat assessment according to source water protection regulations of two Canadian provinces

Milad Taghipour [a,*], Émile Sylvestre [a,b], Ahmad Shakibaeinia [a], Samira Tolouei [a], Raja Kammoun [a], Michèle Prévost [a], Sarah Dorner [a]

[a] *Civil, Geological and Mining Engineering, Polytechnique Montréal, C.P.6079, Station Centre-ville, Montréal, Québec H3C 3A7, Canada*
[b] *Sanitary Engineering, Delft University of Technology, Stevinweg 1, 2628CN Delft, the Netherlands*

ARTICLE INFO

Keywords:
Source water protection
Hydrodynamic model
Fate and transport model
CSO
Event-based QMRA
Log-removal requirements

ABSTRACT

Source Water Protection in Canada is regulated primarily by provincial governments, leading to a variety of approaches for characterizing threats to drinking water. This paper compares the key elements of vulnerability and threat assessments for microbial contaminants for two Canadian provinces. Drinking water intakes of two municipalities in Quebec and Ontario, Canada, located on opposite sides of a large transboundary river impacted by Combined Sewer Overflow (CSO) discharges were used as a case study to evaluate the two provincial approaches. Québec's vulnerability classification for microbial contaminants is data driven based on regulatory monitoring (concentrations of *Escherichia coli*) at the drinking water intake) while that of Ontario's is model driven and dependent on the physical and hydraulic characteristics of zones around an intake. To establish a quantitative criterion to compare these two threat assessment frameworks, the impacts of a series of CSO events upstream of the drinking water intakes were simulated using a calibrated hydrodynamic and water quality model. Corresponding enteric pathogen concentrations in the intakes were estimated and used as input for Quantitative Microbial Risk Assessment (QMRA) to calculate treatment requirement levels to meet human health targets. Unlike Ontario's threat assessment approach, Quebec's approach provides an opportunity to investigate the effectiveness of risk reduction strategies such as an adjustment of the frequency of CSO events or corrective actions to improve treatment. Considering the influence of CSO events on log removal requirements to remain compliant with human health targets permitted the differentiation of CSO risk levels for threat prioritization.

1. Introduction

Surface waters, commonly used as sources of drinking water, face contamination from various sources including agricultural activities (livestock waste, and runoff from pastureland), and urban discharges (sewage effluents, Combined Sewer Overflows (CSOs), urban surface runoff and stormwaters) (Alegbeleye and Sant'Ana, 2020; Bertels et al., 2023; Dorner et al., 2004; Edge et al., 2012; Ferguson et al., 2003; Gerba and Smith, 2005; Kammoun et al., 2023b; Kammoun et al., 2023a; Zan et al., 2023). These sources can introduce pathogens like bacteria, protozoa, and viruses, posing a risk to the quality of drinking water (Cabral, 2010; Jung et al., 2014; Krewski et al., 2004; Kristanti et al., 2022; World Health Organization (WHO), 2016). Recognizing the global importance of public health concerns associated with the microbiological quality of drinking water sources (Bourli et al., 2023), governments and water authorities have implemented targeted measures, including risk evaluation and management strategies, to address these issues (NSCEP, 2005; WHO, 2017a). The adoption of Water Safety Plans (WSPs) to ensure the quality of drinking water sources, using a multi-barrier approach consisting of policies, activities and plans to prevent/control contamination from source to tap, is recommended by the World Health Organization (WHO), and is now widespread, with nearly 93 countries implementing them (WHO, 2017b; WHO, 2009a). Early adopters like Australia, Iceland, and New Zealand have integrated the WSP programs into their national legislative frameworks (Schmiege et al., 2020). The European Union has also embedded a risk-based approach to WSP in the revised European Directive 2020/2184 on the quality of water intended for human consumption (Dettori et al., 2022).

* Corresponding author.
E-mail address: milad.taghipour@polymtl.ca (M. Taghipour).

https://doi.org/10.1016/j.envc.2025.101193
Received 23 October 2024; Received in revised form 23 May 2025; Accepted 25 May 2025
Available online 26 May 2025

However, Canada's experience with WSP implementation remains limited (Baum and Bartram, 2018).

Source Water Protection (SWP) within WSPs, commonly known as the first barrier, focuses on maintaining the quality of raw water before it undergoes treatment for drinking purposes (Hrudey et al., 2003). Multiple international studies, encompassing both developing and developed countries, have highlighted the issue of wet weather events leading to microbial contamination peaks in surface water sources, potentially raising public health concerns (Farnham et al., 2017; Jalliffier-Verne et al., 2015; Ma et al., 2024; Madoux-Humery et al., 2013; Mailhot et al., 2015; Owolabi et al., 2022; Perry et al., 2023; Wang et al., 2023). However, QMRA studies of well operated drinking water treatment plants have shown no increase in microbial risks during wet weather events emphasizing the importance of treatment barriers for microbial risk reduction (Sylvestre et al., 2021a; Sylvestre et al., 2021b). International regulations regarding the assessment of vulnerability and associated risks pertaining to wet weather events reveals a reliance on predominantly qualitative studies as risk matrices, occasionally supplemented with quantitative analyses, yet often overlooking the short-term impacts of discharge events (Kammoun, 2023; Kammoun et al., 2023a; Prévost et al., 2017). While these regulations typically rely on long-term data collection, recent research has emphasized the significance of evaluating short-term risks caused by peak concentrations using Quantitative Microbial Risk Assessment (QMRA) (De Man et al., 2014; Schijven et al., 2014; Sylvestre et al., 2021a). Moreover, the WHO introduced risk-based sampling, employing QMRA methodologies to comprehend the underlying risk of these short events (WHO, 2017a).

QMRA is an effective tool to investigate risk of waterborne disease and has been widely used for drinking surface water supplies (Dunn et al., 2014; Owens et al., 2020; Petterson et al., 2015; Sokolova et al., 2015; Xiao et al., 2013). While peak event concentrations at drinking water intakes can be accounted for through development of statistical models using long term routine monitoring *of E. coli* (Sylvestre et al., 2018), lack of proper and representative concentration measurements during the peak period encourages application of process-based models to overcome the challenges of continuous monitoring and water quality measurements. Studies have demonstrated successful integration of hydrodynamic and surface water quality models with QMRA in both recreational water use (Eregno et al., 2016) and drinking surface water supplies (Sokolova et al., 2015; Tolouei et al., 2019).

Canada is among the countries facing critical and recurring challenges regarding the CSOs due to events like snow melting and intense rainfall that trigger them (Botturi et al., 2020). Notably, responsibility for managing drinking water, including SWP plans and policies in Canada, primarily lies on local municipalities and provincial authorities or ministries, while the federal government has comparatively limited water-related responsibilities (Cook et al., 2013). Without an enforceable national framework for SWP, there is a range of provincial legislation and strategies leading to different mechanisms for water governance with each aiming to maintain raw water quality for drinking water production (Prévost et al., 2017). The challenge arising from this discrepancy in provincial legislation is the inability to assess CSO risks using uniform methods, despite the same risk sources potentially posing threats to different drinking water intakes across provincial boundaries. This issue of transboundary pollution is addressed at both the national level in Canada and in other international cases (Grover and Krantzberg, 2014; Seilkassymova et al., 2021; Uitto and Duda, 2003).

Understanding the differences in vulnerability assessments of drinking water intakes under varying regulatory frameworks is crucial in the context of transboundary water resources. These insights are key to defining effective management strategies that minimize conflicts and ensure equitable benefits for all stakeholders sharing the resources (Theodore, 2017). Such an approach is vital not only for addressing challenges with Canada but also for informing best practices in other international cases of shared water governance.

Variations in provincial frameworks for assessing the vulnerability of drinking water intakes illustrate the challenges of establishing consistent approaches to water resource management across jurisdictions. In Ontario (Government of Ontario, 2019), vulnerability assessments focus on delineating areas surrounding drinking water intakes that are susceptible to contamination based on their physical and hydrodynamic conditions, regardless of the type of contamination, as detailed in Section 1 of the supplementary material (SM). Each vulnerable area is assigned a vulnerability score from 1 to 10, where higher scores indicate higher vulnerability (Table S2). This scoring system is used to evaluate the threat risk within an Intake Protection Zone (IPZ), emphasizing the vulnerability of the surrounding area rather than the intake itself. Quebec, on the other hand, evaluates intake vulnerability by directly analyzing water quality at the intake, focusing specifically on microorganism (*E. coli*) concentrations. This approach categorizes vulnerability into three classes: low, medium and high (Table S3).

Another component of the assessment approach following the vulnerability assessment of source waters is the threat assessment (or risk potential analysis) where potential contamination sources or activities are identified and categorized by risk levels. Threat assessment is critical for prioritization and mitigation concerns. Ontario's approach relies on recognizing issues within the IPZs that impact water quality and quantity. Activities or conditions worsening these issues are considered threats. In Ontario's approach, a list of 22 specific activities, such as storage, application and discharge of chemicals or pathogenic materials, are deemed threats under regulation 287/07 (Government of Ontario, 2019). Threat level is determined based on vulnerability scores of areas around the intake where the threat is/would be located (Table S4). Ontario's threat assessment is directly dependent on the IPZs' vulnerability and the threat location within those areas. Conversely, Quebec uses a semi-quantitative approach, evaluating threat levels through a risk matrix that combines impact severity of an activity or a condition and its frequency/probability of occurrence (Table S5). Unlike Ontario's threat assessment, Quebec's approach, being independent of the vulnerability assessment, considers the nature of the threat in terms of the magnitude of its negative effects as well as the frequency of the phenomena at intake of drinking water treatment plants. Quebec's framework (Government of Quebec, 2014) provides a more detailed characterization of the threat in the vicinity of the drinking water intakes even though it is based on a qualitative definition of the terms.

The present study addresses the challenges posed by discrepancies in provincial regulatory frameworks for assessing drinking water intakes vulnerability, particularly in transboundary contexts where uniform risk assessments are lacking. To our knowledge, this study is the first to explicitly compare regulatory approaches for the vulnerability assessments of a shared source of drinking water governed by separate regulatory jurisdictions, using a historical data set from the initial period when Quebec first adopted source water protection legislation.

The main objective of this study is to assess the vulnerability of drinking water intakes to microorganisms under two distinct provincial regulations, while also employing QMRA as a complementary tool. This approach evaluates microbial risks posed by CSOs located in transboundary areas within the provinces of Quebec and Ontario. An innovative aspect of this study is also the development of an event-based analysis framework to assess short-term microbial risks to drinking water sources caused by CSOs. This framework integrates these risks into vulnerability and threat assessments, providing quantitative insights into the treatment burden and supporting source water protection decision making. This is particularly critical in contexts where multiple actors are responsible for mitigating threats and providing safe drinking water.

The specific objectives were to: (1) compare the vulnerability to microorganisms of four drinking water treatment plant intakes using Quebec's framework; (2) employ previously calibrated hydrodynamic and water quality model of fate and transport of *E. coli* originating from CSO discharges to simulate the *E. coli* concentrations at downstream intakes of drinking water treatment plant under the influence of individual CSO events, (3) show the application of different approaches to classify the threats associated with CSOs prescribed in Quebec's and Ontario's regulations; and (4) improve SWP practices by developing a novel objective approach for the inclusion of event (CSO)-based QMRA results in the threat assessments.

2. Methods and materials

2.1. Study area

The study area is the part of a large river in the Outaouais region, Canada, dividing Ontario and Quebec. City A is on the river's northern bank in Quebec, and City B is on the southern bank in Ontario. This river serves as the drinking water source for both municipalities, with each having two intakes for their drinking water treatment plants (Fig. 1). Intakes A1 and A2 are on the Quebec side, while B1 and B2 are on the Ontario side. All intakes face water quality concerns due to upstream CSO outfalls and discharge events. Further system details are available in Taghipour (2019). Fig. 1 illustrates CSO outfalls (OA1 to OA6) along the Quebec side. The number of discharge events at OA1 to OA6 for a 5-year period (from 2009 to 2013) (Table 1) served as a simulation reference. This time frame was selected to meet Quebec's regulatory requirements for vulnerability assessment (Government of Quebec, 2014), which requires the use of five years of *E. coli* concentration data to evaluate drinking water intake vulnerability to microbial contamination. These details are further explained in SM (Section 1). While longer records could provide additional insights, the chosen period aligns with objectives of this study and regulatory framework. City A provided the frequency of CSO, event durations, and raw water quality measurements at intakes A1 and A2. Rainfall and snowmelt trigger CSO discharges, with rainfall events typically occurring from May to October and snowmelt-related discharges in March and April.

CSO discharges from the southern bank (City B) of the river were not included in this study because they are located downstream of the drinking water intakes investigated. CSO data from City A were used to evaluate the vulnerability of drinking water intakes while applying and comparing the two distinct regulatory approaches. This limitation further underscores the importance of addressing data-sharing challenges to improve transboundary water resource management and risk management.

Table 1
Observed combined sewer overflow (CSO) discharge frequency (2009 to 2013) from provincial overflow monitoring program (MELCCFP, 2024).

	Cumulative CSO discharge frequency					
Outfall of CSO	2009	2010	2011	2012	2013	5-year-average
OA1	3	0	5	0	22	6
OA2	1	0	0	0	0	1
OA3	11	0	0	0	0	3
OA4	0	0	0	21	35	12
OA5	44	45	43	50	70	51
OA6	7	10	7	12	5	9

2.2. Vulnerability and threat assessment

To examine the difference in vulnerability and threat assessments of drinking water intakes within the transboundary water resources context of this study site (Section 2.1), the studied intakes were evaluated using both Quebec's and Ontario's approaches. A detailed description of these methodologies is provided in Section 1 of the SM.

Under Ontario's approach, vulnerable areas were delineated based on the intake's physical and hydrodynamic characteristics (Table 2). In contrast, to assess microbial contamination vulnerability, fecal coliform and *E. coli* concentrations were analyzed. City A provided fecal coliform and *E. coli* concentration data measured at intakes of City A from 2010 to 2016. Fecal coliforms were primarily monitored from 2010 to 2013, after which weekly *E. coli* measurements were initiated to guide treatment requirements at treatment plants (Government of Quebec, 2014). For periods without direct *E. coli* measurements (2010–2013), concentrations were estimated from fecal coliform measurements using a ratio of 0.75 (Garcia-Armisen and Servais, 2007; Lalancette et al., 2014). This estimation accounted for approximately 47 % of the data at A1 and 45 % at A2. The range of *E. coli* concentrations is shown in Fig. 2.

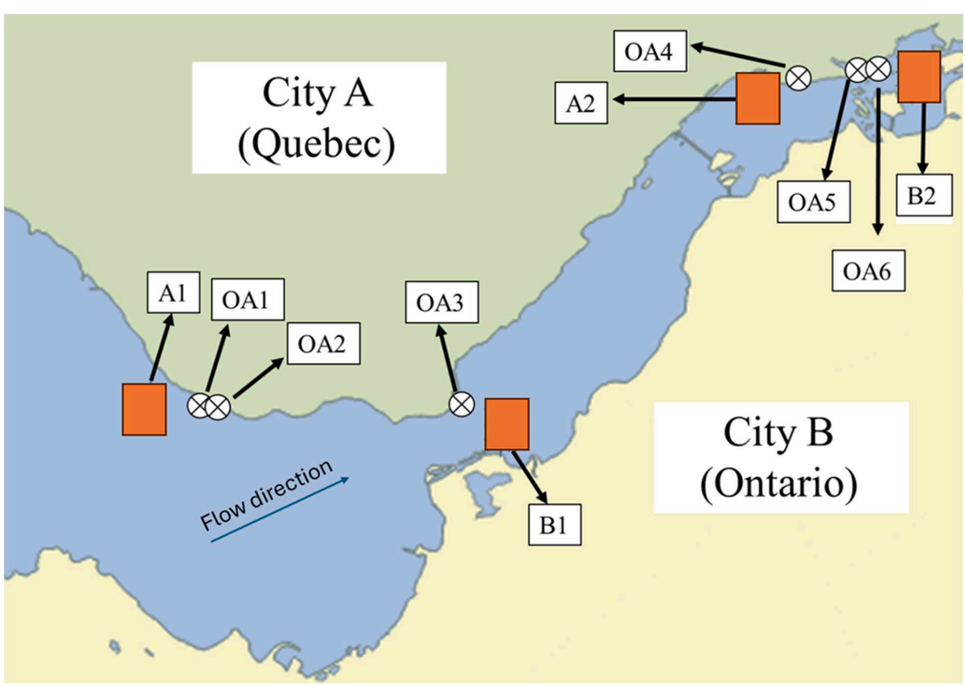

Fig. 1. Schematic representation of the transboundary river case study, showing the location of drinking water intakes (A1, A2, B1, and B2) and combined sewer overflows (CSOs) outfalls.

Table 2
Intake classification and definition of intake protection area proposed in Ontario's (adapted from Government of Ontario (Government of Ontario, 2006)) and Quebec's (adapted from Government of Quebec (Government of Quebec, 2014)) regulatory approaches.

Intake type	Ontario's approach			
	Description	Intake Protection Zone (IPZ)		
		IPZ1	IPZ2	IPZ3
A	Located in a Great Lake	Radius of 1 km around the intake including and (if applicable) 120 m strip of land from high water mark	Extends outward from IPZ1 in water. Based on the travel time of 2 hrs	Extends outward from IPZ2 to include all rivers and tributaries contributing to the intake under the extreme event up to a 100-year return period
B	Located in a connecting channel	1 km-semi circle radius of surface water and land upstream of the intake and 100 m downstream of the intake, modifiable by hydrodynamic conditions		Extends outward from IPZ2 to include all rivers and tributaries contributing to the intake under the extreme event up to a 100-year return period
C	Located in a river, direction and velocity of the flow not impacted by a water structure impoundment	200 m-semi circle radius of surface water and land upstream of the intake and 10 m downstream of the intake, modifiable by hydrodynamic conditions		Extends outward from IPZ2 to include all rivers and tributaries contributing to the intake
D	Other cases not covered as type A, B and C	Radius of 1 km around the intake and (if applicable) 120 m strip of land from high water mark		Extends outward from IPZ2 to include all rivers and tributaries contributing to the intake

Intake type	Quebec's approach			
	Description	Protection areas around the intake		
		Inner	Intermediate	Outer
Lake	Located in a lake	Radius of 300 m around the intake including surface water, tributaries and 10 m strip of land in high water	Radius of 3 km around the intake including surface water, tributaries and 120 m strip of land in high water	Watershed of the intake including surface water tributaries and (where applicable) portion of intermediate area downstream of the intake
Saint Lawrence River	Regions without reversal current (tidal effect)	1 km upstream and 100 m downstream of the intake	15 km upstream and 100 m downstream of the intake	Watershed of the intake including surface water tributaries and portion of intermediate area downstream of the intake
Saint Lawrence River	Regions with reversal current (tidal effect)	2 km upstream of the intake	15 km upstream of the intake	
All other cases	Rivers, stream, etc.	500 m upstream and 50 m downstream of the intake	10 km upstream	

(continued on next page)

Table 2 (*continued*)

Intake type	Quebec's approach			
	Description	Protection areas around the intake		
		Inner	Intermediate	Outer
			and 50 m downstream of the intake	

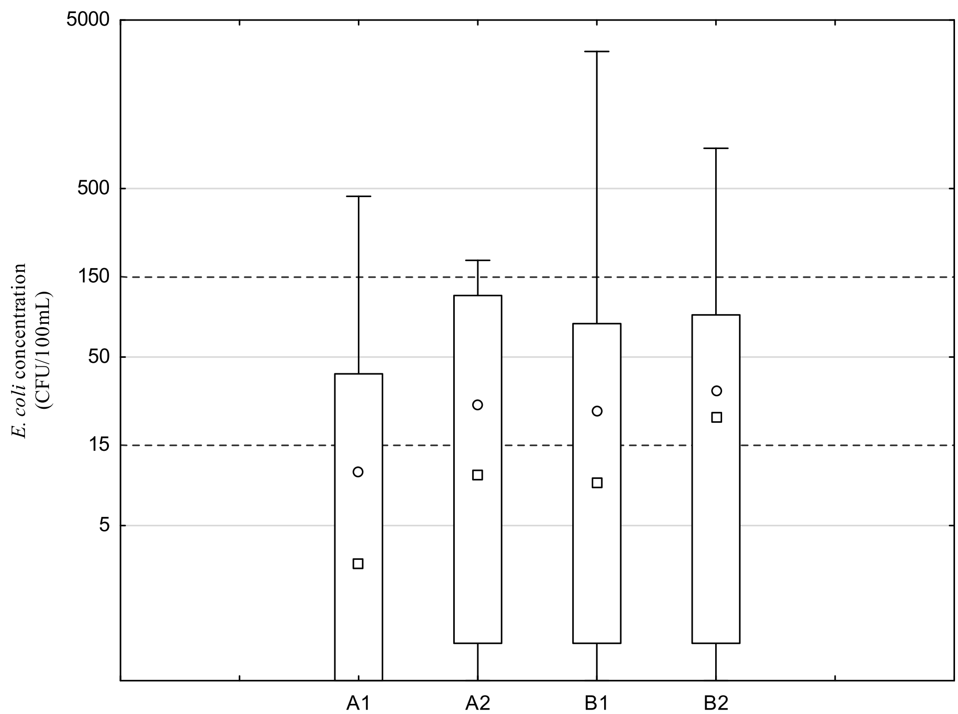

Fig. 2. Ranges of *E. coli* concentrations at the intakes of City A (A1and A2 intakes) and City B (B1 and B2 intakes). Box plots represent 5th and 95th percentile (box), median values (square in the box), mean values (circle in the box) and whiskers show the minimum and maximum concentrations. For City A, data cover the period from 2010 to 2016, with the following number of samples: A1: 333 samples (158 estimated based on the fecal coliform to *E. coli* ratio), A2: 347 samples (157 estimated). For City B, data span from 1999 to 2013, with the following number of samples: B1: 5218 samples, B2: 5223 samples.

City B also provided water quality data including daily measurements of *E. coli* at their two intakes from 1999 to 2013. These results, combined with data from City A, are included in Fig. 2. From the intake farthest upstream (A1) to the most downstream intake (B2), the mean and median *E. coli* concentrations in raw waters increased implying the addition of contamination sources along the river. *E. coli* concentrations varied from 1 to 3 orders of magnitude at the drinking water intakes.

2.3. Quantitative microbial risk assessment (QMRA)

In this study, QMRA was conducted following four key steps: hazard identification, exposure assessment, dose-response assessment, and risk characterization, as illustrated in the conceptual flowchart in Fig. 3. For hazard identification, the study site is located in an urban catchment (Section 2.1), where CSOs represent the primary source of microbial contamination during wet and snowmelt periods. The vulnerability and threat assessment (Section 2.2) indicated a high risk level based on *E. coli* concentrations measured at intakes located upstream of CSO discharge points (Section 3.1).

To evaluate pathogen transport pathways, a hydrodynamic and water quality models were calibrated and validated, as described in Section 2.3.1. These validated models were then used to simulate CSO events, generating estimates of *E. coli* concentrations at drinking water intakes. For exposure assessment, the water quality model outputs, particularly peak *E. coli* concentrations at intakes under different CSO scenarios (Section 2.3.2), were analyzed. The *E. coli* peaks were then converted into pathogen concentrations (*Cryptosporidium* and *Giardia*) to estimate human exposure based on water consumption patterns. The dose-response assessment was conducted using a mathematical model (Section 2.3.3) to evaluate the probability of infection. Finally, in risk characterization, the results from the event (CSO)-based QMR were used to prioritize threats and quantify risks, providing critical information for decision-making, as discussed in Section 3.2.2.

2.3.1. Hydrodynamic and water quality models

This study used a previously calibrated and validated hydrodynamic and water quality model, namely the Mike 21 FM model coupled with the Eco-lab sub-module (Taghipour et al., 2019a), to simulate water flow, fate, and transport of microbial contamination (i.e. *E. coli*) from discharge sources to drinking water intakes within the waterbody. The model numerically solves the incompressible Reynold average Navier-Stokes equations assuming Boussinesq condition and hydrostatic pressure. Continuity, momentum, temperature, salinity, and density equations are included in the model solution. The inputs of Mike 21 FM model were mainly hydrometric data (flow and water level) of the river, bathymetry, shoreline and meteorological data including wind speed and direction, air temperature and relative humidity (DHI, 2017). The hydrodynamic module was first calibrated and validated against

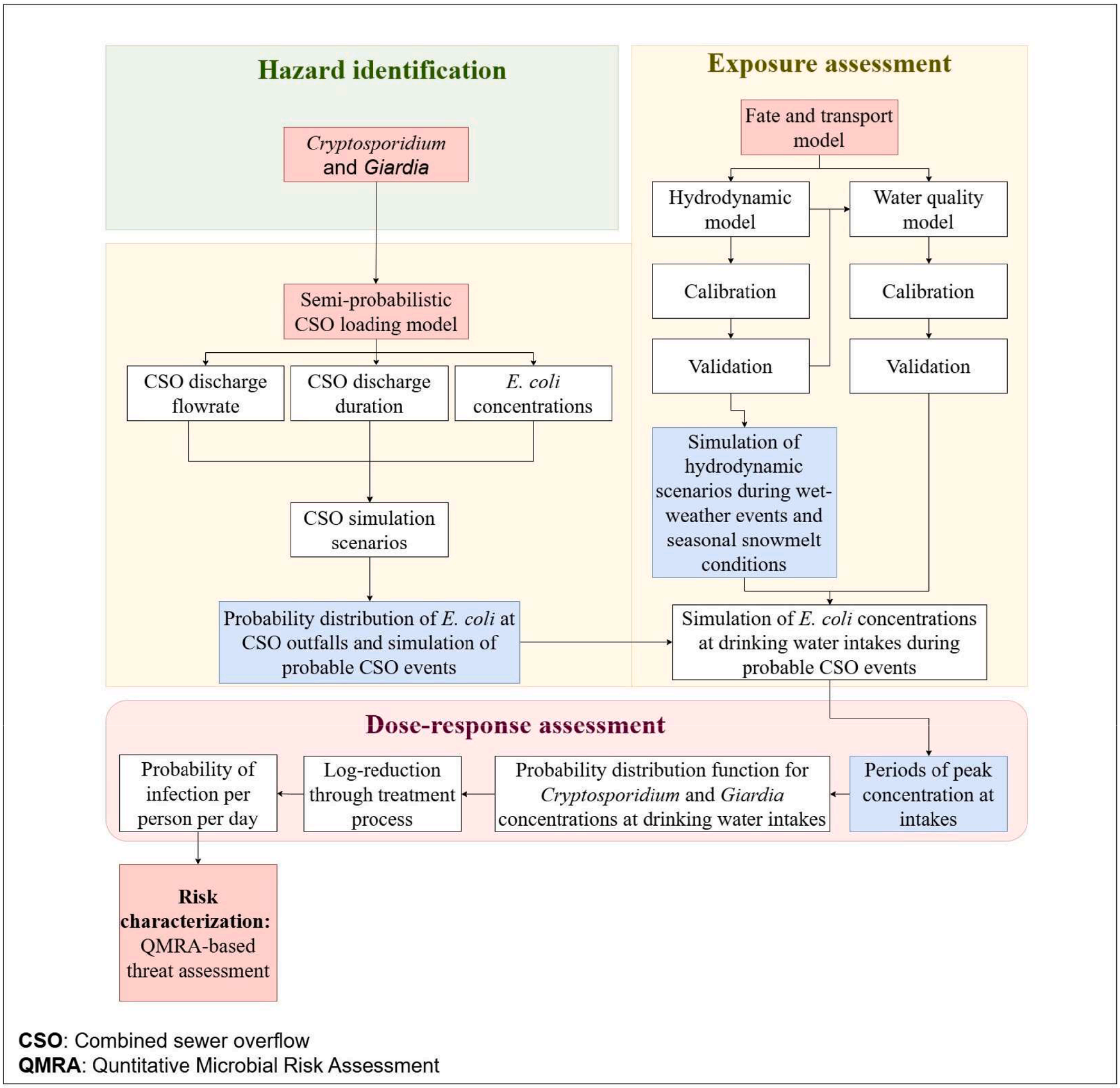

Fig. 3. Conceptual flowchart of Quantitative Microbial Risk Assessment (QMRA) for evaluating CSO-related risks. The QMRA process includes four key steps: hazard identification, exposure assessment, dose-response assessment, and risk characterization.

depth-averaged current velocity. The time step used for the hydrodynamic model simulations was 10 s.

The area defined in the model for simulations included a 20-km distance from upstream to downstream including the drinking water intakes from Quebec and Ontario sides and the CSO outfalls. The model grid configuration was based on flexible triangular mesh with a size ranging from 20 m to 100 m. Two sets of river flow measurements were used in the model setup for calibration (August 2007) and validation (June 2005). The model boundary conditions consisted of river flow (upstream) and water level (downstream) for the two simulation periods. The results showed that the calibrated and validated model provided a sufficiently accurate prediction of the depth-averaged velocity within the river (Taghipour et al., 2019a).

Mike 21 Eco-lab module (DHI, 2017) was used as the water quality model in conjunction with the hydrodynamic model to simulate the fate and transport of *E. coli* within the river. The simulation incorporated velocity field obtained from the hydrodynamic model while accounting for dispersion and first order decay rate as the key mechanisms governing contaminant transport.

To ensure accuracy, the water quality model was calibrated over an 8-day period and validated over a 2-day period by comparing simulated *E. coli* concentrations at the intakes with measured *E. coli* data collected for municipalities (Section 2.2). It was found that water quality model prediction fell well within the range of measurements by setting decay rate and dispersion coefficient as 0.22/d and 1 m^2/s, respectively. A complete description of the model development and the results can be found in Taghipour et al. (2019a), Taghipour et al. (2019b), and Taghipour (2019). With water quality model successfully validated, various CSO overflow scenarios upstream of the intakes were simulated to estimate *E. coli* concentrations at these locations, as detailed in Section 2.3.2.

2.3.2. CSO simulation scenarios

The CSO load model used in this study is based on a stochastic approach developed for the study area (Taghipour et al., 2019b), and integrated into the hydrodynamic and water quality model (Taghipour et al., 2019a). To address the significant variability in CSO discharges and loads, a comprehensive semi-probabilistic CSO loading model was proposed, considering variation in peak discharge flowrate, concentration, and discharge duration. The probabilistic CSO load model involved generating time series of CSO discharges based on the dynamic CSOs behavior regarding overflow and *E. coli* concentrations. This model facilitates consideration of a wide range of CSO discharge conditions, including duration, volume, and peak *E. coli* concentration variability. A more detailed description of the CSO load model can be found in SM, Section 2 and (Taghipour et al., 2019b).

CSO scenarios were developed based on the occurrence of peak discharge and *E. coli* concentrations that could potentially occur at each of six outfalls from March to October, when most discharges are observed because of rainfall and snowmelt events. The scenarios were generated to be representative of the CSOs that could potentially occur by considering the discharge duration, volume of discharge and peak *E. coli* concentration.

A key aspect of the scenario development was the correlation established between measured discharge volume and discharge duration, which was developed specifically for OA5, the most frequent outfall. so that overflow volume could be estimated based on any given discharge duration. A linear correlation was derived to express overflow volume as a function of discharge duration based on available data for OA5. Since a probability distribution function was assigned to discharge duration parameter, this volume-duration correlation was then used to estimate discharge volumes for any given duration at the other CSO locations. Applying this correlation, and using the monthly distribution of discharge period, probability distributions of overflow volume were estimated for each outfall.

To evaluate the scenarios representing peak CSO events, scenarios representing the 90th % value of overflow volume distribution within a relatively short period of time (10th % value from duration distribution) were selected. The scenarios were simulated independently for each CSO outfall to assess their respective impacts on downstream drinking water intakes and to identify which outfalls posed the highest risks. This approach was taken to prioritize CSOs based on their individual contributions to risk at treatment plants. Details of simulated CSO scenarios are provided in Table 3.

Overall, 48 simulations were carried out to explore the potential importance of each of six outfalls for each month from March to October. The impacts of these CSO outfalls on two drinking water intakes were investigated at A2 (in Quebec) and B2 (in Ontario). An important step in scenario development involved characterizing the monthly occurrence and duration of CSO at each outfall individually. To estimate the discharge volume at each outfall, a correlation between discharge volume and event duration that was empirically derived from the OA5 outfall. This correlation was used only to estimate volumes and not to assume that OA5 is representative of other outfalls in terms of frequency, duration, or impact. Each outfall was considered separately based on its own monthly discharge characteristics, which were incorporated in the simulations. The A1 intake was not included in the analysis, as it is not influenced by any CSO outfalls, as shown in Fig.1. However, it may still be affected by microbial contamination from upstream agricultural activities and local wildlife. Although B1 is located downstream of CSO outfalls, simulation results indicated that it is not significantly affected by upstream CSO discharges, whereas A2 and B2 are more vulnerable. Consequently, A1 and B1 intakes were excluded from further discussion.

The most probable river flow for each month was selected to represent typical baseline river conditions during the simulations. The river flow values were estimated based on the daily records of the river flow for each month of simulation (Table S1), ensuring consistency across scenarios. The river's flowrates are driven by regional scale hydrological processes and local flowrates from stormwater are minor in comparison. Monthly background *E. coli* concentrations in the river were selected based on the median *E. coli* concentrations observed at B1 and B2 (Fig. S1, SM), while peak *E. coli* concentrations were calculated based on the 90th percentile of the *E. coli* concentration values. Unlike the A1 and A2 intakes, where *E. coli* monitoring began with weekly sampling, the Ontario intakes (B1 and B2) have been monitored daily for nearly 20 years. This long-term, high-frequency dataset provides a more reliable representation of temporal variations. Therefore, B1 and B2 data were used to establish monthly background *E. coli* level in the river. This approach provides a conservative basis for estimating *E. coli* concentrations and corresponding treatment requirements.

While the chosen flow assumption is appropriate as a baseline for this study, future analyses could benefit from incorporating additional scenarios that reflect higher river flow conditions during both precipitation and snowmelt periods. Scenarios using flow values corresponding to the 75th or 90th percentiles during these periods would better capture the variability introduced by wet-weather events and seasonal snowmelt. Such an approach would provide a more comprehensive understanding of CSO impacts on water quality and treatment requirements by accounting for the full range of hydrological conditions that drive these events.

2.3.3. Exposure and dose-response assessment

2.3.3.1. CSO-based QMRA. The study assessed the impact of CSO discharges on the treatment requirements of the downstream drinking water intakes by analyzing results from simulating the CSO loading scenario using the hydrodynamic and water quality model of the river. The simulation outputs, validated against observed data as described in Section 2.3.1, were used to estimate the treatment requirements to meet health target risk criteria. Various CSO events were simulated, identifying peak *E. coli* concentrations reaching plant intakes.

The probability distribution of the 24-h mean *E. coli* concentrations at A2 and B2, resulting from CSO events at each outfall, was determined. At A2, the 24-h mean *E. coli* concentrations from CSO occurrences at OA1, OA2, and OA3 followed a Gamma distribution. At B2, those from OA1 and OA2 followed a Weibull distribution, while other outfalls (OA3, OA4, OA5, and OA6) adhered to a Gamma distribution. These probability distributions were then converted into *Cryptosporidium* and *Giardia* concentrations for QMRA input using a probability distribution function based on their ratio to *E. coli* in urban drinking water intakes (Sylvestre et al., 2021c). These ratios were selected as they are representative of the study site, derived from a statistical analysis of paired *E. coli* and protozoa (*Cryptosporidium* and *Giardia*) data collected monthly over two years from 27 drinking water intakes supplied by Canadian rivers (Sylvestre et al., 2021c). The *E. coli/Cryptosporidium* and

Table 3
Monthly scenarios for simulated combined sewer overflow (CSO) events.

Month	Extreme Event Scenario (corresponding to Scenario 4 in Taghipour et al. (2019a))				River flow (most probable value) (m^3/s)	Estimated background *E. coli* concentration (CFU/100 mL)
	Volume (m^3)	Duration (h)	Peak Overflow (l/s)	Discharge Peak concentration (CFU/100 mL)		
March	812	1.6	522	1.1E+7	800	6
April	794	0.6	1348	1.1E+7	1416	17
May	481	0.45	1071	1.1E+7	1478	44
June	744	0.64	1173	1.1E+7	996	29
July	447	0.42	1075	1.1E+7	585	24
August	578	0.48	1212	1.1E+7	431	44
September	515	0.48	1062	1.1E+7	620	64
October	609	0.52	1164	1.1E+7	540	87

E. coli/Giardia ratios in source water were modeled as the ratio of two correlated lognormal variables. Protozoa detection was performed by filtering raw water volumes of 10 to 60 iters on-site using an Envirochek HV cartridge (Pall), following U.S. EPA methods 1623 and 1623.1 (Sylvestre et al., 2021c). Enumeration of *Cryptosporidium* oocysts *and Giardia* cysts was conducted according to these same U.S. EPA methods. *E. coli* enumeration was performed using membrane filtration, where samples were passed through a 0.45 μm porosity membrane, placed on a selective agar medium, and incubated at 44.5 °C for 24 h. Colonies were visually identified and counted, with concentrations expressed in CFU per 100 mL. To address non-detects, correlations, and parametric uncertainties, a mixed Poisson model was used. A practical approach for handling non-detects is to assume that each observed count follows a Poisson distribution, with the unknown microbial concentration modeled by a mixture distribution. Given that microbial concentrations in river water often fluctuate across several orders of magnitude, overdispersion relative to the Poisson distribution was anticipated. A mixing distribution was chosen to account for unobserved variability, particularly the temporal variation in concentrations across successive samples. Further details on determination of these ratios can be found in the study by Sylvestre et al. (Sylvestre et al., 2021c).

The selection of *Cryptosporidium* spp. and *Giardia* spp. for QMRA analysis is justified by their significant role in waterborne disease outbreaks, their resistance to treatment, and regulatory requirements for their removal from drinking water sources, as detailed in Section 3 of the SM.

Probability distribution functions of *Cryptosporidium* spp. and *Giardia* spp. concentrations were estimated using the Latin Hypercube Sampling (LHS) method (with 1000 trials). The LHS method avoids sampling repeatedly in the distribution compared to Monte Carlo (Vose, 2008). These converted pathogen concentration probability distribution functions represent a probability of a range of elevated pathogen concentrations at each intake per each outfall because of CSO occurrences. The frequency of CSO occurrences at each outfall was also integrated into the QMRA calculation by considering a 5-year average of occurrences (Table 1) throughout the year. For instance, if outfall OA1 experiences an average of six CSO events per year and outfall OA2 experiences one, the risk contribution from OA1 is considered six times greater than that of OA2, reflecting its higher probability of occurrence. This method was uniformly applied to all outfalls in the study area to account for the relative differences in CSO event frequencies.

Conservative assumptions were applied in establishing the *E. coli* to *Cryptosporidium* and *E. coli* to *Giardia* ratios (Fig. S2). It was assumed that all *Cryptosporidium* and *Giardia* (oo)cysts were infectious and viable (Jung et al., 2014; Ma et al., 2024). It was assumed that the mean analytical recovery rate from 43 matrix spike samples in raw water collected at intakes, which were 0.46 (SD=0.14) for *Cryptosporidium* and 0.50 (SD =0.17) for *Giardia*, as reported by Sylvestre et al. (2021c). However, these assumptions introduce uncertainty to the resulting risk profiles. Differences between *E. coli* and *Cryptosporidium* spp. and *Giardia* spp. with regards to fate and transport characteristics such as persistence and settling also influence their relative abundance (Wu et al., 2011).

2.3.3.2. Log removal requirements. The health target of 1E-06 DALY (per person per year) for drinking water, as described by WHO (2017a), was translated into a corresponding acceptable daily probability of infection ($P_{inf,daily}$) target (i.e. 2.74e-09) (Signor and Ashbolt, 2009). To apply this target in the QMRA framework, following WHO (2017a) recommendations and the approach in Sylvestre et al. (2021c), this was done by first converting the DALY target to an acceptable annual probability of infection using dose-response and disease burden parameters, and then converting it to an acceptable daily probability of infection ($P_{inf,daily}$) assuming independent daily exposures. The relationship used is described in the following equation:

$$\text{DALY} = P_{inf,daily} \text{ x } P_{ill|inf} \text{ x } \textit{Disease Burden Factor} \tag{1}$$

Where: $P_{ill|inf}$ is the probability of illness given infection, and the Disease Burden Facto (in DALYs per case) is based on pathogen-specific values. For *Cryptosporidium*, we used $P_{ill|inf}$= 0.7 and a burden factor of 0.0015 DALY/case. For *Giardia*, $P_{ill|inf}$= 0,4 and a burden factor of 0.0017 DALY per case, as reported in Sylvestre et al. (2021c).

This stricter health-based requirement was selected to estimate daily log reduction target (LRT) needed during pathogen peak periods caused by CSO discharge events, as previously proposed by Sokolova et al. (2015). The LRTs corresponding to the peak concentration of *Cryptosporidium* spp. and *Giardia* spp. were calculated for each CSO outfall at the intakes of A2 and B2 using the QMRA approach outlined in WHO (2017a) and described in the following equation:

$$P_{inf,daily} = 1 - exp^{C \times LRT \times V \times r} \tag{2}$$

Where:

- C is the estimated *Cryptosporidium* spp. or *Giardia* spp. concentration in source water (oocyst/L or cyst/L), with the estimation method detailed in Section 2.3.3.1.
- LRT is the daily log reduction target.
- V is the ingested volume of unboiled drinking water (L), assumed to be 1 L/day per person (WHO, 2017b).
- r is the probability that any single ingested pathogen succeeds in infecting the host. The value of this parameter was assumed to be 0.2 for *Cryptosporidium* WHO (2017a) and 0.0198 for *Giardia* (Regli et al., 1991). As discussed in Sylvestre et al. (2021c), the chosen dose-response model for *Cryptosporidium* aligns with the latest scientific evidence and is consistent with the WHO guidelines for Drinking-water Quality (GDWQ) (WHO 2017a). WHO (2009b) presents an original hierarchical dose-response analysis combining data from four isolates (Iowa, TAMU, UCP, Moredun). The value of 0.2 represents the median of the predictive distribution of the expected value of the single particle infectivity. However, the dose-response relationship remains highly uncertain, particularly at low-dose exposures.
- $P_{inf,\ daily}$ is the probability of infection per person per day.

With estimated potential range of *Cryptosporidium* and *Giardia* at the intakes from each individual threat (CSO occurrence) at A2 and B2, LRTs of *Cryptosporidium* and *Giardia* were calculated. Due to the variable nature of pathogenic contamination and their presence at the source water, the LRT is established based on daily variations of pathogenic concentration. Therefore, the LRT in case of occurrence of each threat (CSO) can be expressed as a function of the probability distribution function of *Cryptosporidium* and *Giardia* at a given intake.

3. Results and discussion

3.1. Comparison of Quebec and Ontario vulnerability and threat assessment

3.1.1. Vulnerability assessment of the intakes (Quebec's approach)

Quebec's vulnerability assessment approach was applied to characterize the drinking water intakes that are stretched along the river with regards to vulnerability to microorganisms (i.e. *E. coli*) using the median or 95th percentile value as classification criteria for vulnerability to microorganisms. The results of the analysis are given in Table 4. Based on Method 1 of Quebec's approach (See Table S3), the vulnerability of intakes A1, A2 and B1 are determined to be low while that of B2 is classified as medium. The median or 95th percentile values of concentration of *E. coli* proposed in Quebec's approach may not be as conclusively representative of the peaks. As *E. coli* distributions can be heavily skewed, the maximum value can be orders of magnitude higher than a

Table 4
Microbial vulnerability analyses at four drinking water intakes in a transboundary source water (Quebec's regulatory approach).

Method	Statistic	Intakes managed by City A		Intakes managed by City B	
		A1	A2	B1	B2
Method 1	Median (CFU/100 mL)	3	10	9	22
	95th % (CFU/100 mL)	40	116	79	89
	Level of vulnerability to microorganisms (Method 1)	Low	Low	Low	Medium
Method 2	Level of vulnerability to microorganisms (Method 2)	High	High	High	High

median and even a 95th percentile. These statistics may not be adequately comprehensive for assessing vulnerability to pathogenic microorganisms. For risk assessment purposes, the arithmetic mean and the maximum concentrations would be more appropriate summary estimates than the median and the 95th percentile (Haas, 1996). Therefore, a good understanding of peak is important to characterize the arithmetic means and maximum. This is even more pronounced in urban rivers where CSO and wastewater discharges have been shown to be the driver of such peaks (Burnet et al., 2019; Haley et al., 2024; Madoux--Humery et al., 2016; Sylvestre et al., 2021a).

In Method 2 of the vulnerability assessment (Table S3), all four intakes are categorized as highly vulnerable to microorganisms, because of the physical location of the intakes in an urban area as well as the presence of the CSO outfalls upstream of each intake located within immediate and intermediate areas. Method 1 and 2 provide different results because of potential urban contaminant contributions, including CSO discharges. Unlike Method 1, Method 2 descriptively highlights the importance of these sources in the vicinity of the intakes.

As previously discussed, Ontario's vulnerability assessment is not related to the intake concentration measurements but is instead applied to delineate the IPZs. The vulnerable IPZs of City B were already available, and the IPZ approach was extended to the A2 intake. The results for area vulnerability factors and source vulnerability factors are presented in Table 5. These results indicate that the area vulnerability factors score range between 7 and 9, reflecting high to very high vulnerability. The area vulnerability was primarily determined based on land use and the extent of land drained by stormwater, as shown in Table S2. The closer a threat is to the intake (from IPZ-3 to IPZ-1), the higher the vulnerability. The results also show that all source vulnerability factors are uniformly very high, with a value of 0.9. This score was determined based on the intrinsic characteristics of the intakes, including their depth from the surface, distance from the riverbank, and the presence or absence of drinking water issues (see Table S2).

These findings, obtained by applying Ontario's approach to vulnerability assessment, demonstrate that this method produces very similar scores in the case of an urbanized environment. Assessing vulnerability without incorporating water quality data appears to be a method that does not effectively support prioritization.

3.1.2. Threat assessment of the intakes (Quebec's and Ontario's approaches)

The frequency of occurrence and severity (loads) of CSO discharges upstream of the A2 and B2 intakes were evaluated using Quebec threat assessment framework. In contrast, Ontario's threat assessment was applied based on vulnerability scores and the identification of threats (CSO outfalls) within the protection zones of both intakes. A comparison of microbial threat assessment results for the A2 and B2 intakes under Quebec and Ontario's regulatory approaches is provided in Table 5.

Three outfalls (i.e. OA1, OA2 and OA3) consisting of threats to A2 are all located within the intermediate zone upstream of the intake. The level of threat to A2's intake was determined to be high for OA2 and very high for OA1 and OA3, primarily due to differences in overflow frequencies. Ontario's approach assesses threat based on their proximity within the IPZs, where closer threats correspond to higher risks. As a result, OA1 and OA2 were classified as moderate threats, while OA3 was defined as a significant threat. In contrast, Quebec's approach considers the historical or potential records (frequency) of overflow events. For example, there is one level of risk difference (i.e. very high to high) between threats OA1 and OA2 because the former is more frequent than the latter (Table 1). However, under Ontario's approach, both are classified at the same threat level.

These findings highlight that Quebec's threat assessment approach, by considering threat characteristics such as frequency and magnitude, provides a more refined basis for comparing and prioritizing mitigation strategies for risk reduction.

The threats for the B2 intake include OA4, OA5 and OA6 in addition to the CSOs affecting the A2 intake. According to Quebec's approach for the B2 intake, OA1, OA3 are still evaluated as very high threat, while OA2 is considered a high threat, despite being located within the outer protection zone of the B2 intake (Table S2). In Quebec's threat assessment approach, both the severity of the activity and the frequency of the event are considered. For example, OA4 and OA5 occur more frequently than OA6; however, all three are classified as very high threats to the B2 intake due to their catastrophic severity. This suggests that risk levels can be reduced by lowering the severity of an activity, not just its frequency. The relative importance of frequency versus severity in determining risk levels vary depending on the threat. A quantitative approach that evaluates both factors would provide comprehensive classification of threats and inform potential mitigation strategies.

According to Ontario's approach, OA1, OA2 and OA3 were classified as moderate threats to B2 with OA3 posing a lower risk compared to A2 due its greater distance from the B2 intake. The differing threat classifications for OA1, OA2 and OA3 illustrate the contrast between Quebec's (threat: high to very high) and Ontario's (threat: moderate) approaches. However, the threat classification for the three downstream CSO outfalls (i.e. OA4, OA5 and OA6) yielded comparable results under both

Table 5
Threat assessment results for A2 (City A) and B2 (City B) drinking water intakes according to Ontario's and Quebec's regulatory approaches.

Intake	Threat (CSO outfall)	Quebec's approach			Ontario's approach			
		Potential risk			Potential risk			
		Severity	Frequency	Risk	Area Vulnerability factor (B)	Source Vulnerability factor (C)	Vulnerability score ($V = B$ X C)	Risk
A2	OA1	Catastrophic	Occasional	**Very high**	IPZ3=7.2	IPZ3= 0.9	6.48	**Moderate**
	OA2	Catastrophic	Rare	**High**	IPZ3=7.2	IPZ3= 0.9	6.48	**Moderate**
	OA3	Catastrophic	Occasional	**Very high**	IPZ2=9	IPZ3= 0.9	8.1	**Significant**
B2	OA1	Catastrophic	Occasional	**Very high**	IPZ3=7	IPZ3= 0.9	6.3	**Moderate**
	OA2	Catastrophic	Rare	**High**	IPZ3=7	IPZ3= 0.9	6.3	**Moderate**
	OA3	Catastrophic	Occasional	**Very high**	IPZ3=8	IPZ3= 0.9	7.2	**Moderate**
	OA4	Catastrophic	Frequent	**Very high**	IPZ2= 9	IPZ2= 0.9	8.1	**Significant**
	OA5	Catastrophic	Frequent	**Very high**	IPZ2= 9	IPZ2= 0.9	8.1	**Significant**
	OA6	Catastrophic	Occasional	**Very high**	IPZ2= 9	IPZ2= 0.9	8.1	**Significant**

provincial frameworks (Quebec: very high, Ontario: significant) due to their proximity to the B2 intake (within the IPZ2).

This demonstrates that qualitative approaches can generate different risk classifications, even for the same source water. Nonetheless, threats located near drinking water intakes are consistently classified as significant or high risk, regardless of the approach used.

3.1.3. Integrating vulnerability and threat assessment approaches for effective source water protection in transboundary contexts

The results presented in Sections 3.1.1 and 3.1.2 highlight that different assessments methodologies can lead to varying risk classifications, with highly urbanized catchments generally exhibiting very high vulnerability and risks. Both Quebec and Ontario's threat assessment approaches rely on delineated protection areas, emphasizing greater vigilance near intakes, where threats could have a more immediate impact. However, both approaches are deterministic and do not explicitly account for uncertainties. As demonstrated by Kammoun et al. (2023a), the point risk levels of the deterministic approach are challenging to compare, as they provide less information and may assign similar ratings to quantitatively distinct risks. Therefore, an effective SWP action plan must identify and prioritize the contamination sources that pose the greatest risk to shared water systems.

The divergence in assessment methodologies underscores the need for a common approach to ensure comparable risk levels for intakes across jurisdictions, especially when contamination source extend beyond provincial or national boundaries. Establishing a collaborative alliance and enhancing intergovernmental cooperation are imperative steps toward advancing integrated water management (Aven, 2019; Aven and Renn, 2019; Kammoun, 2023). Beyond this specific case, participatory governance is essential at a global scale, as transboundary water sources—both surface water and aquifers—require coordinated risk management. Transboundary basins account for 60 % of global river flows, with 145 countries sharing river basins (Pham Do et al., 2012). These figures highlight the importance of developing integrated water resource management systems to prevent conflicts among riparian entities. Several studies emphasize the need for multidisciplinary approaches—encompassing geography, climate, hydrology, environment, socioeconomics, and water quality and quantity—to effectively manage shared water resources (Deribe et al., 2024; Hidayah et al., 2024; Pham Do et al., 2012; Qin et al., 2024; Yasuda and Demydenko, 2024). Examples abound beyond the Canada-United States Great Lakes scenario, extending to Europe, Asia, and other regions grappling with similar challenges.

Travel time calculations based on the river's hydraulics enhance understanding, aiding in effective monitoring, especially during critical periods of the year. The dynamic behavior of microbial contamination is influenced by the flow rate of the receiving water and the volume of wastewater discharged (Winter et al., 2023). Moreover, the transport and fate of microbial contaminants upstream of drinking water intakes varies on a number of factors including currents and riverbank morphology (Ji, 2012; Seo et al., 2016). Given these complexities, the integration of hydrodynamic, water quality modeling with QMRA (See Section 3.2) would enable a more precise and quantitative definition of risk.

A risk-based approach that combines hydrodynamic modeling, water quality assessments, and QMRA would allow decision-makers to move beyond static threat classifications toward adaptive and data-driven source water protection strategies. This approach would help identify CSOs that pose the highest risks to drinking water intakes, facilitating targeted mitigation strategies, such as: installing infrastructure such as retention basins, separating combined sewers to lower the severity of the threat or reducing impervious areas contributing to CSOs using nature-based solutions and blue-green infrastructure (Botturi et al., 2020; Jean et al., 2021; Petrucci et al., 2025; Ryu et al., 2015).

The historical data used in this study was chosen based on the adoption period of Quebec's source water protection regulations, covering a five-year span (see Section 2.1 and 2.2). This period is considered sufficient to capture seasonal variations in water quality, as reported in the review by Burt et al. (2013). The five-year dataset enables assessment of intake vulnerability and provides insight into contamination levels characterizing the study site. However, for a more effective SWP strategy, it is crucial to account for less frequent or extreme events, requiring long-term monitoring.

Urbanization continues to reshape land use patterns, intensifying pollution risks and influencing the vulnerability of drinking water intakes. Long-term water quality data analysis can reveal significant trends and highlight areas of concern for water intake systems. As demonstrated by Gomes and Karunatilaka (2022), long-term monitoring is crucial for identifying vulnerabilities in drinking water supplies, as it allows for a more comprehensive evaluation of urbanization's impact on water resources. Furthermore, monitoring periods exceeding ten years are essential for assessing climate change impacts on water quality (Burt et al., 2013; Robinson et al., 2020). Changing precipitation patterns and an increase in extreme weather events further complicate source water protection efforts (Leveque et al., 2021). Therefore, integrating vulnerability assessment with continuous water quality monitoring represents a potential development to enhance this study, allowing for a more comprehensive assessment of drinking water supply resilience and safety in urban areas.

3.2. QMRA-based threat assessment

3.2.1. Modelled microbial contamination at A2 and B2 intakes

CSO events and their associated *E. coli* loads, fate and transport processes were simulated by integrating the probabilistic CSO load model scenarios into the previously developed hydrodynamic and water quality model of the river. Ranges of simulated *E. coli* concentrations are provided in Table 6. A review of the results indicates that OA1, OA2 and OA3 have a negligible impact on B2 due to the large dilution capacity of the river in month of May when river flow increases because of snowmelt and the spring freshet. Also, simulated *E. coli* concentrations at B2 because of CSO events from OA4, OA5 and OA6 discharges are similar because they are located at a similar distance to the B2 intake.

3.2.2. Log reduction targets (LRTs)

LRTs were determined based on the probability distribution functions of *Cryptosporidium* and *Giardia* concentrations from CSO discharges at the studied intakes (Fig. 4). Depending on the location of the outfalls as well as the average number of CSOs per year, the LRTs had different ranges for both plants, implying different microbiological contributions from the CSOs arriving at the intakes.

At A2, the LRTs required for *Cryptosporidium* to meet the daily health target under CSO impacts from the outfalls OA1, OA2 and OA3 for 50th percentile are 1.4, 0.8 and d 1.3 (respectively). For *Giardia*, the LRTs for 50th percentile of the time are 2.4,1.7 and 2.3 for OA1, OA2 and OA3, respectively. The LRTs for OA1 and OA3 are more stringent than what is required in the case of events from the outfall OA2 for both *Cryptosporidium* and *Giardia*. Although OA1 and OA2 are located close to each other, CSO events at OA1 are 5 times more frequent than for OA2. The difference in CSO frequency is great enough to influence the LRTs associated with OA1 and OA2. The log difference in LRTs for OA1 and OA2 can reach up to 0.7 for both *Cryptosporidium* and *Giardia*. These results are consistent with the results from Quebec's threat assessment for A2 where OA1 and OA3 are the same level of threat (i.e. very high risk) and OA2 as one level lower (i.e. high risk). The simulation results from the hydrodynamic water quality model for CSO-based QMRA demonstrated the CSO discharge frequencies affect LRTs. Including the frequency of threats is beneficial for prioritizing threats as prescribed by Quebec's approach. Simulation results with frequencies of CSOs could potentially inform decisions with regards to sampling campaigns to allocate monitoring resources more efficiently for sources of contamination with a stricter LRT requirement.

Table 6
Simulated *E. coli* concentrations at A2 (City A) and B2 (City B) drinking water intakes as a result of individual CSO discharges.

	Average (and maximum) *E. coli* concentrations from March to October (CFU/100 mL)								
	A2 intake (City A)			B2 intake (City B)					
	OA1	OA2	OA3	OA1	OA2	OA3	OA4	OA5	OA6
March	104 (502)	104 (502)	137 (2491)	30 (75)	30 (75)	21 (192)	12 (132)	12 (132)	12 (132)
April	78 (509)	78 (509)	165 (1680)	23 (40)	23 (40)	39 (91)	18 (47)	18 (47)	18 (47)
May	59 (231)	59 (231)	63 (855)	–	–	–	33 (54)	33 (54)	33 (54)
June	61 (320)	61 (320)	94 (1033)	20 (39)	20 (39)	17 (52)	17 (95)	17 (95)	17 (95)
July	37 (91)	37 (91)	73 (345)	20 (39)	20 (39)	22 (114)	18 (191)	18 (191)	18 (191)
August	39 (50)	39 (50)	80 (192)	34 (51)	34 (51)	41 (132)	37 (302)	37 (302)	37 (302)
September	85 (340)	85 (340)	135 (1214)	49 (99)	49 (99)	50 (206)	45 (243)	45 (243)	45 (243)
October	153 (356)	153 (356)	223 (985)	100 (188)	100 (188)	98 (368)	83 (410)	83 (410)	83 (410)

OA= Combined sewer overflow outfall.

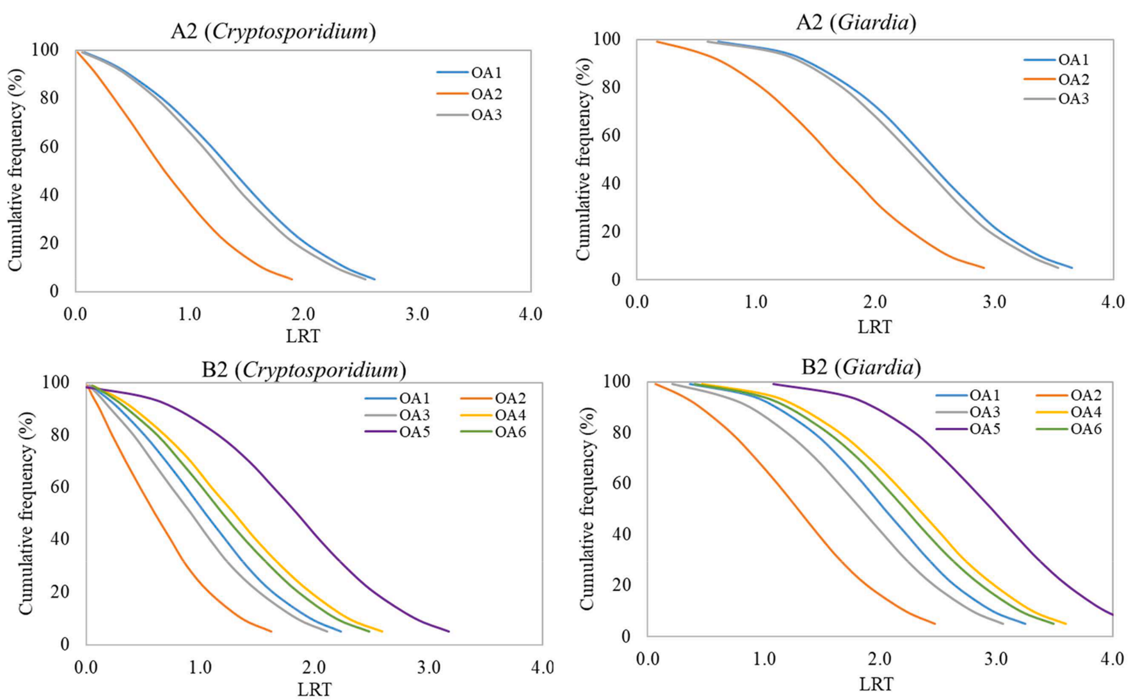

Fig. 4. Log reduction target (LRT) in the drinking water treatment plants considering the impacts of upstream CSO discharges on reaching a daily risk level of 2.7 10ˆ−9 DALY. City A intake: A2 and City B intake: B2.

The B2 intake was under the influence of all six CSO outfalls. Impacts from the OA2 outfall continue to correspond to the lowest LRT requirement. Considering the 50th percentile, the LRTs from all six CSO outfalls range from 0.6 to 1.8 for *Cryptosporidium* and 1.3 to 3.0 for *Giardia*. The overall LRT requirements at B2 from OA1, OA2, OA3, OA4 and OA6 are comparable. The difference in LRT requirements for these CSO outfalls is pertinent to different frequency of occurrences as well as different distances to B2 from the location of the outfalls. However, OA5 requires a relatively higher LRT for both *Cryptosporidium* and *Giardia* due to a higher frequency of occurrence, given that OA4, OA5 and OA6 are roughly in the same vicinity of B2. Considering the 50th percentile, the corresponding LRT related to OA5 events at B2 is 3.0 and 1.8 for *Cryptosporidium* and *Giardia*, respectively.

The log difference in LRTs between the events discharged through OA1 to OA6 can reach up to 1.6 and 1.8 for *Cryptosporidium* and *Giardia*, respectively. The LRT requirements associated with the farthest downstream CSOs (i.e. OA4, OA5 and OA6) are higher than those for upstream CSOs due to the frequency of events and the proximity of these downstream CSOs to the B2 intake. The LRT requirement for the B2 intake resulting from OA5 stands out from other outfalls. However, using the regulatory frameworks, OA5 is classified as the same risk level (See Table 5) as the other threats while the LRT results show that there is a difference of more than 1 log removal requirement. Therefore, the regulatory threat assessments may not sufficiently differentiate among CSO of the same frequency. OA4 and OA5 are both classified as frequent and defined as "very high risk" while their LRTs are different.

The application of an event-based QMRA to prioritize threats with their associated LRTs provides quantitative information in support of current regulatory approaches. Furthermore, this study used the most probable river flows as a baseline for evaluating CSO impacts, which ensured consistency across scenarios. Sensitivity analyses under higher river flow conditions, such as those representing the 75th and 90th percentiles during wet-weather or snowmelt periods, could provide additional insights into the variability of *E. coli*, *Cryptosporidium*, and *Giardia* concentrations. This would help refine treatment plant design and operational strategies under a range of hydrological conditions.

It should be noted that the daily LRT introduced here is not an official regulatory log reduction target. The concept of daily (short term) LRTs should be only treated as an index or criterion to provide supplementary information on the relative importance of different sources of contamination (i.e. CSOs) located upstream of intakes. While a daily health target could be used to account for and compare acute and extreme events (Owens et al., 2020; Sokolova et al., 2015), not all events lead to a significant increase in the mean annual risk (Sylvestre et al., 2021b). Taghipour et al. (2019a) previously showed that the mean annual health target for the studied intakes did not exceed considering the long-term risk of CSO occurrences if a specific LRT was maintained. The uncertainty in the pathogen concentration distributions and CSO characteristics was incorporated in the analysis using Latin Hypercube Sampling (1000 trials). This uncertainty is reflected in the resulting infection probabilities and estimated log reduction targets. The simplified representation of LRT trends in the figure was chosen to enhance interpretability, especially given the high variability in input parameters and the overlap in potential LRT values across different CSOs.

To apply the WHO (WHO, 2009b) model, we assumed all *Cryptosporidium* are *C. parvum*. This assumption is likely conservative, as other *Cryptosporidium* species may have lower human infectivity, as suggested by Burch et al. (2024). However, we believe that using the WHO (WHO, 2009b) model is a conservative and pragmatic approach when data on species distribution in surface waters are unavailable.

LRT derived for an annual infection risk target accounts for cumulative threats over time as well as individual events. Caution is needed with regards to the interpretation of the daily risk or LRT profiles as SWP measures might differ when considering a daily risk versus a mean annual risk. Daily versus mean annual risks become important when comparing contaminant sources that discharge either continuously or intermittently.

In this study, CSOs were analyzed individually to assess their respective impacts on drinking water intakes and identify those posing the highest risks to public health and treatment plant operations. This targeted approach enables precise identification of wastewater volumes and pathogen emissions, improving source water protection by pinpointing contamination hotspots. Pollutant load variations are influenced by the land use characteristics of each urban drainage basin (Kammoun et al., 2023a; Pribak and Siegrist, 2015), and examining individual CSOs provides valuable insights into localized contamination sources. This level of detail facilitates targeted interventions (Petrucci et al., 2025), such as implementing green infrastructure to reduce overflow frequency and contaminant loads in priority areas. However, while analyzing individual CSOs allows for focused mitigation efforts, it does not account for cumulative effects when multiple overflows occur simultaneously due to precipitation or snowmelt events. A cumulative approach offers a broader perspective by capturing the combined impacts of multiple CSO events over time, which is crucial for assessing long-term trends and understanding the effects of global change on fecal contamination in drinking water sources (Jalliffier-Verne et al., 2015; Jalliffier-Verne et al., 2016; Jalliffier-Verne et al., 2017). Simulating the cumulative effects of CSO discharges would provide a more comprehensive understanding of contamination loads and their implications for treatment requirements. It is anticipated that simultaneous CSO events could lead to higher downstream *E. coli* concentrations and stricter LRT requirements.

Further research is needed to integrate both approaches, ensuring a balance between precise source identification and a holistic assessment of cumulative contamination risks. Additionally, future studies should explore how QMRA-based index can be interpreted in terms of robustness (i.e., ability to withstand varying source water conditions without compromising performance) and reliability (i.e., consistency of the performance over time) of the drinking water treatment systems. Investigating these cumulative effects would improve the robustness and reliability of risk-based management strategies and provide additional insights for optimizing source water protection. The choice between individual and cumulative CSO analyses ultimately depends on the specific objectives of the water quality protection framework.

3.3. Integrating event-based QMRA into conventional threat assessment framework

The varying classes of vulnerability or threat levels for assigned to water source, as determined by provincial jurisdiction (Section 3.1), illustrates the fragmented governance of water resources in Canada, as described by Bakker and Cook (2011). Improving threat assessment by integrating LRTs facilitates the prioritization of threats and the corresponding mitigation strategies. Ontario employs a qualitative approach, while Quebec uses a semi-quantitative one. QMRA offers a robust framework for quantifying the impact of both the magnitude and frequency of threats, particularly when combined with LRTs, providing a more comprehensive classification of the events. Although the objectives were related to comparing and prioritizing threats, the QMRA approach could be also extended to evaluate cumulative threats.

QMRA can provide justification for allocation of resources to risk control measures (Bichai and Smeets, 2013). Although other risk assessment approaches can also justify investments in improvements, QMRA can provide a more precise evaluation, making it particularly useful for supporting significant investments decision. However, an important consideration is the availability of a hydrodynamic model for the source water and a first-pass prioritization of CSOs. Although pathogens will remain a priority for drinking water treatment, many other sources of contamination exist.

The proposed approach can improve source water threat assessments across both provinces and over time. However, its results are inherently dependent on the quality and availability of microbiological data, as well as the accessibility and uncertainties in hydrodynamic and water quality models. Those factors represent the primary limitation of applying QMRA to estimate drinking water treatment requirements for event-based discharges, as discussed in Section 2.3.3.

Uncertainty in the inputs to QMRA models—such as microbial concentrations, treatment efficiency, and environmental conditions—can substantially affect the outputs and risk estimates (de Brito Cruz et al., 2024; Hamilton et al., 2024). Variations in treatment efficiency and pathogen concentrations, particularly during extreme events like heavy precipitation, introduce additional uncertainty. Thus, normalized sensitivity analyses are essential for identifying the factors that influence model predictions. In this study, we leveraged our prior experience with sensitivity analyses in river systems and QMRA (Dorner et al., 2006; Jalliffier-Verne, 2015; Jalliffier-Verne et al., 2017; Jalliffier-Verne et al., 2016; Leveque, 2020; Sylvestre, 2020; Sylvestre et al., 2021b; Sylvestre et al., 2018). For systems with relatively short travel times and strong flow rates, models are predominantly driven by 1) the discharged load and 2) parameters that influence the flow toward the intakes (Brookes et al., 2004; Dorner et al., 2006). Factors such as pathogen inactivation in the water column are of lesser importance. In QMRA, risk estimates are particularly sensitive to dose-response relationships. While *E. coli* serves as an indicator of overall water quality, it is not a reliable predictor of specific pathogen concentrations or health risks. Its presence does not always correlate with harmful pathogens due to differences in environmental persistence, dilution effects, and microbial morphology (Harwood et al., 2014; Payment and Locas, 2011; Skiendzielewski et al., 2024). Extrapolating *E. coli* concentrations to estimate pathogen levels can therefore introduce uncertainty. To improve the accuracy of health risk assessment and minimize uncertainty, we quantified the relationship between *E. coli* and *Cryptosporidium* or *Giardia* using paired microbial data collected from source water at 27 drinking water intakes within a similar watershed, as detailed in Section 2.3.3. Site-specific *E. coli/Cryptosporidium* and *E. coli/Giardia* ratios were estimated by modeling the relationship between two correlated lognormal variables. This approach accounted for non-detects, microbial correlations, and parametric uncertainties (Sylvestre et al., 2021c). Clearly communicating these uncertainties is essential to ensure that QMRA results are appropriately interpreted for policy development and resource allocation.

4. Conclusions

This research compares SWP strategies currently applied in two Canadian provinces, Quebec and Ontario. The developed hydrodynamic and water quality model of the river coupled with QMRA was used as a complementary tool to prioritize threats to drinking water intakes. QMRA was conducted to quantify the potential impacts of threats in terms of treatment requirements and is being suggested as a supplementary component to SWP strategies. The following conclusions can be drawn:

- Given that vulnerability assessments are the drivers of actions to protect drinking water sources, there are notable differences in the approaches of Quebec and Ontario. Both approaches have been in effect with the goal of evaluating drinking water sources to guide actions and policies to ensure that drinking water sources do not degrade over time and that public investments in drinking water treatment infrastructure are sustainable in the long term.
- The vulnerability and threat assessments proposed in Quebec and Ontario's regulations yield different vulnerability and threat classes even for the same source of drinking water. Ontario's regulations prioritize the intake's position relative to threats, while Quebec's approach focuses more on regulatory monitoring at the intake. These differences emphasize the potential benefits of adopting a unified framework for intakes in shared jurisdictions. When two cities share the same river but apply different approaches to prioritize risks, the resulting mitigation measures may be suboptimal, as threats originating in one jurisdiction may not be adequately addressed by the other. For instance, out-of-province threats may remain unmitigated due to a lack of jurisdiction or coordination between provinces. Developing a unified framework would enable the integration of risk assessments, ensuring consistency and facilitating effective prioritization of threats across jurisdictions. Proposed measures to address these challenges include harmonizing data collection, mapping vulnerabilities and threats from one system to another, and establishing collaborative mechanisms for prioritization and mitigation.
- A comprehensive threat classification should be based on a more quantitative approach as current practice of threat classification or prioritization do not comprehensively characterize threats based on measurable criteria where the role of frequency and severity of the threat could be evaluated or even quantified for potential mitigation strategies in reducing the risk based on adjusting the frequency of a threat or its severity.
- Event-based QMRA can enhance our understanding of the role of the magnitude and frequency of occurrence of the subject source of microbial and provide quantitative criteria for threat classification strategies. Event-based QMRA can be a reliable and informative tool to be included in conventional threat assessment practices conducted worldwide.
- LRT requirement as a part of event-based analysis showed that treatment requirements of threats could be one order of magnitude different while belonging to the similar class of threats in terms of frequency and severity according to the conventional threat classification. This can be considered as an example where current classification of threats could potentially fail to quantitatively characterize and distinguish the importance of threats to sources of drinking water, making it more difficult for decision-makers to identify and prioritize corrective actions.
- Threat classification based on the frequency, magnitude and the corresponding treatment requirements can potentially provide a platform where threats are not only characterized in terms of a quantitative criterion (i.e. LRT), but also the associated risk can be reduced with drinking water treatment.

CRediT authorship contribution statement

Milad Taghipour: Writing – original draft, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Émile Sylvestre:** Writing – review & editing, Validation, Methodology, Investigation. **Ahmad Shakibaeinia:** Validation, Supervision. **Samira Tolouei:** Methodology, Data curation. **Raja Kammoun:** Writing – review & editing, Resources. **Michèle Prévost:** Writing – review & editing, Validation, Supervision. **Sarah Dorner:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work supported was by Canadian Water Network and Canada Research Chair on Source Water Protection. The authors thankfully acknowledge the help of the staff of the municipalities involved in this project for providing technical assistance as well data support.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.envc.2025.101193.

Data availability

The authors do not have permission to share data.

References

Alegbeleye, O.O., Sant'Ana, A.S., 2020. Manure-borne pathogens as an important source of water contamination: an update on the dynamics of pathogen survival/transport as well as practical risk mitigation strategies. Int. J. Hyg. Env. Health 227, 113524. https://doi.org/10.1016/j.ijheh.2020.113524.

Aven, T., 2019. Fundamental principles of risk management and governance: review of recent advances. Jpn. J. Risk Anal. 29 (1), 3–10. https://doi.org/10.11447/sraj.29.3.

Aven, T., Renn, O., 2019. Some foundational issues related to risk governance and different types of risks. J. Risk Res. 23 (9), 1121–1134. https://doi.org/10.1080/13669877.2019.1569099.

Bakker, K., Cook, C., 2011. Water governance in Canada: innovation and fragmentation. Int. J. Water Resour. Dev. 27 (2), 275–289. https://doi.org/10.1080/07900627.2011.564969.

Baum, R., Bartram, J., 2018. A systematic literature review of the enabling environment elements to improve implementation of water safety plans in high-income countries. J. Water Health 16 (1), 14–24. https://doi.org/10.2166/wh.2017.175.

Bertels, D., De Meester, J., Dirckx, G., Willems, P., 2023. Estimation of the impact of combined sewer overflows on surface water quality in a sparsely monitored area. Water Res. 244, 120498. https://doi.org/10.1016/j.watres.2023.120498.

Bichai, F., Smeets, P.W., 2013. Using QMRA-based regulation as a water quality management tool in the water security challenge: experience from The Netherlands and Australia. Water Res. 47 (20), 7315–7326. https://doi.org/10.1016/j.watres.2013.09.062.

Botturi, A., Ozbayram, E.G., Tondera, K., Gilbert, N.I., et al., 2020. Combined sewer overflows: a critical review on best practice and innovative solutions to mitigate impacts on environment and human health. Crit. Rev. Env. Sci. Technol. 51 (15), 1585–1618. https://doi.org/10.1080/10643389.2020.1757957.

Bourli, P., Eslahi, A.V., Tzoraki, O., Karanis, P., 2023. Waterborne transmission of protozoan parasites: a review of worldwide outbreaks - an update 2017-2022. J. Water Health 21 (10), 1421–1447. https://doi.org/10.2166/wh.2023.094.

Brookes, J.D., Antenucci, J., Hipsey, M., Burch, M.D., et al., 2004. Fate and transport of pathogens in lakes and reservoirs. Env. Int. 30 (5), 741–759. https://doi.org/10.1016/j.envint.2003.11.006.

Burch, T.R., Stokdyk, J.P., Firnstahl, A.D., Opelt, S.A., et al., 2024. Quantitative microbial risk assessment with microbial source tracking for mixed fecal sources contaminating recreational river waters, Iowa, USA. ACS ES&T Water 4 (7), 2789–2802. https://doi.org/10.1021/acsestwater.3c00652.

Burnet, J.-B., Sylvestre, E., Jalbert, J., Imbeault, S., et al., 2019. Tracking the contribution of multiple raw and treated wastewater discharges at an urban drinking water supply using near real-time monitoring of beta-d-glucuronidase activity. Water Res. 164, 114869. https://doi.org/10.1016/j.watres.2019.114869.

Burt, T.P., Howden, N.J.K., Worrall, F., 2013. On the importance of very long-term water quality records. WIREs Water 1 (1), 41–48. https://doi.org/10.1002/wat2.1001.

Cabral, J.P., 2010. Water microbiology. Bacterial pathogens and water. Int. J. Env. Res. Public Health 7 (10), 3657–3703. https://doi.org/10.3390/ijerph7103657.

Cook, C., Prystajecky, N., Ngueng Feze, I., Joly, Y., et al., 2013. A comparison of the regulatory frameworks governing microbial testing of drinking water in three Canadian provinces. Can. Water Resour. J. 38 (3), 185–195. https://doi.org/10.1080/07011784.2013.822186.

de Brito Cruz, D., Schmidt, P.J., Emelko, M.B., 2024. Drinking water QMRA and decision-making: sensitivity of risk to common independence assumptions about model inputs. Water Res. 259, 121877. https://doi.org/10.1016/j.watres.2024.121877.

De Man, H., Van den Berg, H.H., Leenen, E.J., Schijven, J.F., et al., 2014. Quantitative assessment of infection risk from exposure to waterborne pathogens in urban floodwater. Water Res. 48, 90–99. https://doi.org/10.1016/j.watres.2013.09.022.

Deribe, M.M., Melesse, A.M., Kidanewold, B.B., Dinar, S., et al., 2024. Assessing international transboundary water management practices to extract contextual lessons for the Nile river Basin. Water 16 (14), 1960. https://doi.org/10.3390/w16141960.

Dettori, M., Arghittu, A., Deiana, G., Castiglia, P., et al., 2022. The revised European Directive 2020/2184 on the quality of water intended for human consumption. A step forward in risk assessment, consumer safety and informative communication. Env. Res. 209, 112773. https://doi.org/10.1016/j.envres.2022.112773.

DHI, *MIKE 21 & MIKE 3 Flow Model FM Hydrodynamic and Transport Module - Scientific Documentation.* 2017: Denmark. p. 64.

Dorner, S.M., Anderson, W.B., Slawson, R.M., Kouwen, N., et al., 2006. Hydrologic modeling of pathogen fate and transport. Env., Sci. Technol. 40 (15), 4746–4753. https://doi.org/10.1021/es060426z.

Dorner, S.M., Huck, P.M., Slawson, R.M., 2004. Estimating potential environmental loadings of Cryptosporidium spp. and Campylobacter spp. from livestock in the Grand River Watershed, Ontario, Canada. Env. Sci. Technol. 38 (12), 3370–3380. https://doi.org/10.1021/es035208+.

Dunn, G., Harris, L., Cook, C., Prystajecky, N., 2014. A comparative analysis of current microbial water quality risk assessment and management practices in British Columbia and Ontario, Canada. Sci. Total Env. 468-469, 544–552. https://doi.org/10.1016/j.scitotenv.2013.08.004.

Edge, T.A., El-Shaarawi, A., Gannon, V., Jokinen, C., et al., 2012. Investigation of an *Escherichia coli* environmental benchmark for waterborne pathogens in agricultural watersheds in Canada. J. Env. Qual. 41 (1), 21–30. https://doi.org/10.2134/jeq2010.0253.

Eregno, F.E., Tryland, I., Tjomsland, T., Myrmel, M., et al., 2016. Quantitative microbial risk assessment combined with hydrodynamic modelling to estimate the public health risk associated with bathing after rainfall events. Sci. Total Env. 548–549, 270–279. https://doi.org/10.1016/j.scitotenv.2016.01.034.

Farnham, D.J., Gibson, R.A., Hsueh, D.Y., McGillis, W.R., et al., 2017. Citizen science-based water quality monitoring: constructing a large database to characterize the impacts of combined sewer overflow in New York City. Sci. Total Env. 580, 168–177. https://doi.org/10.1016/j.scitotenv.2016.11.116.

Ferguson, C., Husman, A.M.d.R., Altavilla, N., Deere, D., et al., 2003. Fate and transport of surface water pathogens in watersheds. Crit. Rev. Env. Sci. Technol. 33 (3), 299–361. https://doi.org/10.1080/10643380390814497.

Garcia-Armisen, T., Servais, P., 2007. Respective contributions of point and non-point sources of *E. coli* and enterococci in a large urbanized watershed (the Seine river, France). J. Env. Manag. 82 (4), 512–518. https://doi.org/10.1016/j.jenvman.2006.01.011.

Gerba, C.P., Smith, J.E., 2005. Sources of pathogenic microorganisms and their fate during land application of wastes. J. Env. Qual. 34 (1), 42–48. https://doi.org/10.2134/jeq2005.0042a.

Gomes, P.I.A., Karunatilaka, P.D., 2022. Investigation of long-term river water quality variations using different urbanization indices and assessment of common scientific perspectives of urbanization on water quality. Environ. Qual. Manag. 32 (3), 239–249. https://doi.org/10.1002/tqem.21900.

Government of Ontario, *Clean Water Act.* 2006: Ontario, Canada.

Government of Ontario, 2019. Source Protection Committees- Ontario Regulation 288/07- Clean Water Act, 2006. Ontario, Canada, p. 8.

Government of Quebec, 2014. Water Withdrawal and Protection Regulation. Quebec, Canada, p. 56.

Grover, V.I., Krantzberg, G., 2014. Transboundary water management: lessons learnt from North America. Water Int. 40 (1), 183–198. https://doi.org/10.1080/02508060.2014.984962.

Haas, C.N., 1996. How to average microbial densities to characterize risk. Water Res. 30 (4), 1036–1038. https://doi.org/10.1016/0043-1354(95)00228-6.

Haley, B.M., Sun, Y., Jagai, J.S., Leibler, J.H., et al., 2024. Association between combined sewer overflow events and gastrointestinal illness in Massachusetts municipalities with and without river-sourced drinking water, 2014–2019. Env. Health Perspect. 132 (5), 57008. https://doi.org/10.1289/EHP14213.

Hamilton, K.A., Ciol Harrison, J., Mitchell, J., Weir, M., et al., 2024. Research gaps and priorities for quantitative microbial risk assessment (QMRA). Risk Anal 44 (11), 2521–2536. https://doi.org/10.1111/risa.14318.

Harwood, V.J., Staley, C., Badgley, B.D., Borges, K., et al., 2014. Microbial source tracking markers for detection of fecal contamination in environmental waters: relationships between pathogens and human health outcomes. FEMS Microbiol. Rev. 38 (1), 1–40. https://doi.org/10.1111/1574-6976.12031.

Hidayah, E., Wiyono, R.U.A., Widiarti, W.Y., Indarto, I., et al., 2024. Literature review on optimization of transboundary water for irrigation. Water Supply 24 (12), 3979–4008. https://doi.org/10.2166/ws.2024.247.

Hrudey, S.E., Payment, P., Huck, P.M., Gillham, R.W., et al., 2003. A fatal waterborne disease epidemic in Walkerton, Ontario: comparison with other waterborne outbreaks in the developed world. Water Sci. Technol. 47 (3), 7–14.

Jalliffier-Verne, I., 2015. Débordements D'égouts Unitaires Et Protection Des Sources D'eau potable: intégration des Changements Globaux. Université de Montréal, p. 215.

Jalliffier-Verne, I., Heniche, M., Madoux-Humery, A.S., Galarneau, M., et al., 2016. Cumulative effects of fecal contamination from combined sewer overflows: management for source water protection. J. Env. Manag. 174, 62–70. https://doi.org/10.1016/j.jenvman.2016.03.002.

Jalliffier-Verne, I., Leconte, R., Huaringa-Alvarez, U., Heniche, M., et al., 2017. Modelling the impacts of global change on concentrations of *Escherichia coli* in an urban river. Adv. Water Resour. 108, 450–460. https://doi.org/10.1016/j.advwatres.2016.10.001.

Jalliffier-Verne, I., Leconte, R., Huaringa-Alvarez, U., Madoux-Humery, A.-S., et al., 2015. Impacts of global change on the concentrations and dilution of combined sewer overflows in a drinking water source. Sci. Total Environ. 508 (0), 462–476. https://doi.org/10.1016/j.scitotenv.2014.11.059.

Jean, M.È., Morin, C., Duchesne, S., Pelletier, G., et al., 2021. Optimization of real-time control with green and gray infrastructure design for a cost-effective mitigation of combined sewer overflows. Water Resour. Res. 57 (12). https://doi.org/10.1029/2021wr030282.

Ji, Z.-G., 2012. River fate and transport. In: Meyers, R.A. (Ed.), Encyclopedia of Sustainability Science and Technology. Springer New York, New York, NY, pp. 9049–9062.

Jung, A.V., Le Cann, P., Roig, B., Thomas, O., et al., 2014. Microbial contamination detection in water resources: interest of current optical methods, trends and needs in the context of climate change. Int. J. Env. Res. Public Health 11 (4), 4292–4310. https://doi.org/10.3390/ijerph110404292.

Kammoun, R., 2023. Évaluation des risques avec des approches déterministe et probabiliste: apports et limites dans la protection des sources d'eau de surface au Québec. Département Des Génies civil, Géologique Et Des Mines. Polytechnique Montréal, Québec, Canada, p. 341.

Kammoun, R., McQuaid, N., Lessard, V., Goitom, E.A., et al., 2023b. Risk assessment of drinking water intake contamination from agricultural activities using a Bayesian network. PLOS Water 2 (7), e0000073. https://doi.org/10.1371/journal.pwat.0000073.

Kammoun, R., McQuaid, N., Lessard, V., Prévost, M., et al., 2023a. Comparative study of deterministic and probabilistic assessments of microbial risk associated with combined sewer overflows upstream of drinking water intakes. Environ. Chall. 12, 100735. https://doi.org/10.1016/j.envc.2023.100735.

Krewski, D., Balbus, J., Butler-Jones, D., Haas, C., et al., 2004. Managing the microbiological risks of drinking water. J. Toxicol. Env. Health A 67 (20–22), 1591–1617. https://doi.org/10.1080/15287390490491909.

Kristanti, R.A., Hadibarata, T., Syafrudin, M., Yılmaz, M., et al., 2022. Microbiological contaminants in drinking water: current status and challenges. Water Air Soil Pollut. 233 (8), 299. https://doi.org/10.1007/s11270-022-05698-3.

Lalancette, C., Papineau, I., Payment, P., Dorner, S., et al., 2014. Changes in *Escherichia coli* to Cryptosporidium ratios for various fecal pollution sources and drinking water intakes. Water Res. 55, 150–161. https://doi.org/10.1016/j.watres.2014.01.050.

Leveque, B., 2020. Analyse Des Vulnérabilités Des Prises D'eau Potable De La Rivière Des Mille-Îles (Québec) Aux étiages estivaux En Contexte De Changements Globaux Par Une Approche Ascendante. Polytechnique Montréal, Montréal, p. 234.

Leveque, B., Burnet, J.B., Dorner, S., Bichai, F., 2021. Impact of climate change on the vulnerability of drinking water intakes in a northern region. Sustain. Cities Soc. 66, 102656. https://doi.org/10.1016/j.scs.2020.102656.

Ma, S., Zayed, T., Xing, J., Shao, Y., 2024. A state-of-the-art review for the prediction of overflow in urban sewer systems. J. Clean Prod. 434, 139923. https://doi.org/10.1016/j.jclepro.2023.139923.

Madoux-Humery, A.S., Dorner, S., Sauve, S., Aboulfadl, K., et al., 2013. Temporal variability of combined sewer overflow contaminants: evaluation of wastewater micropollutants as tracers of fecal contamination. Water Res. 47 (13), 4370–4382. https://doi.org/10.1016/j.watres.2013.04.030.

Madoux-Humery, A.-S., Dorner, S., Sauvé, S., Aboulfadl, K., et al., 2016. The effects of combined sewer overflow events on riverine sources of drinking water. Water Res. 92, 218–227. https://doi.org/10.1016/j.watres.2015.12.033.

Mailhot, A., Talbot, G., Lavallée, B., 2015. Relationships between rainfall and Combined Sewer Overflow (CSO) occurrences. J. Hydrol. 523, 602–609. https://doi.org/10.1016/j.jhydrol.2015.01.063.

MELCCFP, Suivi des ouvrages municipaux d'assainissement des eaux usées (OMAEU): station d'épuration et ouvrages de surverse, d.l.E.e.d.l.L.c.l.c.c. Ministère du Développement durable, Direction générale des politiques de l'eau., Eds.. 2024: Québec, Canada.

Owens, C.E.L., Angles, M.L., Cox, P.T., Byleveld, P.M., et al., 2020. Implementation of quantitative microbial risk assessment (QMRA) for public drinking water supplies: systematic review. Water Res. 174, 115614. https://doi.org/10.1016/j.watres.2020.115614.

Owolabi, T.A., Mohandes, S.R., Zayed, T., 2022. Investigating the impact of sewer overflow on the environment: a comprehensive literature review paper. J. Env. Manag. 301, 113810. https://doi.org/10.1016/j.jenvman.2021.113810.

Payment, P., Locas, A., 2011. Pathogens in water: value and limits of correlation with microbial indicators. Ground Water 49 (1), 4–11. https://doi.org/10.1111/j.1745-6584.2010.00710.x.

Perry, W.B., Ahmadian, R., Munday, M., Jones, O., et al., 2023. Addressing the challenges of combined sewer overflows. Env. Pollut. 343, 123225. https://doi.org/10.1016/j.envpol.2023.123225.

Petrucci, J., Jalbert, J., Dorner, S., McQuaid, N., et al., 2025. Strategic prioritization of sewersheds to mitigate combined sewer overflows under climate change. Environ. Chall. 18, 101088. https://doi.org/10.1016/j.envc.2025.101088.

Petterson, S., Roser, D., Deere, D., 2015. Characterizing the concentration of Cryptosporidium in Australian surface waters for setting health-based targets for drinking water treatment. J. Water Health 13 (3), 879–896. https://doi.org/10.2166/wh.2015.282.

Pham Do, K.H., Dinar, A., McKinney, D., 2012. Transboundary water management: can issue linkage help mitigate externalities? Int. Game Theory Rev. 14 (01), 1250002. https://doi.org/10.1142/s0219198912500028.

Prévost, M., Madoux-Humery, A.-S., Dorner, S., 2017. Protection Measures for Surface Water Withdrawals for Human consumption: Protection Areas and Source Vulnerability - Literature Review (Mesures De Protection Des Prélèvements D'eau De Surface Effectués à Des Fins De Consommation Humaine: Aires De Protection Et Vulnérabilité Des sources- Revue bibliographique). Polytechnique Montréal, Québec, p. 101.

Pribak, M., Siegrist, J., 2015. A simplified approach to pollutant load modeling. J. Water Manag. Model. https://doi.org/10.14796/jwmm.C387.

Qin, J., Fu, X., Wu, X., Wang, J., et al., 2024. Transboundary water allocation under water scarcity based on an asymmetric power index approach with bankruptcy theory. Water 16 (19), 2828. https://doi.org/10.3390/w16192828.

Regli, S., Rose, J.B., Haas, C.N., Gerba, C.P., 1991. Modeling the risk from giardia and viruses in drinking water. J. (Am. Water Works Assoc.) 83 (11), 76–84.

Robinson, B., Cohen, J.S., Herman, J.D., 2020. Detecting early warning signals of long-term water supply vulnerability using machine learning. Environ. Model. Softw. 131, 104781. https://doi.org/10.1016/j.envsoft.2020.104781.

Ryu, J., Baek, H., Lee, G., Kim, T.-H., et al., 2015. Optimal planning of decentralised storage tanks to reduce combined sewer overflow spills using particle swarm optimisation. Urban Water J. 14 (2), 202–211. https://doi.org/10.1080/1573062x.2015.1086004.

Schijven, J., Farnleitner, A., Derx, J., and Blaschke, A., *QMRAcatch – a user-Friendly computational tool for microbial quality simulations of fresh water including risk assessment*. 2014.

Schmiege, D., Evers, M., Zugner, V., Rickert, B., 2020. Comparing the German enabling environment for nationwide Water Safety Plan implementation with international experiences: are we still thinking big or already scaling up? Int. J. Hyg. Env. Health 228, 113553. https://doi.org/10.1016/j.ijheh.2020.113553.

Seilkassymova, R., Urazymbetov, T., Zhunispayeva, A., Kopbassarova, G., et al., 2021. Environmental problems of international legal regulation of transboundary pollution. J. Environ. Manag. Tour. 12 (2), 392. https://doi.org/10.14505//jemt.v12.2(50).08.

Seo, I.W., Choi, H.J., Kim, Y.D., Han, E.J., 2016. Analysis of two-dimensional mixing in natural streams based on transient tracer tests. J. Hydraul. Eng. 142 (8). https://doi.org/10.1061/(asce)hy.1943-7900.0001118.

Signor, R.S., Ashbolt, N.J., 2009. Comparing probabilistic microbial risk assessments for drinking water against daily rather than annualised infection probability targets. J. Water Health 7 (4), 535–543. https://doi.org/10.2166/wh.2009.101.

Skiendzielewski, K., Burch, T., Stokdyk, J., McGinnis, S., et al., 2024. Two risk assessments: evaluating the use of indicator HF183 Bacteroides versus pathogen measurements for modelling recreational illness risks in an urban watershed. Water Res. 259, 121852. https://doi.org/10.1016/j.watres.2024.121852.

Sokolova, E., Petterson, S.R., Dienus, O., Nystrom, F., et al., 2015. Microbial risk assessment of drinking water based on hydrodynamic modelling of pathogen concentrations in source water. Sci. Total Env. 526, 177–186. https://doi.org/10.1016/j.scitotenv.2015.04.040.

Sylvestre, É., 2020. Systematic assessment of microbial risks associated with hydrometeorological events for drinking water safety management. Département Des Génies civil, Géologique Et Des Mines. Polytechnique Montréal, Quebec, p. 245.

Sylvestre, E., Burnet, J.-B., Prévost, M., Cantin, P., Robert, C., Villion, M., Dorner, S., 2018. Using quantitative microbial risk assessment to evaluate treatment requirements at 26 drinking water systems. In: Water Microbiology Conference. University of North Carolina.

Sylvestre, E., Dorner, S., Burnet, J.B., Smeets, P., et al., 2021c. Changes in *Escherichia coli* to enteric protozoa ratios in rivers: implications for risk-based assessment of drinking water treatment requirements. Water Res. 205, 117707. https://doi.org/10.1016/j.watres.2021.117707.

Sylvestre, E., Prevost, M., Burnet, J.B., Pang, X., et al., 2021a. Demonstrating the reduction of enteric viruses by drinking water treatment during snowmelt episodes in urban areas. Water Res. X 11, 100091. https://doi.org/10.1016/j.wroa.2021.100091.

Sylvestre, E., Prevost, M., Burnet, J.B., Smeets, P., et al., 2021b. Using surrogate data to assess risks associated with microbial peak events in source water at drinking water treatment plants. Water Res. 200, 117296. https://doi.org/10.1016/j.watres.2021.117296.

Taghipour, M., 2019. Characterization of CSO microbial contamination and their risks to drinking water sources. CGM. Polytechnique Montréal: Quebec, p. 230.

Taghipour, M., Shakibaeinia, A., Sylvestre, E., Tolouei, S., et al., 2019a. Microbial risk associated with CSOs upstream of drinking water sources in a transboundary river using hydrodynamic and water quality modeling. Sci. Total Env. 683, 547–558. https://doi.org/10.1016/j.scitotenv.2019.05.130.

Taghipour, M., Tolouei, S., Autixier, L., Prevost, M., et al., 2019b. Normalized dynamic behavior of combined sewer overflow discharges for source water characterization and management. J. Env. Manag. 249, 109386. https://doi.org/10.1016/j.jenvman.2019.109386.

Theodore, O., 2017. Management of transboundary natural resources. J. Law Confl. Resolut. 9 (4), 42–52. https://doi.org/10.5897/jlcr2016.0266.

Tolouei, S., Dewey, R., Snodgrass, W.J., Edge, T.A., et al., 2019. Assessing microbial risk through event-based pathogen loading and hydrodynamic modelling. Sci. Total Env. 693, 133567. https://doi.org/10.1016/j.scitotenv.2019.07.373.

Uitto, J.I., Duda, A.M., 2003. Management of transboundary water resources: lessons from international cooperation for conflict prevention. Geogr. J. 168 (4), 365–378. https://doi.org/10.1111/j.0016-7398.2002.00062.x.

USEPA, N.S.C.f.E.P. (NSCEP), 2005. Economic Analysis for the Final Long Term 2 Enhanced Surface Water Treatment Rule. United States Environmental Protection Agency: United States, p. 319.

Vose, D., 2008. Risk analysis: a Quantitative Guide. John Wiley & Sons.

Wang, T., Zhang, Y., Li, H., Xu, Z., et al., 2023. Policies on combined sewer overflows pollution control: a global perspective to inspire China and less developed countries. Crit. Rev. Env. Sci. Technol. 54, 1–20. https://doi.org/10.1080/10643389.2023.2286956.

WHO, 2009b. Risk Assessment of Cryptosporidium in Drinking Water. Public Health and Environment Water, Sanitation, Hygiene & Health, p. 143.

WHO, 2009a. Water safety plan manual: step-by-step risk management for drinking-water suppliers. Available from: http://apps.who.int/iris/bitstream/handle/10665/75141/9789241562638_eng.pdf;jsessionid=5F1375DBFE309F380F53E635B035FE27?sequence=1.

WHO, *Global status report on water safety plans: a review of proactive risk assessment and risk management practives to ensure the safety of drinking-water*. 2017b.

WHO, 2017a. Guidelines for Drinking-Water Quality,4th edition, Incorporating the 1st Addendum. Radiation and health (RAD), Water, Sanitation, Hygiene and Health (WSH), p. 631.

Winter, H.V., van Keeken, O.A., Kleissen, F., Foekema, E.M., 2023. Wastewater plumes can act as non-physical barriers for migrating silver eel. PLoS One 18 (6), e0287189. https://doi.org/10.1371/journal.pone.0287189.

World Health Organization (WHO), 2016. Protecting Surface Water for Health. Identifying, Assessing and Managing Drinking-Water Quality Risks in Surface-Water Catchments. Geneva, p. 178.

Wu, J., Long, S.C., Das, D., Dorner, S.M., 2011. Are microbial indicators and pathogens correlated? A statistical analysis of 40 years of research. J. Water Health 9 (2), 265–278. https://doi.org/10.2166/wh.2011.117.

Xiao, G., Qiu, Z., Qi, J., Chen, J.A., et al., 2013. Occurrence and potential health risk of Cryptosporidium and Giardia in the three Gorges Reservoir, China. Water Res. 47 (7), 2431–2445. https://doi.org/10.1016/j.watres.2013.02.019.

Yasuda, Y., Demydenko, Y., 2024. Enhancing transboundary freshwater security: from online learning to global knowledge exchange platform. Water 16 (7), 976. https://doi.org/10.3390/w16070976.

Zan, R., Blackburn, A., Plaimart, J., Acharya, K., et al., 2023. Environmental DNA clarifies impacts of combined sewer overflows on the bacteriology of an urban river and resulting risks to public health. Sci. Total Env. 889, 164282. https://doi.org/10.1016/j.scitotenv.2023.164282.