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POLYTECHNIQUE MONTRÉAL

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Characterization of CSO microbial contamination and their risks to drinking water sources

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Département de génies civil, géologique et des mines

Thèse présentée en vue de l'obtention du diplôme de *Philosophiae Doctor*

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Characterization of CSO microbial contamination and their risks to drinking water sources

présentée par **Milad TAGHIPOUR**

en vue de l'obtention du diplôme de *Philosophiae Doctor*

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DEDICATION

To my beloved parents and my love, Aram

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RÉSUMÉ

Les débordements d’égouts unitaires (DEU) sont reconnus comme l'une des principales causes de dégradation de la qualité de l'eau de surface, en particulier des sources d’approvisionnement en eau potable. Lorsque les DEU, des rejets combinés d’eaux usées non traitées et d’eaux pluviales, se produisent dans les sources d’eau potable, ceux-ci peuvent momentanément augmenter les charges de contamination microbienne à l’eau brute des usines de production d’eau potable. Les concentrations de micro-organismes doivent être évaluées afin d’assurer une réduction adéquate des concentrations acceptables à l’eau potable. Le risque microbien estimé à partir de concentrations mesurées à l’eau brute peut être sous-estimé si les évènements de pointes de contamination reliés aux DEU ne sont pas mesurés parce que la fréquence d’échantillonnage est trop faible. L’impact de la contamination microbienne des DEU aux usines de production d’eau potable est influencé par les charges déversées en amont de la prise d’eau potable et les processus de transport de la contamination dans le cours d’eau. En raison de la forte variabilité inter et intra-évènement des DEU, la caractérisation de la dynamique des quantités déversées est une tâche difficile. Une des limitations des modèles actuels d’estimation des charges de DEU est que ceux-ci ne représentent pas la variabilité des paramètres lors de la simulation de conditions potentielles de DEU ou qu’ils sont trop complexes pour être appliqués simultanément à un grand nombre de DEU en amont des prises d’eau potable. Puisqu’une des exigences en protection des sources d’eau est d’assurer la protection de la santé publique, l’évaluation de la contamination microbienne aux prises d’eau potable doit inclure l’apport des DEU pour l’estimation des risques microbiens à court terme (c.-à-d., journalier) et à long terme (c.-à-d., annuel).

Les principaux objectifs de ce projet étaient de développer un modèle d’estimation des charges de DEU ne tenant pas seulement compte de la variabilité des déversements de DEU selon le débit et la concentration de manière probabiliste, mais aussi ajustable au modèle de déversement de DEU à différents niveaux. Le modèle est conçu afin d’être utilisé pour quantifier le risque microbien aux usines de production d’eau potable en aval de DEU. Cette approche peut être intégrée aux analyses de vulnérabilité et de menaces aux prises d’eau potable par l’utilisation d’un modèle d’hydrodynamique et de qualité de l’eau combiné à un modèle d’analyse quantitative du risque microbien (AQRM). Une rivière située le long de la frontière provinciale entre le Québec et l’Ontario a été choisie pour l’étude de cas. Cette rivière reçoit des rejets de DEU du côté du Québec. En aval de ces rejets, deux municipalités de chacune des provinces ont des usines de production

d'eau potable s'approvisionnant dans cette rivière. Cette étude de cas permet également d'étudier la manière dont les deux règlementations provinciales abordent la gestion du risque microbien lors d'évènement de contamination. Pour atteindre ces buts, l'approche de recherche a été structurée en trois étapes : (1) développement d'un modèle d'estimation des charges de DEU, 2) développement d'un modèle du devenir et du transport de la contamination pour une rivière influencée par des rejets de DEU, 3) intégration des résultats de simulation comme paramètres d'entrée dans un modèle AQRM, 4) introduire une approche AQRM axée sur les DEU.

Durant la première étape, la dynamique des rejets lors d'évènements de DEU (données obtenues dans la littérature) a été étudiée et les principales caractéristiques des DEU (c.-à-d., débit et matière en suspension totale (MES), *Escherichia coli* (*E. coli*), caféine (CAF) et acétaminophène (ACE)) ont été déterminées. En utilisant des valeurs normalisées pour les paramètres reliés à l'échelle (c.-à-d., débit, concentration et durée des rejets), il a été montré que les pointes de débit surviennent régulièrement à l'intérieur de 2^{e} décile de la durée des rejets avec une croissance linéaire et une décroissance logarithmique avant et après la pointe de débit, respectivement. Le 1er décile de la période de rejet correspond aux périodes de pointe de concentration de MES, *E. coli*, CAF et ACE. En faisant la description des tendances de débit normalisé à l'aide d'un modèle déterministe et des concentrations normalisées à partir de distributions de probabilité, un modèle semi-probabiliste axé sur les paramètres normalisés a été développé. Le modèle d'estimation des charges de DEU proposé permet de représenter une gamme de valeurs de charges probables par rapport à la valeur de la charge de pointe pour toutes les portions de la durée du rejet. Les résultats du pire scénario de charge ont montré que le 2^{e} décile représentait potentiellement la période avec les plus fortes charges de MES, d'*E. coli* et de CAF, même si les concentrations de pointe étaient principalement reliées au 1er décile. Le temps restant au-delà du 2^{e} décile ne correspond généralement pas à la période de pointe de la charge, mais les charges restent importantes durant les évènements lorsque l'effet cumulatif des rejets de DEU est considéré. Les paramètres de sortie du modèle semi-probabiliste d'estimation des charges peuvent être utilisés comme paramètres d'entrée d'un modèle d'hydrodynamique et de qualité de l'eau en ajustant les paramètres reliés à l'échelle d'un évènement de DEU.

Lors de la deuxième étape, un modèle d'hydrodynamique et de qualité de l'eau (*E. coli*) de la rivière a été développé afin d'étudier l'impact microbien des DEU aux prises d'eau potable en aval des points de rejet. À la suite de la calibration et la validation du modèle de la rivière, des séries de différents scénarios de DEU axés sur le modèle probabiliste (c.-à-d., variabilité intra-évènement) et la caractérisation mensuelle des rejets de DEU locaux (c.-à-d., variabilité inter-évènement) de mars à octobre ont été générées en tenant compte d'une gamme d'évènements probables. La simulation des scénarios a permis d'obtenir une gamme de pointes de concentration d'*E. coli* causées par des évènements de DEU sous forme de fonction de distribution de probabilité qui pourrait potentiellement survenir aux prises d'eau potable. Un modèle AQRM a ensuite été utilisé lors de la troisième étape en utilisant les résultats de simulation reliant les concentrations d'*E. coli* aux concentrations de *Cryptosporidium* à partir d'une distribution de probabilité des ratios historiques.

Le risque microbien journalier a été quantifié pour deux conditions de traitement (3 log et 4 log) à deux usines de production d'eau potable. Le risque à court-terme causé par les DEU a été incorporé au risque moyen annuel afin d'étudier comment chaque évènement peut influencer le profil de risque annuel. Les résultats indiquent que le maintient d'une efficacité de réduction de 4 log à l'usine est suffisante pour atteindre l'objectif relié à la santé publique pour différentes gammes d'évènement de DEU. Toutefois, l'objectif relié à la santé publique est seulement atteint la moitié du temps lorsque la réduction est abaissée de 4 à 3 log. Il a également été déterminé que le profil de risque était essentiellement fonction du niveau de traitement et de la moyenne de la concentration microbienne à l'eau brute. Il est possible de conclure que les DEU peuvent être importants pour les risques à court terme, mais que pour caractériser le risque annuel, il était important de réduire l'incertitude sur la concentration moyenne des contaminants microbiens.

À la dernière étape de cette recherche, deux différents programmes de protection des sources d'eau utilisés pour encadrer les analyses de vulnérabilité et de menaces au Québec et en Ontario ont été comparés et appliqués dans la région étudiée. Le modèle AQMR axé sur les DEU a été utilisé pour évaluer le niveau de traitement nécessaire à l'usine de production d'eau potable pour un évènement de DEU (comme menace) tout en respectant un objectif relié à la santé publique spécifique. Les résultats indiquent que la classification conventionnelle des menaces proposée par les deux provinces ne dépend pas des exigences de traitement pour une menace donnée. Cependant, l'approche québécoise montre une ouverture pour intégrer le traitement dans les analyses de vulnérabilité, mais la méthodologie n'est pas explicite.

Globalement, ce projet de recherche a permis de caractériser les débits en temps de pluie des DEU de la source jusqu'au risque microbien à l'eau potable. Les résultats de cette étude peuvent être utilisé par des gestionnaires d'eau potable afin de concevoir de meilleures stratégies d'échantillonnage permettant de caractériser les pointes de concentration aux usines de production d'eau potable. Les résultats pourraient être utilisés par les municipalités comme un outil permettant d'évaluer différentes alternatives de mitigation comme la réduction de la fréquence des DEU comparativement à une amélioration de l'efficacité des procédés de traitement.

ABSTRACT

Combined sewer overflows (CSOs) have been recognized as one of the major causes of surface water quality impairment, particularly drinking water supplies. Occurrence of CSOs as a discharge of an untreated mixture of wastewater effluents and stormwater into waterbodies upstream of drinking water sources may potentially deliver high amounts of fecal loads to downstream intakes, causing periods of elevated concentrations. The CSO-induced peak periods at the intakes must be characterized with regards to the level of microorganisms during these periods while treatment processes in drinking water treatment plants must effectively reduce concentrations by the required amounts. Microbial risk estimates based on concentration measurements may fail to include the peak events associated to discharge events due to the insufficiently frequent raw water quality sampling procedures. Microbiological-related impacts of CSOs at drinking water intakes are influenced by upstream loading conditions and transport process to the point of intakes. Given high inter and intra-event variability of CSO discharges, identifying their dynamic behavior and the corresponding loading characteristics remains a challenging task. Of the shortcomings of existing CSO load models, is that they do not reflect the variability of the event parameters to project a range of probable CSO loading conditions, instead of fixed loading estimates in course of events, or are too detailed to apply for the large numbers of CSOs upstream of intakes. As one of the requirements in source water protection for safeguarding source waters and public health, assessment of drinking water intakes with regards to microbial contamination should address the CSO microbiological contributions in terms of short-term (i.e. daily) and long-term (i.e. annual) risks.

The main objectives of this project were to develop a CSO loading model that not only takes into account the variability of CSO discharges in terms of flowrate and concentration in a deterministic-probabilistic manner but is scale-adjustable to model CSO discharges of different scales. The model is to be used to quantify the CSO associated microbial risk of drinking water supplies with upstream CSOs. This approach can be incorporated into drinking water intakes' vulnerability and threat assessment through application of a hydrodynamic and water quality model combined with Quantitate microbial Risk Assessment (QMRA). A river located along the Quebec-Ontario provincial boundary line was considered as the case study. The river receives CSO discharges from the Quebec side, downstream of which two municipalities from two provinces use the river water for their drinking water treatment plants. This case study also provides a chance to investigate the

provincial regulations in addressing the microbial-related issues in case of event occurrence. To achieve these goals, the research approach was structured in four steps: 1) development of a CSO load model, 2) development of fate and transport model of a river that receives CSO discharges, 3) employing simulation results as the proper inputs of QMRA, 4) introducing CSO-based QMRA.

In the first step, discharge dynamics of CSO events (data obtained from the literature) were investigated and the underlying common characteristics of discharges (i.e. flowrate and concentration of Total Suspended Solid (TSS), *Escherichia coli* (*E. coli*), caffeine (CAF) and acetaminophen (ACE)) were determined. Using normalized values of the scale-related parameters (i.e. flowrate, concentration and discharge duration), peak flowrates were shown to regularly occur within the 2^{nd} decile of the discharge duration while showing linear increasing trend and logarithmical decreasing pattern before and after the peak flowrate, respectively. The 1^{st} decile of the discharge period corresponds to the periods of peak concentration of TSS, *E. coli*, CAF and ACE. Describing normalized flowrate pattern by a deterministic model and that of normalized concentrations by probability distributions, a semi-probabilistic model was introduced based on the normalized parameters. The proposed CSO load model reflects a range of probable loading values with regards to the peak loading value in any portion of discharge duration. The results of the worst-case loading scenario showed that the 2^{nd} decile potentially represents the period of highest TSS, *E. coli* and CAF loading rates, even though the peak concentrations were mostly associated with the 1^{st} decile. The remaining time beyond the 2^{nd} decile does not generally correspond to a peak loading period, but loads do remain important throughout events when considering the cumulative effects of CSO discharges. The outputs of the semi-probabilistic CSO loading model can be treated as the inputs of a hydrodynamic and water quality model by adjusting the scale-related parameters of a CSO event.

In the second step, a hydrodynamic and water quality model (*E. coli*) of the river was developed to study the microbiological-related impacts of CSOs on the intakes downstream of the discharge points. After calibration and validation of the river model, a series of different CSO scenarios based on the probabilistic model (i.e. intra-event variability) and the monthly characterization of local CSO discharges (i.e. inter-event variability) from March to October were generated to account for a range of probable events. The simulation of scenarios resulted in obtaining a range of of *E. coli* peak concentration caused by CSO events in the form of probability distribution functions that could potentially occur at the intakes.

In the third step, QMRA was then used using the simulation results relating *E. coli* to *Cryptosporidium* concentrations based on historical data and probability distributions. Daily CSO-associated microbial risk was quantified for two treatment conditions (3 log and 4 log removal) at two of the drinking water plants. The short-term risk caused by CSOs was incorporated in the mean annual risk to investigate how individual event can alter the mean annual risk profile. The results showed that maintaining 4 log removal efficiency in the plant is sufficient to respect health target in case different range of CSO events. However, compliance with the health target for 3 log removal condition was reduced by half of the time compared to 4 log removal. It is also found that the risk profile was driven by the treatment level and the mean raw water microbial concentrations. The conclusion is that CSOs can be important for short term risk, but to appropriately characterize annual risk, it is important to reduce the uncertainty of the mean microbial contaminant concentrations.

In the final stage of the research, the two different source water protection policies in the intake's vulnerability and threat assessment conducted in Quebec and Ontario were applied for the intakes in the studied area separately and the results were compared. The CSO-based QMRA was then employed to evaluate the level of treatment required at the intakes for a given CSO event (as a threat) while respecting a specific health target. The results showed that the conventional threat classification proposed by the two provinces do not rely on the treatment requirement criteria for a given threat, although the Québec approach offers perspectives of how treatment can be integrated in the overall vulnerability assessments despite the methodology not being explicitly described.

Overall, this research project has characterized wet weather flow of CSOs from their source to the associated microbial risk in drinking water. Results of this study can be used by water authorities and managers to design more efficient sampling campaigns for capturing peak concentrations at drinking water intakes. The results could be used by the municipalities as a tool to evaluate different CSO-related mitigation alternatives such as CSO frequency reduction versus improvement of treatment processes.

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LIST OF SYMBOLS AND ABBREVIATIONS

ACE	Acetaminophen
CAF	Caffeine
CSO	Combined Sewer Overflow
DALY	Disability Adjusted Life Year
E. coli	*Escherichia coli*
ENT	*Enterococci*
FC	Fecal Coliform
FIB	Fecal Indicator Bacteria
IPZ	Intake Protection Zone
QMRA	Quantitative Microbial Risk Assessment
SWP	Source Water Protection
TC	Total Coliform
TSS	Total Suspended Solid

CHAPTER 1 INTRODUCTION

Pathogens have been recognized as a major concern for the production of safe drinking water. In particular, *Cryptosporidium* and *Giardia,* two of the most common protozoan parasites, have been linked to waterborne disease outbreaks all over the world (Baldursson and Karanis, 2011). Outbreaks were often related to the consumption of drinking water rather than through recreational activities or food-related ingestion (Karanis et al., 2006). Pathogens can break through the treatment chain if there is a treatment unit malfunction (e.g. sub-optimal performance particle removal or disinfection malfunction) (Cummins et al., 2010). In a study of theoretical microbial risks, the majority of water-borne infections were estimated to be related to pathogens passing through treatment processes during normal operating conditions (Westrell et al., 2003). Waterborne disease outbreaks in Walkerton, Canada (O'Connor, 2002) and Milwaukee, USA (Mac Kenzie et al., 1994) are two examples in which large number of individuals were infected while water supplies were contaminated. Therefore, the quality of raw water at the source is of great importance in terms of treatment challenges and treatment objectives for removing pathogenic agents from source waters. As a result, Source Water Protection (SWP) practices were implemented (Hrudey et al., 2003).

With regards to urban SWP, wet weather pollution is recognized as a major microbiological source of water quality impairment in many receiving waters (Marsalek and Rochfort, 2004). Urban runoff following a wet weather event may reach the receiving waters as discharges of stormwater from storm sewers or as Combined Sewer Overflows (CSOs). Although some sanitary sewers may overflow in wet weather, they are not as frequent as two previous forms of discharges (Marsalek and Rochfort, 2004). The occurrence of CSOs and their effects on the level of contamination in receiving waters are great concern for water managers, particularly municipalities that are responsible for providing safe drinking water for their residents. A CSO event during intense rainfall is the result of either insufficient transport capacity of the sewer to allow water flow to reach the wastewater treatment plant or the insufficient treatment capacity of wastewater treatment plant to treat all the water flow (Passerat et al., 2011). Receiving waters of CSO discharges could be the sources of drinking water and CSO discharges without any treatment would deliver high loads of fecal pollution in a short period. CSO occurrences were reported to be of probabilistic nature, with respect to their duration, magnitude and contaminant concentrations (Marsalek and

Rochfort, 2004). In spite of numerous CSO-related studies in the literature, characterization of dynamic behavior of such phenomena with regard to overflow and contaminant concentrations (i.e. microbiological and pharmaceutical) have not been adequately addressed. CSO discharge models are required to take into account the variability of the loading parameters. Therefore, a probabilistic approach is needed to more efficiently characterize such discharge-based events, a proper alternative for commonly used deterministic loading estimates based on an assumption of constant concentration in course of events (e.g. Jalliffier-Verne et al., 2016).

Drinking water treatment plants must be able to handle peak concentrations of pathogens (Dorner et al., 2004). Measurements at the intakes do not necessarily reflect the periods of highest concentration as they are regularly set on a daily or weekly basis (e.g. MDDELCC, 2014; USEPA, 2005). Therefore, determining the period and the magnitude of peak concentration caused by discharge events remains a challenge. Given that continuous monitoring of the level of fecal contamination to capture the periods of peaks has not previously been economically and practically feasible (McCarthy et al., 2007), the application of fate and transport models of microbial contamination within a water body can be considered as an alternative tool. Hydrodynamic models coupled with water quality models have been employed to address different objectives including identifying critical governing processes, assessing mitigation alternatives, and evaluating different point sources in contributing to fecal contamination. Impacts of discharge-based events, particularly CSOs on the downstream of a receiving water have been investigated using different hydrodynamic models coupled with water quality models (Hellweger and Masopust, 2008; Passerat et al., 2011; Sokolova et al., 2012; Jalliffier-Verne., 2016). However, the probability distributions of microbial indicator concentrations caused by CSOs under various potential loading events in source waters has not been given much attention. Such models can significantly improve our understanding of contamination dynamic and periods of peak in the sources of drinking water following a discharge event.

Moreover, coupling modeling results with Quantitative Microbial Risk Assessment (QMRA) approaches would not only provide an opportunity to complete monitoring data gaps regarding the period of peaks and the associated human-health risk, but also improve the quality of appropriate QMRA inputs (Sokolova et al., 2015). While QMRA has been extensively employed to estimate the human health risk related to consumption of drinking waters (e.g. Howard et al., 2006; Sato et al., 2013; Swaffer et al., 2018) or being exposed to recreational waters (McBride et al., 2013), a limited number of studies have merged the results of fate and transport model with QMRA to investigate the short term risk of infection upon consumption of treated water (e.g. Sokolova et al., 2015; Signor et al., 2007). However, CSO-associated human health risk upon consumption of treated drinking have not been addressed.

In Canada, provincial governments are primarily responsible for SWP policies and not the federal government (Cook et al., 2013). Therefore, there is a wide range of SWP-related legislation and strategies across Canada. For example, there are notable differences in vulnerability and threat assessment approaches between Quebec and Ontario. The question arises if the proposed vulnerability and threat assessment are sufficiently protective with regards to short-term impacts of discharge-based events like CSOs. It is therefore of interest to evaluate the provincial SWP approaches for microbial threats from CSO discharges and their associated health risks.

As part of a project funded by the Canadian Water Network, this thesis describes a component of the project related to a water supply shared by two cities. As such, the study site is an approximately 20 km section of the Ottawa River (also known as *Kitchissippi*), forming a natural boundary between the provinces of Québec and Ontario, Canada. Along the studied portion of the river, there are the intakes of 4 municipal drinking water treatment plants, some of which are located downstream of CSO outfalls. The Ottawa River provides an opportunity to compare the Ontario and Québec SWP approaches for vulnerability and threat assessments.

This thesis is organized into 8 chapters. A critical review of the literature on sources of pathogenic microorganisms, pathogen fate and transport processes and models, and Quantitative Microbial Risk Assessments is presented in Chapter 2. Chapter 3 summarizes the detailed objectives, hypotheses and methodologies. Research results are presented in Chapter 4 through Chapter 6 in the form of submitted manuscripts (Chapter 4 and Chapter 5) and a manuscript in preparation (Chapter 6). The first manuscript (Chapter 4) describes the process in which scale independent dynamic behavior of CSO discharges were estimated for characterization of the period of peak loads during a CSO event. A semi-probabilistic CSO loading model was proposed to be used for generating scenarios for source water threat assessments. The second article (Chapter 5) demonstrates the fate and transport of microbial contamination (*E. coli*) discharged by CSOs into a river using the developed semi-probabilistic CSO loading model. A range of probable peak concentrations of *E. coli* at drinking water supplies were estimated, and their corresponding health risks were quantified. Two management alternatives, i.e. reducing number of CSO occurrences versus improving the treatment performance were also compared. Chapter 6 summarizes and compares the source water protection approaches adopted in Quebec and Ontario, Canada, for vulnerability and threat assessments for microbial contaminants using the study site as a case study. Finally, a general discussion is provided followed by conclusions and recommendations.

CHAPTER 2 LITERATURE REVIEW

Concerning the scope of the present research project, different aspects of microbial contamination in source waters were reviewed. The discussion has been divided in four sections: 1) general overview of water-borne pathogens of concern and their sources, fate and transport processes to drinking water supplies, 2) modeling these processes, 3) CSO characterization for water impairment assessments and 4) evaluation of human health risk associated with the pathogenic contamination at those sources using a QMRA tool. The following section is intended to briefly and more efficiently highlight the state of the art as well as the literature gaps.

2.1 Water-borne pathogenic microorganisms

2.1.1 Overview

Pathogens are disease-causing microorganisms that are major concerns for drinking water treatment and their removal from raw water is one of the primary goals of treatment plants. According to Guidelines for Canadian Drinking Water Quality, the most significant risks for drinking water are posed by microbiological contaminants such as bacteria, protozoa and viruses (Health Canada, 2017). Surface water can be contaminated even with low levels of pathogenic microorganisms (Ferguson et al., 2003). The presence of these microorganisms in water sources is often an indication of fecal contamination from human or animal origins. Various pathogenic agents such as bacteria (e.g. *Campylobacter*, *E. coli* O157:H7 and *Salmonella*), parasites (e.g. *Cryptosporidium*, *Giardia*) and viruses (such as Norovirus, Rotavirus) have been recognized as the reason for water quality impairments in recreational or drinking water sources that could potentially cause gastrointestinal illnesses upon consumption or direct contact.

Municipal wastewater treatment plants and onsite wastewater treatment systems are known to contribute to human health risk because they may contain pathogenic microorganisms in their effluents (Xiao et al., 2018). Among a variety of sewage-related pathogens identified, protozoan parasites such as *Cryptosporidium* and *Giardia*, are among the most common waterborne infectious agents causing diarrhea in industrialized and developed countries (Sato et al., 2013; Swaffer et al., 2018; Xiao et al., 2018). *Cryptosporidium* and *Giardia* were recognized to cause at least 60% and 35%, respectively, of worldwide waterborne outbreaks of human disease from 2004 to 2010

(Baldursson and Karanis, 2011) and 63% and 37%, respectively, of the protozoan-related outbreaks over the period of 2011-2016 (Efstratiou et al., 2017). Disease outbreaks have been reported in many countries including the United States and Canada (Hrudey et al., 2003; Charron et al., 2004), United Kingdom (McCann et al., 2014), Ireland (Cummins et al., 2010) and Brazil (Sato et al., 2013). The most severe waterborne disease outbreak through drinking water contamination by *Cryptosporidium* occurred in Wisconsin, United States in 1993 infecting almost 403,000 individuals (Mac Kenzie et al., 1994). In fact, the widespread disease outbreaks (associated with these protozoan pathogens) has been primarily linked to the contamination of drinking water supplies compared to outbreaks through recreational-related activities and food consumption (Karanis et al., 2006). Detailed information on the worldwide outbreaks have been provided by (Baldursson and Karanis, 2011; Efstratiou et al., 2017) with regards to the date, location, type of water sources, and associated pathogenic agents.

As demonstrated by continuing outbreaks worldwide, the presence of *Cryptosporidium* and *Giardia* in drinking water sources remains a concern for water and public health authorities. Only a low number of parasites is required to induce infection (especially for immune-compromised individuals) and given their resistance to water treatment and disinfection, they generally drive microbial risk in drinking water (Swaffer et al., 2018). Roughly spherical with a diameter of 4 to 6 μm, *Cryptosporidium* oocysts can survive in harsh environmental conditions for months in surface waters (Arnone and Walling, 2006; Medema et al., 1998). Infection by *Giardia* is transmitted via tiny spores or egg-like cells (cysts) ranging 9 to 12 μm in length. *Giardia* cysts can also survive weeks or months in fresh water because of the thick wall around its cell (Arnone and Walling, 2006). Faeces of infected animals or humans contain large quantities of *Cryptosporidium* oocysts and *Giardia* cysts that can enter surface waters from point (i.e. treated or untreated sewage effluents) and non-point sources (i.e. spread of excreta from livestock or runoff from the fields contaminated by manure or sewage sludge, wildlife species) (Ferguson et al., 2003; Dorner et al., 2004; Xiao et al., 2013; Hofstra et al., 2013).

Lack of regulatory monitoring programs, costly pathogen enumeration techniques, poor detection limits and uncertainty in measurements of pathogens as a result of the low recovery rate may result in poor quality pathogen characterization in drinking water supplies. This, partnered by non-complete removal of (oo)cyst as a result of their resistance to environmental stress and conventional water processes (Xiao et al., 2018), result in continuous challenges through the whole drinking water production process from source to tap. Besides, variable source water quality combined with variable treatment techniques and efficiencies and the elements of distribution networks also add up to the concern of tab water quality. Potential breakthrough the treatment chain, failure of a process within the treatment plant, cool temperatures, sub-optimal particle removal and disinfection malfunction are known as common causes of (oo)cyst contamination event (Cummins et al., 2010). However, the majority of waterborne infections are estimated to be most probably as a result of pathogens passing through the treatment processes during normal operational conditions rather than treatment system failure (Westrell et al., 2003). *Cryptosporidium* and *Giardia* are required (by federal or provincial governments such as USEPA, 2005 or MDDELCC, 2014) to be removed by an amount based on raw water concentrations. The better raw water quality (microbial) status in drinking water supplies, the less risk of infection is expected at the end of the drinking water treatment process but depends on the available treatment barriers. Increasingly, SWP practices and strategies have become the main focus of the municipalities and provincial governments to ensure safer drinking water quality of raw water before entering the treatment chains. Water utilities constantly improve their knowledge on pathogen-related human health risk, implement tighter microbiological thresholds as regulatory controls for potable water and characterize the complex interactions between landuse, human, wildlife, seasonal and climatic conditions that potentially cause source waters to be contaminated (Swaffer et al., 2018).

2.1.2 Pathogen indicators

Since detecting all existing pathogens in water is not technically and economically feasible, indicators of fecal pollutions (bacterial) or indicators of pathogen presence have been used instead to ensure the quality of sources of recreational or drinking water (Wilkes et al., 2009). An ideal indicator should be quickly measurable in a cost-effective manner and have transport characteristics similar to pathogens (Yates, 2007). Fecal Indicator Bacteria (FIB) (such as Total Coliform (TC), Fecal Coliform (FC) E*nterococci* (ENT) and particularly *Escherichia coli* (*E. coli*)) are the most common indicators for the evaluation of microbiological water quality of raw and treated drinking waters as well as recreational waters (WHO, 2017; USEPA, 2005; Health Canada, 2017). The microbiological treatment requirement in drinking water treatment plants in Quebec is based on the mean of *E. coli* concentration measurements in raw waters (MDDELCC, 2014). FIB may not necessarily indicate the presence of a specific pathogen, however, the relation of FIB to a specific pathogen has been extensively evaluated due to the reported gastroenteritis associated with FIB (Duris et al., 2013). Such studies do not result in similar findings with regards to indicator-pathogen correlation. For example, no relations between pathogen and indicator (Lemarchand and Lebaron, 2006) were found while other studies established relation between FIB and pathogens (Wade et al., 2003; Wilkes et al., 2009; Duris et al., 2009; Walters et al., 2011; Tolouei et al., 2019). Assumption of different constant ratios between indicator and pathogens have been widely employed in the literature to extrapolate pathogen concentrations from those of indicators ranging in drinking water supplies (Howard et al., 2006; Machdar et al., 2013) wastewater samples (Labite et al., 2010; Jalliffier-Verne et al., 2016) or even in fresh fecal matter (Sokolova et al., 2012). In fact, Lalancette et al., (2014) demonstrated that *E. col*i as a reliable *Cryptosporidium* surrogate is largely dependent of the source of contamination where *E. coli* may be either featured as a good indicator when dealing with source waters impacted by recent municipal sewage or as a conservative one while considering raw sewage. Therefore, use of single estimate of indicator-to-pathogen ratio may potentially lead to overestimation or underestimation of the associated health risk according to variability of the correlations in different conditions. Taking into account a range of indicator-to-pathogen ratios may be a more useful approach in interpretation of the pathogen-related characteristics to include the possibilities of different values. The variability of *E. coli* (or other indicators) to pathogens can be attributed to the different sources of contamination, health status of excreting host, different fate and survival mechanism of pathogens and indicators and hydrodynamic and hydrological processes in the environment (Dorner et al., 2004; van Lieverloo et al., 2007).

On the other hand, the occurrence of pharmaceuticals and wastewater micropollutants in surface waters have also been reported on a large scale, particularly for the areas that receive inputs from municipal wastewater systems. Their physicochemical properties, mostly exclusive to human-related sources, low background level in nature and detection limit suggest their use as wastewater tracers (Benotti and Brownawell, 2007). The presence of such components in source waters (e.g. drinking water sources) is an indication of fecal pollution from human source and consequently potential presence of human pathogens (Tolouei et al., 2019). For example, caffeine (CAF) has been introduced by several authors to be a tracer of domestic sanitary contamination as being highly persistent in the discharge and receiving waters, ubiquitous with no agricultural or industrial releases (Sauvé et al., 2012; Daneshvar et al., 2012). Acetaminophen (ACE) has been used as another tracer but for raw or insufficiently treated wastewater, indicating potential wastewater treatment malfunction or CSOs (Kasprzyk-Hordern et al., 2009). The relationships between pathogens or FIB and wastewater micropollutants or pharmaceuticals components have been assessed in the literature (e.g. Tolouei et al., 2019; Madoux-Humery et al., 2013). However, analysis of their dynamic discharge characteristics in course of CSO events may not have been properly addressed.

2.1.3 Sources, fate and pathways

Identifying the origins of pathogens and the pathways through which they enter into streams, rivers and other water bodies is relatively difficult. Determining sources of pathogenic contamination plays an important role in estimating pathogen concentration as well as applying proper control measures. Human and animal feces are sources of most waterborne pathogens (Arnone and Walling, 2007). Contamination may occur within some possible pathways such as lateral inputs from pastures or riparian zones, direct deposits of fecal matter by livestock and wildlife, discharges of wastewater treatment plants. Livestock production-related activities as well as agricultural activities have been reported as common sources of microbial contamination in a watershed sale, specifically in rural areas. Pathogens of greatest concerns are shed in to environment in significant numbers that are highly infectious to humans (and animals) at relatively small doses. In the Walkerton outbreak, pathogens that originated in manure contaminated the town's water system (O'Connor, 2002). Manure storage facilities, utilization of livestock waste, feedlots, runoff form grazed pasture lands, rangelands and manure-applied lands are examples of such sources of contamination (Jamieson et al., 2004; Haack et al., 2016). Animal feeding operations is estimated to generate 100 times as much manure as municipal wastewater treatment plants produce sewage sludge in the USA (Gerba and Smith Jr, 2005). While manure is an important source of plant nutrient and energy, it can lead to substantial water pollution if managed improperly given that the pathogenic microorganisms in manure cause serious illness and death in humans (Pachepsky et al., 2006). The peer-reviewed literature on transport mechanisms of manure-origin pathogens have studied the key elements of the process from releasing of microorganism in form of manure particulates flowing into water, being transported by surface and sub-surface water or being free cell or attached to soil particles (e.g. Brookes et al., 2004, Ferguson et al., 2003, Jamieson et al., 2004, Unc and Goss, 2004; Goss and Richards, 2008). Livestock sources of contamination within an agricultural watershed would be impacted by some of livestock characteristics including, but not limited to, its densities, confinement and grazing schedule, access to waterbodies, manure application rate and timing and their locations (Jamieson et al., 2004). Health status, animal type, age, diet, stress level and season also plays important roles in determining the pathogen shedding rate (Goss and Richards, 2008). For example, Dorner et al., (2004) simulated the production of *Cryptosporidium* spp. and *Campylobacter* spp based on the animal prevalence and fecal shedding intensity in a Watershed in Canada.

In urban areas, the most significant source of microbial pollution is municipal activities such as wastewater discharges, sewage sludge and urban runoff. Pathogens contribute to water quality impairments of receiving waters by discharges from CSO or SSO and stormwater outfalls and wastewater by-passes generally referred to as an urban wet-weather pollution (Ferguson et al., 2003; Marsalek and Rochfort, 2004; Gerba and Smith Jr, 2005; Dechesne and Soyeux, 2007). Malfunctioning or poorly treated on-site septic systems and cross-connected storm sewers have also been recognized as factors causing pathogenic contamination (Gerba and Smith Jr, 2005; Dechesne and Soyeux, 2007). Table 2.1 presents a number of studies in which municipal-induced sources of microbial contamination (i.e. municipal wastewater treatment discharges, CSO and stormwater discharges) and their impacts have been investigated.

Identifying the influencing factors controlling survival and transport of microorganisms within the environment has also been another objective of the microbiological studies in the literature. A list of influencing factors on microbial survival is presented in Table 2.2, some of which contribute to fate of microorganisms in the environment, and some cause their transport. These transport processes are fully discussed in Ferguson et al. (2003) and Brookes et al. (2004). Adsorption/desorption is a tendency of a microorganism to adsorb/desorb to surfaces depending on the presence of salts, organic matter and pH. Hydrological movement is another transport mechanism of microorganism. It has been tried to show correlation between the incidence of rainfall or rainfall intensity and waterborne disease outbreaks. This linkage supports the view that water flow caused by meteorological condition and ambient features such as runoff in a watershed is one of the most important parameters affecting transport of microbial contamination. Hydrodynamic movement is also another transport process in water bodies. The processes of turbulence, shear dispersion and advection are the governing mechanisms in transport and distribution of particles. The horizontal and vertical transport in lakes and reservoirs primarily

Table 2.1: Studies on sources of microbial contamination in different water bodies.

Source of contamination	Author(s) (year)	Microorganism	Remarks
Effluents from municipal wastewater treatment plant	Rechenburg et al. (2006)	*E. coli*, TC, Fecal Streptococci, *Cryptosporidium*, *Giardia*	6 wastewater treatment plants varying in size (service population) and complexity of treatment stages considered under regular and heavy rainfall conditions along the Swist River, Germany Affluent and effluents regularly sampled over a course of 15 months. Treatment plants turned out to be the main source of *Giardia* in the river as Reduction of *Cryptosporidium* not measurable due to a very low number of oocysts in raw sewage.
	Garcia-Armisen and Servais (2007)	*E. coli* and intestinal *ENT*	Relative contributions of point and non-point sources evaluated in Seine River watershed, France. Fecal indicator numbers estimated from raw and treated waters of wastewater treatment plants Fecal indicator abundance estimated from water samples collected in small streams for non-point source assessment. Point sources predominantly important at watershed scale. In case of UV disinfection stage, non-point sources of greater importance.

Table 2.1: Studies on sources of microbial contamination in different water bodies (cont'd).

Source of contamination	Author(s) (year)	Microorganism	Remarks
Effluents from municipal wastewater treatment plant	Fu et al. (2010)	Somatic Coliphages, FC *Cryptosporidium*, and *Giardia*	50 samples from untreated wastewater as well as primary, secondary and tertiary treatment effluents collected in three municipal wastewater treatment plants from 2005 to 2007, China. The concentrations of *Cryptosporidium* and *Giardia* ranged from 33-600 oocysts/L and 130-3600 cysts/L in untreated wastewater, 67-333 oocysts/L and 533-2033 cysts/L in primary treatment effluents, below 9 oocysts/L and 32 cysts/L in secondary treatment effluents and below 0.4 oocysts/L and 2.1 cysts/L in tertiary treatment effluents. Tertiary treatment process (i.e. Membrane ultrafiltration) notably had a better *Cryptosporidium*, and *Giardia* removal efficiency than conventional process (i.e flocculation sedimentation and sand filtration). *Cryptosporidium* and *Giardia* in untreated wastewater and secondary treatment shown to be better correlated with somatic coliphages.

Table 2.1: Studies on sources of microbial contamination in different water bodies (cont'd).

Source of contamination	Author(s) (year)	Microorganism	Remarks
Effluents from municipal wastewater treatment plant	Fong et al. (2010)	Adenoviruses	Wastewater effluents and wastewater-impacted surface water (recreational park) monitored for a year in Grand Rapids, MI, USA. Adenovirus detected in 100% and 30% of wastewater samples and surface water samples (avg concentration of 7.8×10^3 viruses/L), respectively. High concentrations of adenovirus may be due to the insufficient removal during treatment as well high persistence of these viruses in the environment.
	Dungeni and Momba (2010)	*Cryptosporidium*, and *Giardia*	Samples of treated and untreated wastewaters collected weekly from four municipal wastewater treatment plants during 4 months in South Africa. *Cryptosporidium* oocysts and *Giardia* cysts detected in influents and effluents from all the plants with the lower counts for *Cryptosporidium* in both influent and effluents. Parasites absence in the influents and their presence in the effluents or lower counts in the influents coupled with higher counts in the effluents may due to the survival capability of parasites (days or months) in the environmental water.

Table 2.1: Studies on sources of microbial contamination in different water bodies (cont'd).

Source of contamination	Author(s) (year)	Microorganism	Remarks
Effluents from municipal wastewater treatment plant	Kitajima et al. (2014)	*Cryptosporidium*, and *Giardia*	Monthly samples from influents and effluents of two wastewater treatment plants collected over the course of 12 months in Arizona, USA. Log_{10} reduction of *Giardia* cysts for the plant utilizing activated sludge significantly higher than the other plant equipped with trickling filter. Efficacy of conventional treatment processes at physically removing (oo)cysts is limited and further treatment processes such as membrane separation and UV disinfection required.
	Dienus et al. (2016)	*E. coli*, Somatic Coliphages, Norovirus	160 samples, collected in one year, from effluents of four wastewater treatment plants discharging into a river serving as a drinking water supply.

Table 2.1: Studies on sources of microbial contamination in different water bodies (cont'd).

Source of contamination	Author(s) (year)	Microorganism	Remarks
Effluents from municipal wastewater treatment plant	Ribeiro Dos Santos and Daniel (2017)	*E. coli* TC, *Cryptosporidium*, and *Giardia*	41 wastewater and sludge samples collected from different stages of treatment chain in a municipal wastewater treatment plant in Brazil over 8 months. Although significant overall removal of cysts achieved, a great portion of (oo)cysts still reaches the environment daily with the discharge of treated effluent into a receiving water body. The high densities of parasites in sewage sludge also represent a potential threat for public health.

Table 2.1: Studies on sources of microbial contamination in different water bodies (cont'd).

Source of contamination	Author(s) (year)	Microorganism	Remarks
CSOs	Arnone and Walling (2006)	*Cryptosporidium*, *Giardia*, TC, FC, *E. coli*,	6 CSO events sampled from three outfalls, one in Atlanta, GA and two others in Louisville, KY, USA, discharging to drinking water sources with the drainage areas consist of different land use characteristics. *Cryptosporidium* and *Giardia* found in 12% (not significant) and 96% of samples (significant), respectively. Correlation between FIB and *Giardia* established. Detection and measurement of *Cryptosporidium* and *Giardia* difficult, expensive and time consuming.
	McLellan et al. (2007)	*E. coli*	*E. coli* distribution and persistence in nearshore Lake Michigan, USA investigated in storm events following heavy rains and with and without CSO/SSO events over a 5-year period (2001-2005). Highly variable levels of *E. coli* in storm events within the studied regions. *E. coli* levels in the Milwaukee estuary and harbor following SSO/CSO events ranged from 10^4 to nearly 10^5 CFU/100 mL, significantly higher than levels following rainfall alone.

Table 2.1: Studies on sources of microbial contamination in different water bodies (cont'd).

Source of contamination	Author(s) (year)	Microorganism	Remarks
CSOs	Passerat et al. (2011)	*E. coli* and intestinal *ENT*	Microbial contamination discharged during an intense CSO occurred at the Clichy outfall, Seine River, France. 12 successive samples collected in a 6-hour CSO event and 4 series of samples in upstream and downstream of the outfall. FIB discharged during the CSO represented 80-100 times the dry weather. FIB concentrations in downstream from the CSO outfall where 7-9 times higher than directly upstream.
	Madoux-Humery et al. (2013)	*E. coli*	11 CSO events in two sewage outfalls with different land uses monitored over a course of a year in Greater Montreal Area, Canada. Samples collected every 5 min for the first 15 min, and then every 30 min. Median *E. coli* concentration measured in CSOs reported as 1.5×10^6. Snowmelt identified as a critical period as high contaminant concentrations and long lasting events observed. *E. coli* remained the best indicator of fecal contamination in strongly diluted water samples.

Table 2.1: Studies on sources of microbial contamination in different water bodies (cont'd).

Source of contamination	Author(s) (year)	Microorganism	Remarks
CSOs	Al Aukidy and Verlicchi (2017)	*E. coli* and *ENT*	Total of 124 overflow water samples collected at 5 CSO outfalls (30-min interval) discharging ultimately into touristic coastal area from Jun to Sep, 2014 in Italy. Median concentrations ranged from 4.89 $\times10^5$ to 2.4×10^6 MPN/100mL (*E. coli*) and from 1.18 $\times10^5$ to 2.66×10^6 MPN/100mL (*ENT*). It is highlighted that the CSO microbiological load is much higher than that of wastewater treatment plant, even though CSO water volume is much lower than that released by the wastewater treatment plant. UV irradiation as a natural purification process may be effective due to less penetration in water column because of higher turbidity as well as reduction in UV intensity because of cloudy weather.

Table 2.1: Studies on sources of microbial contamination in different water bodies (cont'd).

Source of contamination	Author(s) (year)	Microorganism	Remarks
Stormwater	Selvakumar and Borst (2006)	Two human-related pathogens TC, FC, fecal streptococci, E*NT*, *E. coli*	Stormwater runoff samples collected from small municipal stormwater sewer system outfalls from three different land use areas, i.e. high and low-density residential as well as landscaped commercial, in Navesink River Watershed, NJ, USA. Generally, the concentrations in runoff from high density residential areas higher than the concentrations in other tested land uses. Major sources of microorganisms to the stormwater runoff reported to be most likely from the feces of domestic animals and wildlife in residential areas. Concentrations of microorganisms significantly affected by the season with lowest concentration during winter. Relationships between indicators and pathogens poorly correlated and not statistically significant. The correlation between the concentration of the traditionally monitored indicators (TC and FC) and the suggested substitutes (ENT and *E. coli*) weak, but statistically significant.

Table 2.1: Studies on sources of microbial contamination in different water bodies (cont'd).

Source of contamination	Author(s) (year)	Microorganism	Remarks
Stormwater	McCarthy (2009)	*E. coli*	*E. coli* data collected from wet weather flows of four urban catchments in Melbourne, Australia. Investigating *E. coli* first flush phenomena using cumulative mass versus volume curves, *E. coli* first flush phenomena not consistently present in stormwaters from studied areas. No consistent relationships could be found to determine any event-based characteristics were able to explain the existence, and the magnitude, of the *E. coli* first flush.
	Pan et al. (2012)	*E. coli*	An urban stormwater monitored to investigate the varying patterns of common water quality parameters (e.g. *E. coli*), in Texas, USA. The event increased *E. coli* concentration, followed by decreasing trend. The peak intensity of different pollutants in the storm runoff occurred at different times rather than at peak flow. High bacteria and TSS concentrations in the initial stage should be considered in water resource managements and low impact designs.

Table 2.1: Studies on sources of microbial contamination in different water bodies (cont'd).

Source of contamination	Author(s) (year)	Microorganism	Remarks
Stormwater	Hathaway et al. (2015)	*E. coli*, FC and *ENT*	Flow and water quality samples collected during 20 storm events (an average of 10 samples per event) from a watershed in Raleigh, NC, USA. FIB showed higher variability than TSS among intra-event characteristics. FIB intra-event statistics appear to be influenced by climate variables whereas TSS statistics most influenced by hydrologic variables. FIB correlations with rainfall intensity weak and inconsistent between events, unlike TSS.
	Galfi et al. (2016)	FC, *E. coli*, *ENT* and *Clostridium perfringens*	The magnitude of indicator bacteria concentrations in stormwater runoff from four urban catchments in central Sweden investigated. Stormwater (13 events) and snowmelt (14 events) samples collected FC, *E. coli*, *ENT* found in the highest mean concentrations during both rainfall and snowmelt. Snowmelt and storm-concentrations 10 and 100 times higher, respectively than that of dry weather. In wet weather, the levels of indicator bacteria observed to be of an intermediate magnitude (generally < 10^3–10^4 CFU/100 mL).

caused by inflows, wind-driven currents and internal wave are included in this category as well.

In general, field monitoring and assessment analyses are inseparable part of the studies which aim to identify the level of contamination in a water course. Attempts are usually made to estimate the extent of microbial contamination and recognize the effect of different parameters on concentration within a series of measurement and statistical analysis. In addition to improving the knowledge of existing condition of water quality, results out of these studies can be utilized for development of new transport model or modification of an existing one. Overall, it is the matter of the objectives of the investigation to plan for monitoring. Considering the type of water body, the scale of the case study, the microorganism and other factors, there is no unique strategy or result for the same problems or solutions. Dry and wet weather measurements, the number and frequency of sampling, duration and location of sampling, the type of pathogenic agents to be measured and many other factors need to be determined prior to field activities.

Table 2.2: Influencing factors on microbial survival in aquatic environment.

Factor	Author(s) (year)	Description
Solar Radiation	Kim and Hur (2010)	One of the most important inactivation mechanisms for all forms of pathogens and indicators. Impact may vary depending on depth of water, type of water and type of microorganism. Most dominant inactivation mechanism in highly clear water.
Temperature	Walker Jr and Stedinger (1999) Brookes et al. (2004)	First order decay function often introduced. Metabolic processes increase as temperatures rises. Relationship between decay rate and temperature intensively studied.
pH	Hipsey et al. (2008)	Less emphasis on pH influence comparing to the solar radiation and temperature, probably due to the stable pH level (7) in water bodies. Most authors found mortality rates significantly increase outside of the 'neutral' range.
Salinity	Bordalo et al. (2002) Evanson and Ambrose (2006)	Higher survival in low salinities. Salinity found to be correlated (negatively) with water TC and *E. Coli* level.

Table 2.2: Influencing factors on microbial survival in aquatic environment (cont'd).

Factor	Author(s) (year)	Description
Predation	Brookes et al. (2004)	Impact on pathogen mortality
Sediment and solid attachment	Gerba and Smith Jr (2005) Wu et al. (2009)	Longer survival of pathogens as attached to solid particle due to the presence of organic matter Depending on the surface properties of the organism and the nature of the suspended material within the system, the attached fraction can vary considerably.
Dissolved oxygen	Gordon and Toze (2003)	Influence on pathogen concentration may not be that significant, but it can increase pathogen inactivity.

2.2 Fate and transport modeling

Determining the concentrations of microbial contaminants have been a great challenge for environmental engineers since continuous monitoring of every different microorganisms at all sites and their laboratory analyses are not feasible in terms of cost and time (McCarthy et al., 2007). Hence, modeling can be considered as a potential alternative to monitoring, which is in fact a more practical way of predicting pathogen concentrations. Models in this regard, can be classified as empirical or mechanistic (Bai and Lung, 2006; Hellweger and Masopust, 2008). Empirical models are based on an inductive or data-based approach. Due to the natural complexity in fate and transport of microorganism, empirical models such as regression models are not capable enough to express reliable load-concentration relationships. Moreover, they might fail to record variations and peaks in concentration. However, empirical models have been applied widely. A brief overview of the literature in applying empirical models can be found in McCarthy et al. (2007). Mechanistic models, on the other hand, are based on a deductive or theoretical approach. Equations are those of physical or biological laws. As so called 'process-based models', they typically solve a set of governing physically based equations describing the principals of flow, fate and transport of contaminants (Bedri et al., 2011). The more accurately they reflect the actual physical processes, the more precise and reliable the results.

Among a significant number of mechanistic modeling studies, there are two major modeling types concerning fate and transport of microbial contamination; hydrodynamic modeling and hydrological modeling, both coupled with a water quality model. The former concerns solving the advective and dispersive transport processes in waters such as lakes, reservoirs, estuaries, and coastal waters while the latter deals with land surface processes within a watershed (Bai and Lung, 2006). Table 2.3 and Table 2.4 briefly summaries the most recent hydrodynamic and hydrological modeling studies, respectively.

Table 2.3: Hydrodynamic modeling of fate and transport of microbial contamination.

Author(s) (year)	Model description and remarks
Hipsey et al. (2004)	ELCOM (lake hydrodynamic 3D model, capable of simulating waterbody inflow and thermal dynamics) coupled with the model of *cryptosporidium* dynamics within lakes and reservoirs. *Cryptosporidium* fate and transport processes such as inactivation (through natural mortality or exposure to different bands of UV), resuspension, settling and aggregation onto particles included in the water quality model. The hydrodynamic and water quality model (propagation of oocysts through the water column) results compared with transactional thermal profile and oocyst data during riverine intrusion collected from comprehensive field experiment in a drinking water reservoir in Myponga, South Australia. Resutls revealed that oocysts do not readily attach to inorganic particles but settle as free-floating particles.
McCorquodale et al. (2004)	A 3D hydrodynamic model of Princeton Ocean Model with bacteria fate–transport submodel used for a recreational lake receiving multiple stormwater runoffs, in Louisiana, USA. Calibration and validation based on 6 years of field studies, laboratory analyses, and experiments. Storm water runoff discharges found to last for 2 to 3 days after a significant rainfall event (>12 mm). Process of settling determined to be significant while die-off rate found to be slow. An effective tool to assess the pathogen indicators concentration (FC, ENT and *E. coli*) in near real-time rather than conventional beach monitoring program. Modeling methodology suggested to be used as a management tool for updating swimming advisories.

Table 2.3: Hydrodynamic modeling of fate and transport of microbial contamination (cont'd).

Author(s) (year)	Model description and remarks
Garcia-Armisen et al. (2006)	A 3D hydrodynamic model (Siam-3D) coupled with the FC dynamics model (mortality and settling included), Seine estuary, France. Three inputs of FC considered: transported by the river flow; brought in through the tributaries; wastewater treatment plant effluents. Longitudinal and vertical distribution of FC along the river calculated for a given discharge. Disinfection in the wastewater treatment plant along the estuary more influential than reduction of the upstream input. A useful tool to test the impact of alternative sanitation strategies on estuarine water quality.
Hellweger and Masopust (2008)	*E. coli* fate and transport processes in Boston's Charles River, USA studied with a 3D time-variable, hydrodynamic model (ECOMSED) coupled with the model of fate of *E. coli* (RCA) using a number of die-off formulations. Model results compared with high-resolution spatial and temporal pattern observed in the River. Predominant sources of *E. coli* determined to be the upstream tributaries. Spatial and temporal variation primarily driven by the hydrodynamics caused by the Dam, wind conditions and die-off rate. Finally, fate and transport modeling framework suggested as to be considered as a potential alternative to the more traditional empirical models.

Table 2.3: Hydrodynamic modeling of fate and transport of microbial contamination (cont'd).

Author(s) (year)	Model description and remarks
Rodrigues et al. (2011)	A 3D hydrodynamic model (SELFE) coupled with a fecal contamination model (*E. coli* and *ENT*) used to understand fecal contamination behavior in a small coastal stream (Aljezur), Portugal. The advection-dispersion process and the first-order decay of the bacteria due to mortality and settling considered. Model sensitivity observed to the varying forcing functions such as river flow, wind, die-off rate and settling velocity. Direct relation observed between tidal propagation upstream and the reduction of the fecal bacteria concentration. Establishment of a framework for the most appropriate discharge times
Bedri et al. (2011)	A 2D and 3D hydrodynamic model (TELEMAC) coupled with the model of fate and transport of *E. coli* (SUBIEF-3D) employed to assess the impact of *E. coli* emissions from a sewage treatment plant on the bathing water quality of Liffey Estuary and Dublin Bay, Ireland. Outperformance of 3D compared to 2D model on the prediction of *E. coli* distribution. *E. coli* decay rate considered as a governing parameter of water quality model. Wind scenarios of different magnitude and directions produced to investigate the effect of wind forcing on the transport of *E. coli*. Effect of wind showed to be more pronounced in 3D model application while2D simulations seemed to be less sensitive to the wind scenarios and significantly understudied *E. coli* delivery rate to the Bay.

Table 2.3: Hydrodynamic modeling of fate and transport of microbial contamination (cont'd).

Author(s) (year)	Model description and remarks
Sokolova et al. (2012)	A 3D hydrodynamic model (Mike 3) coupled with microbiological model (ECO Lab) used to evaluate contribution from different contamination sources to pathogen concentrations at drinking water sources in a Lake, Sweden. Pathogen (norovirus, *Cryptosporidium*, *E. coli* O157/H7) concentrations estimated using the ratio of pathogens to fecal indicators in fresh fecal matter. The simulated concentration of pathogens discharged to the lake from sources considered as 5^{th}, 50^{th} and 95^{th} % values of estimated pathogen concentrations at the source. Sources with the highest pathogen concentration shown to be not necessarily the main contributor at the intake The modeling approach addressed the limitations of monitoring and provides data for the inputs of risk management.
Sokolova et al. (2013)	A 3D hydrodynamic and water quality model (*E. coli*) developed for the lake Radasjön in Sweden, used as source of drinking water. Different sources contributing to fecal contamination at the water intake quantified and implemented in the model. Model calibrated against measured data on vertical temperature profile in the lake well. Fate and transport of *E. coli* released from different sources simulated within the lake to the water intake points and compared with measurements. Results showed that on-site sewers and main inflow to the lake (a river) contributed the most to fecal contamiantion

Table 2.3: Hydrodynamic modeling of fate and transport of microbial contamination (cont'd).

Author(s) (year)	Model description and remarks
Gao et al. (2015)	A 1D and 2D hydrodynamic and fate and transport model of fecal bacteria developed (i.e. calibrated and validated) to predict fate and transport fecal bacteria in receiving surface waters. Effects of tidal process, river discharge and inputs of fecal bacteria from upstream rivers, wastewater treatment works on the on the concentrations of fecal bacteria in the Ribble Estuary, England. Results revealed that the tide and upstream boundary bacteria inputs were the primary factors controlling the distribution of fecal bacteria.
Jonsson and Agerberg (2015)	A model for calculation of *E. coli* transport in oligotrophic river waters developed by using temperature dependent inactivation rate for *E. coli* and flow velocity characteristics of the river and lakes, in northern Scandinavia. Transport distance of *E. coli* estimated based on the 90% inactivation of the *E. col* and temperature measurements of 11-year surveillance. Model results demonstrated that slow inactivation rates of *E. coli* leads to considerable transport distances in a cold and oligotrophic river with low total load of fecal pollution. Clear and structured seasonal variations observed with longest monthly average transport distances in spring (April and May) and shortest in summer (July and August). The modeling framework suggested to be employed for water management decisions for programming of seasonal activities that may affect water quality in terms of fecal pollution.

Table 2.4: Hydrological modeling of fate and transport of microbial contamination.

Author(s) (year)	Model description and remarks
Dorner et al. (2006)	An existing hydrological model, WATFLOOD augmented for a pathogen transport model to determine the primary sources of pathogenic contamination in a watershed used for drinking water supply in Southwestern Ontario, Canada. *E. coli* and several waterborne pathogens: *Cryptosporidium* spp, *Giardia* spp, *Campylobacter* spp, and *E. coli* O157:H7 studied. Overland flow, subsurface flow to tile drainage systems and in-stream routing included Land-based microorganism mostly enter the stream through tile drainage system rather than overland transport. Highest concentrations corresponded to the overland entering in spite of its rare occurrence. Sediment resuspension of significant importance considered to be a cause of rapid increase in *E. coli* concentration.
Haydon and Deletic (2006)	Two conceptual continuous pathogen models of *E. coli* developed to model pathogen discharges from 3 catchments in southern Autralia being tested against base flow and storm event *E. coli* concentration measured in the catchment. 1) EG: Pathogen transport model (surface and subsurface pathogen (within catchemnt) transport processes using washoff and loss equations) coupled with an existing hydrologic model (SimHyd for flow prediction) 2) ASP: Pathogen transport model (only surface transport) coupled to stormflow-baseflow separation model Reasonably good prediction of pathogen peak concentrations by the EG. Howver, better performance of more complex EG model than the oversimplified ASP model

Table 2.4: Hydrological modeling of fate and transport of microbial contamination (cont'd).

Author(s) (year)	Model description and remarks
Liu et al. (2010)	FC dynamics investigated in St. Louis Bay, USA by integration of previously calibrated and validated hydrodynamic (EFDC) and hydrologic (HSPF) models under 2 flow scenarios (dry and wet weather). HSPF as to compute the flows and FC loadings from watershed and tributaries while EFDC as to model hydrodynamic condition and FC transport within the receiving water. Non-point source loadings of FC considered in the HSPF including wildlife, land application of hog and cattle manure, land application of poultry litter, and grazing animals. Near-shore urban runoff, the most significant impact upon the Bay FC level. Greater loading stress of fecal associated more with the wet weather than the dry weather.
Petersen et al. (2011)	A water-quality model in the HSPF calibrated and validated to evaluate the impacts of the bacterial sources (temporally and spatially) in the watershed in Buffalo Bayou, Texas, USA. Nonpoint-source loading found to be still impacting *E. coli* concentrations in spite of returning to antecedent conditions from a hydrologic standpoint. Significant role of runoff in maintaining high levels of *E. coli* in regions with frequent rainfall Understanding the spatial and temporal variations of bacterial source loading of great importance to ensuring proposed load reduction strategies meet the water quality standard.

Table 2.4: Hydrological modeling of fate and transport of microbial contamination (cont'd).

Author(s) (year)	Model description and remarks
Coffey et al. (2013)	The Soil and Water Assessment Tool (SWAT) with microbial sub-model calibrated and validated to predict daily loading of *E. coli* in a small-scale agricultural catchment in Ireland. The majority of moderate-peak flow events fared reasonably with daily observations in spite of erratic and inconsistent model predictions of *E. coli*. Direct stream deposition from livestock or other agricultural operation identified as a key variable in the model's performance for small-scale catchments. The model applicable to compare different land management scenarios on occurrence of total bacteria concentrations. The framework could provide adequate data to develop a human exposure assessment to pathogen indicator organisms in surface water and assist policy-makers in developing appropriate risk management strategies.
Niazi et al. (2015)	Fate and transport of pathogen contamination (*E. coli* and FC) simulation conducted with SWAT for the Upper Salem River Watershed (agricultural), in, New Jersey, USA. Pathogen loading to the surface soil layer, pathogen decay and pathogen run-off on the surface soil layer considered. Livestock (i.e. feeding operations, manure spreading from grazing on pasture land, and animal feeding facilities), human (i.e. Septic system failure) and wildlife (i.e. a range of mammals) as three potential pathogen sources. The developed model could adequately predict the watershed outlet flows.

Table 2.4: Hydrological modeling of fate and transport of microbial contamination (cont'd).

Author(s) (year)	Model description and remarks
Sterk et al. (2016)	Pathogen concentrations (*Cryptosporidium* and *Campylobacter*) reaching surface waters through runoff calculated by usinf a model for catchment pathogen loads combined with a rainfall-runoff simulator model (WALRUS), to evaluate the impacts of climate change on pathogen runoff in Netherland. Input scenarios of fecal contamination considered for dairy cows, geese and manure fertilization considered along with climate change scenarios. Results showed limited impact of climate change on *Cryptosporidium* and *Campylobacter* transported from land to the surface waters.
Kim et al. (2017)	Watershed-scale fate and transport of *E. coli* simulated using SWAT, in in a 60-ha catchment in Northern Laos. Influence of three on-stream processes (i.e. bacteria deposition and resuspension, bacterial regrowth, and hyporheic exchange) on predicted *E. coli* concentration assessed. Implementation of release of *E. coli*, sediment resuspension and hyporheic exchange improved the model's performance while that of regrowth process did not improve the model predictions.

As seen inTable 2.3, hydrodynamic fate and transport modeling of microbiological contamination may address a variety of issues and is not limited to specific pathogens or indicators, time or areas (e.g. recreational water or drinking source water). Depending on the nature of the water body (e.g. river, lake, reservoir, estuary), 1D, 2D or 3D models might be utilized. Models can be developed for specific case studies, or may be a modified version of an existing one. Application of the modeling tools can target a wide range of objectives. As seen, identification of critical governing processes (as Hipsey et al., 2004, Hellweger and Masopust, 2008), comparison of different fate mechanisms (as McCorquodale et al., 2004), evaluation of spatial and temporal variation of concentration (as Hellweger and Masopust, 2008), sensitivity analyses of varying parameters on concentration (as Bedri et al., 2011), estimation of concentration and variation at intakes (as Sokolova et al., 2012), assessment of possible mitigation measures along with the comparison of the alternatives (as Garcia-Armisen et al., 2006) can be examples of model applications. Overall application of such models could greatly improve our knowledge of contamination dynamics. Besides, coupling the hydrodynamic/hydrologic models to/with a water quality model (model of fate, particularly) is common in almost all studies.

Microbial contamination in water bodies is influenced by the surrounding land use. Development of models at watershed scale plays an important role in evaluation of water quality of source waters and helps decision-making to meet regulatory requirements. Therefore, various management practices and microbial fate and transport controls have been implemented to improve the quality of water. Cho et al., (2016) critically reviewed existing watershed-modeling systems and the influencing components from surface runoff to different fate and transport within a series of complex environmental matrices.

Hydrologic-based studies are often performed in a watershed-scale while hydrodynamic models mostly focus on the water body itself. In other words, hydrologic models are responsible for modeling of the fate and transport of microbial organisms from their source to the receiving water in the watershed while hydrodynamic modeling involves the contaminant dynamics within the aquatic environment. Hydrological modeling can be used to calculate the concentration that leaves a catchment. Therefore, results from hydrologic models might be considered as loading of a specific source (such as load by livestock transported by run-off to a river) and serve as the inputs to hydrodynamic models.

In general, recognizing sources of microbial contamination and even quantifying these sources are of great importance for building a reliable predictive tool. In this regard, there have been some efforts to estimate microbial loads such as *Cryptosporidium* spp. and *Campylobacter* spp. from livestock by Dorner et al. (2004); FC loading from an urbanizing watershed by Im et al. (2004); pathogen budgets from a catchment by Ferguson et al. (2007). All of these investigations are hydrologic-based studies.

Previous efforts in loading estimation have, for the most part, resulted in a development of deterministic relationship that leads to a rough estimation of microbial concentration from sources. As said, these deterministic models significantly contribute to understanding of influencing factors and processes. However, high level of uncertainty in the model parameters, and in some cases, probable magnitude of the loadings should be somehow considered in the computations. Hence, accounting for a range of parameter values and then employing them into the model seem reasonable. This can be addressed by using probabilistic approach which acknowledges the uncertainty of the system, incorporates the random driving forces of the system and provide outputs in the form of probability distribution (useful particularly for management practices) (Walker et al., 1990). To the best of our knowledge, loadings based on the probabilistic model have rarely been integrated with hydrodynamic fate and transport models. However, other aspects of probability distributions have been utilized in some works as briefly presented in the followings.

Dorner et al. (2004) introduced, for the first time, a new approach in quantifying the loads from livestock in a watershed in Canada. Since, concentrations of pathogenic microorganisms from different sources are naturally variable, a probabilistic model was developed for estimating the production of pathogenic agents. Fitting two different distributions to data of prevalence of pathogenic microorganism and pathogen shedding intensity, they were able to highlight the contributing role of each livestock in the watershed as well as to prioritize the most vulnerable regions. This study showed that confronting with transient and variable nature of pathogenic microorganisms in the environment, probability approach seems to be more applicable. Later, Dorner et al. (2006) and Wu et al. (2009) successfully applied the same probability loading in their hydrological fate and transport model confirming the reliability of the approach. Lack of probability studies in the area of fate and transport modeling within a water course such as lake or river is of considerable gap among the literature.

2.3 CSOs

2.3.1 Impact studies

CSOs as a result of wet weather flows can intensify the level of microbial contamination in the receiving water as being discharged untreated, delivering acute fecal pollution whose manifestation in these sources is almost instant. CSOs have been recognized as an important source of pollution during rain and snowmelt events. Field surveys and simulation studies to investigate the effect of CSO magnitude and duration on receiving water are limited. For example, variation in contaminant concentration, either in source of entrance or within the drinking water sources, during and after CSO event has not been well documented. Occurrence of CSOs and their effects on the level of contamination in receiving waters are great concerns for water managers, particularly municipalities who are responsible for providing safe drinking water for their residents. A CSO event during an intense rainfall is the result of either the insufficient transport capacity of the sewer to allow water flow to reach the wastewater treatment plant or the insufficient treatment capacity of the wastewater treatment plant to treat all the water flow (Passerat et al., 2011). CSOs represent a mixture of sanitary sewage and contaminated stormwater, therefore, the level of indicator bacteria in CSOs are perceived to be higher than in the stormwater. The importance of CSOs in wet weather events in drinking water sources is further magnified by the fact that wet weather pollution is of a probabilistic nature, with respect to its occurrence in time and duration, intensity and frequency of rain events, magnitude of overflows and contaminant concentrations (Marsalek and Rochfort, 2004).

CSO impacts in terms of common physical-chemical parameters of receiving water (such as chemical and biochemical oxygen demand, suspended solid) are extensively studied (e.g. Even et al., 2007; Piro et al., 2012; Riechel et al., 2016; Quijano et al., 2017) while impacts of microbial and pharmaceutical contaminant have been relatively less considered (Madoux-Humery et al., 2013). Studies provided in Table 2.1 investigated the microbiological impacts of CSO events by field monitoring and sampling either in near receiving water or at the outfalls. Pathogenic contamination at drinking water sources as a result of CSO discharges are inevitable and requires comprehensive analysis of fate and transport of contaminant of interest (i.e. microbiological). Determining post-CSO microbiological impact within the water body, particularly the critical period of peak contaminant concentration can be addressed by hydrodynamic and water quality model of the receiving waters. In particular, analysis of fate and transport of microbiological contamination induced by CSO events to drinking water sources, receives fewer attention in the literature. Table 2.5 presents a summary of the studies assessing the CSO impacts (microbiological) on the receiving water (including drinking water sources) by applying a hydrodynamic and water quality model.

Table 2.5: Modeling of CSO-induced microbiological contamination within the receiving water.

Author(s) (year)	Model description and remarks
Marchis et al. (2013)	A 3D hydrodynamic and water quality model of a coastal area used to simulate the propagation of *E. coli* in time and space as a result of CSO events in Acicastello Bay, Italy. 6 CSO outfalls monitored and sewer flow and water quality samples captured during discharges. Results showed that the meteorologic–marine conditions play a fundamental role in the dispersion of the *E. coli* in an open waterbody. *E. coli* concentration at the outfalls rapidly decreases with the hydrodynamic effect. *E. coli* concentration exceeded the bathing limit in 50 % to 70% of shore length.
Shibata et al. (2014)	A 3D hydrodynamic and water quality model (*E. coli*) developed to investigate the role of urban rivers receiving CSOs in fecal contamination of a coastal area, Japan. Two urban rivers flowing into the Bay investigated with and without inflow pollutant loads. Discharge volume and *E. coli* loads of the rivers under CSO impacts estimated. The model reproduced the general trend that *E. coli* rapidly increased and then decreased gradually. Results showed that 10 days required for *E. coli* concentration to decrease to swimmable criteria level. The developed model can be useful to discuss effective CSO control measures and to provide an alarm system for fecal contamination.

Table 2.5: Modeling of CSO-induced microbiological contamination within the receiving water (cont'd).

Author(s) (year)	Model description and remarks
Jalliffier-Verne et al. (2016)	A 2D hydrodynamic and water quality model (transport-dispersion model of *E. coli*) calibrated and validated to investigate dispersion and diffusion of *E. coli* as a result of CSO discharges in a river used as a drinking water source, Canada. *E. coli* concentration from CSO events estimated and then applied to active CSO outfalls within the studied area. Results demonstrated cumulative effects of CSOs on the degradation of water quality downstream. It is suggested the cumulative effects of discharges and their concentrations must be taken into account as simultaneous discharge of overflows could potentially lead to elevated *E. coli* concentrations at a drinking water intake.

2.3.2 CSO concentration variation

Variation of concentration either between different CSO events (inter-event variation) or over the course of one event (intra-event variation) are two other topics discussed in the literature. While variability in microbial concentration described by inter-event studies could be correlated to season, temperature, rainfall duration and intensity (McCarthy et al., 2007), there are fewer data or knowledge available on intra-event dynamics of FIB in CSOs. Even though inter-event studies are beneficial to detect specific pattern between events, the analyses only capture the inter-event variability and do not fully explain dynamics of microbial concentrations in the source. In general, inter-event CSO studies may not be able to provide sufficient data on the peak concentration. Information about the time of peak concentration as well as how variable they would be in terms of different wet weather conditions and loadings has not received much of attention.

This is highly important in SWP point of view for urban municipalities where they need to identify threats during peak events. Peak concentration of microbial contamination in course of discharge puts a great treatment challenges in treatment process (Hrudey et al., 2003). While some of investigations attempted to determine the temporal, spatial and even dynamic variability of microbial contamination during or after a stormwater event (such as McCarthy et al., 2012; Pan et al., 2012), a little has been done in terms of CSO events (See Madoux-Humery et al., 2013). Madoux-Humery et al. (2013) examined the temporal variations of concentration in wet weather by comparing with dry weather conditions, evaluating seasonal and inter and intra-event fluctuations. The latter analyses showed that concentrations in CSO events may vary widely due to the background concentrations (i.e. different sewershed). It is also found that the peak concentrations of *E. coli* were observed at the beginning of events and remained elevated throughout each event. As a conclusion, studying the dynamic behavior of concentrations would provide an opportunity to characterize the fluctuations in concentration. This type of study would also provide knowledge about the peak loading characteristics, which is important for SWP.

There are also some other studies in the literature aiming to elaborate the behavior of CSO based on the rainfall characteristics (Thorndahl and Willems, 2008; Sandoval et al., 2013; Mailhot et al., 2015; Gooré Bi et al., 2015; Yu et al., 2018). However, most of the studies concerning CSOs are more qualitatively oriented and less are based on quantitative descriptions. Available deterministic models of CSOs (such as Pongmala et al., 2015) requirs detailed data for the the model development and are not easily applied to a large number of CSOs upstream of drinking water intakes. It can be inferred that a less complex approach in quantifying or even predicting CSO behavior is of interest in which CSO dynamics would be considered.

2.4 Quantitative Microbial Risk Assessment

Relying on the compliance of treated water through monitoring treatment processes with measurements of FIB is common practice, but might not be sufficient to prevent disease outbreaks (Hamouda et al., 2016), particularly with regards to chlorine resistant pathogens (i.e. *Cryptosporidium* and *Giardia*). The strategies to prevent illness from consumption of treated drinking water has been increasingly switched from end product (tap) water quality considerations to a larger scale source-to-tap framework with a focus on human health. Assessing the human health risk from a water supply is of great importance when trying to make a judgment of water safety levels (Howard et al., 2006). Microbial contamination from pathogens represents the greatest risk to drinking water sources (Teng et al., 2012). Risk reduction in drinking water sources involves recognizing the reference pathogens present in source water, installing treatment barriers depending on the level of contamination and monitoring their performances and maintenance of the distribution system (Jaidi et al., 2009). Quantitative Microbial Risk Assessment (QMRA) is the application of principles of risk assessment to quantify the risk to human health (i.e. risk of infection) resulting from disease caused by exposure to specific types of waterborne pathogen or infectious microorganisms (Howard et al., 2006). It is a science-based method used by water utilities and risk managers to improve their understanding of pathogen-related human health risk considering all components in a source-to-tap framework. QMRA typically consists of four major steps: hazard identification (i.e. recognizing the appropriate microorganism), exposure assessment (i.e. routes of human exposure), dose-response assessment (probability of infection due to a given dose of microorganism) and risk characterization.

The outputs of risk assessment can be presented in different forms such as risk of infection which is number of illnesses per population, a metric representing a burden of disease (e.g. economic) or Disability Adjusted Life Year (DALY) (WHO, 2017). Acceptable risk levels recommended by guidelines or legislation are very low (e.g. 1 infection per 10000 people per year) to ensure safe drinking water production (Smeets et al., 2010). In fact, WHO (2017) guidelines for safe drinking water recommends a comprehensive approach based on the human health risk that incorporates all components of source to tap system, called as “water safety plan”. QMRA is considered as valuable tool to support water safety planning by defining treatment targets with regards to the quality of source water (Petterson and Ashbolt, 2016). For any contamination level in source, the level of pathogen removal can be determined depending on health-based tolerable risk that is targeted. In Canada, an acceptable annual risk has been established to comply with the health-based target of 10E-6 DALY risk Health Canada. As a result, QMRA can be employed to determine health-based targets and treatment requirements while helping authorities set regulatory or operational priorities to ensure safe drinking waters (WHO, 2017).

QMRA has been extensively employed to estimate the human health risk related to exposure to infectious pathogens under various exposure routes in drinking waters (Howard et al., 2006; Cummins et al., 2010; Pintar et al., 2012; Sato et al., 2013; Xiao et al., 2013; Zhou et al., 2013; Swaffer et al., 2018), recreational water (Ashbolt et al., 2010; Kundu et al., 2013; Soller et al., 2014; Vergara et al., 2016) or reclaimed water for agricultural purposes (Chhipi-Shrestha et al., 2017; Kouame et al., 2017; Moazeni et al., 2017; Busgang et al., 2018). QMRA model inputs for potable water applications in these studies may mainly include, but are not limited to, microorganism concentrations and their occurrences, treatment processes and removal efficiency and dose-response relationships in the form of stochastic or deterministic variables. QMRA models are highly sensitive to dose-response assumptions that are often based on human or epidemiological studies with large uncertainties (WHO, 2017).

Application of practical QMRA for drinking water sources requires quantification of pathogen concentrations in untreated water sources or raw water intakes. As a result of infrequent sampling, insufficient information on the concentration variation, failure in detecting hazardous peaks, costly procedures and detection limit of analytical methods, QMRA may suffer from lack of appropriate inputs (Sokolova et al., 2015). To overcome this challenge, it has been suggested to use information on the source of pathogenic contamination at the point of entrance to water bodies and then rely on the computer models (hydrodynamic and water quality models) to simulate the whole fate and transport processes to any points of interest (McBride et al., 2013). Use of QMRA combined with outcomes of hydrodynamic models can address the limitation regarding the lack of water quality data including the periods of peaks in the source (McBride et al., 2012). Such combination would provide valuable information on the variation of the health risk status for a wider range of environmental forcing and conditions that may potentially occur at the source. Therefore, hydrodynamic and water quality models can be used to investigate the impacts of loading events, particularly discharge-based events (wet weather flows or wastewater treatment effluents) on the water quality of receiving waters. Discharge-based QMRA has been introduced accordingly to assess the risk associated with such loading events (McBride et al., 2013). Given that pathogen concentration in source waters are primarily driven by upstream loading events, Sokolova et al. (2015) primarily integrated the discharge-based QMRA with the results of hydrodynamic and water quality models in the context of drinking water sources. Different sewage discharge conditions were included in the model simulation scenarios to estimate the corresponding concentrations of contaminant (norovirus) in the source water. The results were then implemented in QMRA steps to determine norovirus removal level required within the treatment unit. The results demonstrated successful application of QMRA, when combined fate and transport model, as a tool to examine the adequacy of the treatment performance to deal with a range of possible loading condition.

There are several QMRA approaches that are significantly different in level of complexity and mathematical methods providing risk results in form of either single point risk estimate or a more complex in a distribution profile format. While risk levels vary over the course of a year due to the high variability of pathogen concentration and distribution in the source, water-borne outbreaks have been linked to shorter-duration periods of heightened risk (Signor and Ashbolt, 2009). Therefore, probabilistic QMRA has been used to capture the impacts of such temporal variability on the overall risk level applying Monte Carlo simulation techniques (Howard. et al., 2006). A shorter-duration reference (i.e. daily, instead of annual) would provide guidance on control practices to deal with a short-term risk fluctuation events and assess management initiatives.

The outcomes of QMRA models are pathogen dependent and may vary from one agent to another. Pathogen-associated risk may not be assessed due to the many prohibitive reasons, in particular, the cost-related issues. In case of unavailability of pathogen data, many initial QMRA analyses would be based on the occurrence of indicator organisms. In order to extrapolate from the data of FIB to that of unavailable pathogen data, it is suggested to assume a relationship between the pathogens and FIBs (Howard. et al., 2006; McBride et al., 2012).

CHAPTER 3 RESEARCH OBJECTIVES, HYPOTHESES AND METHODOLOGY

3.1 Problem identification

As concluded from the previous section, CSOs from urban wet weather discharges into source waters contribute to the microbiological contamination of receiving waters, particularly drinking water sources. One of the gaps in the literature pertains to CSO models that integrate the variability of the event parameters to project a range of probable CSO loading conditions, instead of deterministic loading estimates. Considering the highly variable nature of the phenomena with regards to overflow duration and concentrations as well as the uncertainty associated with these event parameters, a stochastic approach would be appropriate and well suited to characterize randomly occurring events. Overflow and contaminant concentration dynamics over the course of events have not been quantitatively addressed in the literature. A method for characterizing the discharge behavior of CSOs that is independent of the scale of the events and applicable to different events is needed. Determining the dynamic behavior of the contamination source is a critical step in understanding the resulting concentration variation or distribution at any downstream points of interest including intakes of drinking water treatment plants as they are primarily driven by the upstream loading conditions. Concentration dynamics and period of peak concentrations at the intake of drinking water treatment plant have been always a concern for water utilities as treatment processes must be able to handle peaks and reduce them to an acceptable level. Therefore, a CSO loading framework is required to evaluate the subsequent impacts under various discharge scenarios and event characteristics. The outputs of such model can be potentially considered as the inputs of hydrodynamic model for the estimation of probable concentrations in the receiving waters.

To the best of our knowledge, no study has investigated the probability distribution of concentration (*E. coli*) at intakes of drinking water treatment plants caused by a series of probable CSO events generated from a semi-probabilistic CSO load model. Moreover, due to the increase of human health risk during discharge events, CSO-associated health risk upon consumption of treated water during these peak periods has not been quite well documented. In this regard, application of QMRA combined with the result of hydrodynamic and water quality model can to investigate the impacts of CSOs in terms of risk expression or treatment requirement for a given health-based target.

Characterizing the period of peak concentrations at drinking water intakes is of the basic demand for source water protection practices. In Canada, source water protection falls within the jurisdiction of the local and provincial authorities. As a result, various source water protection approaches have been developed across Canada. For example, methodology for vulnerability and threat assessment of drinking water intakes regulated in Quebec and Ontario are totally different. Therefore, it is of great interest to highlight the components of the current approaches conducted in these two neighboring provinces and assess if the proposed assessment criteria can be improved by including the impact of CSO discharges and their associated health risk.

3.2 Research objectives

The general objective of this research project is to evaluate the microbiological impacts of CSO discharges at the intakes of downstream drinking water treatment plants in terms of elevated health risk during peak periods upon consumption of treated water.

The specific objectives of this proposed research are:

1. Characterize general CSO discharge behavior without the need for detailed hydraulic models,
2. Develop a semi-probabilistic model of CSO loads,
3. Generate CSO loading scenarios based on the CSO magnitude in terms of concentration, discharge volume and duration,
4. Develop, calibrate and validate a hydrodynamic and water quality model of a river used as a source of drinking water,
5. Select CSO scenarios and simulate the transport of *E. coli* following discharge events,
6. Identify periods of peak concentration and time of occurrence following discharge event at the drinking water intakes,

7. Acquire the probability distribution of concentrations at the intakes caused by a range of probable CSO events,
8. Incorporate the simulation results of the hydrodynamic model in QMRA analysis,
9. Quantify the impacts of CSOs on human health risk and treatment requirements,
10. Compare two different source water approaches for vulnerability and threat assessment conducted in Quebec and Ontario considering one transboundary river as a case study.
11. Assess and identify the appropriate mitigation strategies in reducing the risks induced by CSOs
12. Propose a new framework improving vulnerability assessments by taking CSO impacts into account.

By achieving the objectives mentioned above, it would be possible to answer the research questions concerning the implications of CSO probabilistic modeling framework coupled with QMRA:

- How can the variable nature of CSO discharges be expressed in fate and transport modeling?
- What is the range of microbial concentration at the intakes in the case of different probable CSO occurrences?
- How can water managers ensure the safe drinking water consumption while CSO-caused periods of peak microbial concentrations occur?
- What is the level of treatment required while dealing with peak periods?
- How can short-term risk analysis be implemented in source water protection strategies?

The objectives are derived from the following research :

1. The dynamics of flowrate and contaminant concentrations over the course of CSO events are dependent of the scale of the event. Therefore, normalizing techniques can reveal the underlying characteristics of discharge behavior of CSOs.

Originality: *This is the first study to identify shared characteristics of CSO discharge behaviors in terms of normalized flowrate and concentration parameters among different events that could be useful for vulnerability assessments.*

2. CSO events significantly increase the annual microbial risk at drinking water treatment plants.
   Originality: *This is the first study quantifying the CSO-associated risk of drinking water considering the peak conditions obtained from modeling results and linking them to daily and annual microbial risks.*

3. Despite different approaches for assessing the vulnerability of drinking water treatment plants to microbial risks, Ontario and Québec's approaches will lead to similar vulnerability classification of drinking water treatment plants.
   Originality: *This is the first quantitative study comparing the vulnerability and threat assessment approaches for two Canadian provinces.*

The results of this study were structured in three sections of the thesis as three articles. The first article which has been submitted to the journal of *Environmental Management* is about quantitative characterization of CSO discharges that leads to development of a semi-probabilistic CSO load model. The second article that has been submitted to the journal of *Science of the Total Environment* is about the evaluation of CSO-associated health risk using hydrodynamic and water quality model combined with QMRA. Another results chapter compares the microbial vulnerability and threat assessment approaches for Quebec and Ontario.

3.3 Methodology

In order to achieve the aforementioned goals, this research project was structured in four steps described as a flowchart in Figure 3.1. The first step was to understand the dynamic behavior of CSO discharges. Step two was to implement the CSO loading model into a hydrodynamic and water quality model to investigate the impacts of CSO discharges on the downstream drinking water sources. In the next step, simulated *E. coli* concentrations at drinking water intakes were used as the inputs of QMRA to evaluate the corresponding microbial risk of CSO discharges. In the final step, the vulnerability and threat assessment of the studied intakes was conducted according to

Quebec's and Ontario's approaches given that the drinking water intakes are located on a transboundary river between Quebec and Ontario.

The initial step was to introduce a CSO loading framework that captures the intra-event variability of flowrate and concentration. Flowrate and concentration data measured in course of CSO events were collected from the published literature to investigate patterns in dynamics of discharges. Having identified common characteristics among events, a CSO load model was developed based on the deterministic flowrate model and probability distribution function of contaminant concentration. Using the combination of flowrates and concentrations, a semi-probabilistic CSO load model based on the normalized values were established to be used for CSO load simulation.

The next step was related to the development of fate and transport model of a water body, a river as case study to study the impacts of CSO discharges on downstream drinking water intakes. This step is considered as the key component of the research as the microbiological contamination (*E. coli*) concentration at drinking water intakes were modeled incorporating the CSO load model developed in phase 1 into the river model. The peak periods were characterized under different probable range of CSO events that are expected to occur in a year from March to October (other months have few precipitation or snowmelt driven CSO events). Having obtained concentration values from simulation of CSO events, probability distributions of *E. coli* were then defined.

Describing the implications of CSO events in terms of microbial risk to water consumers, QMRA was used for two treatment efficiency conditions, 3 log removal and 4 log removal in the third step of the project. The results of QMRA reflected the short-term microbial risk induced by CSOs, but also provided a platform to identify potential improvements for reducing uncertainties of risk assessments.

In the last and final step, a method to include microbial risk of discharge-based event and in particular, CSOs, in the vulnerability and threat assessment of drinking water intakes was shown.

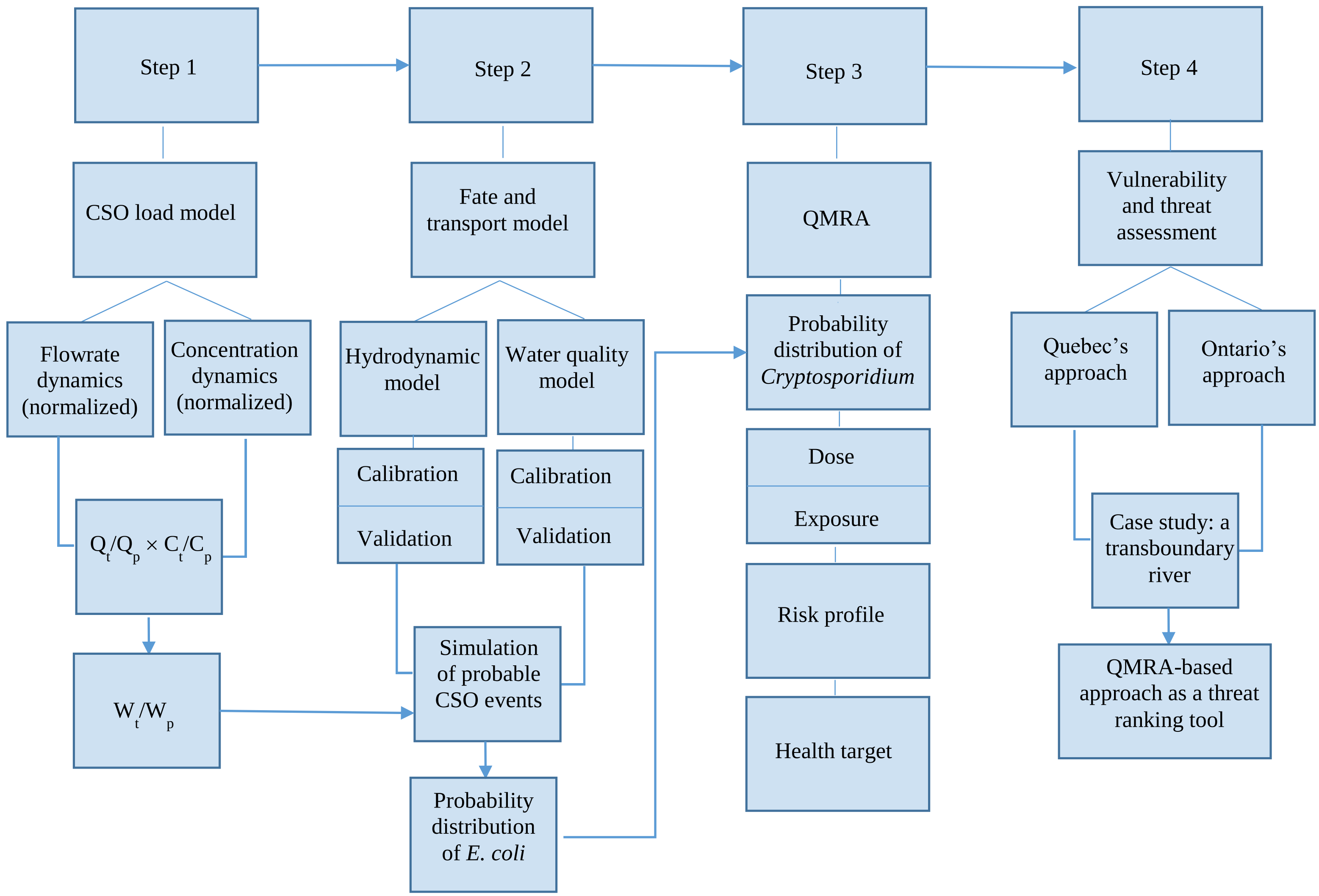

Figure 3.1: The structure of the research project.

CHAPTER 4 ARTICLE 1: NORMALIZED DYNAMIC BEHAVIOR OF COMBINED SEWER OVERFLOW DISCHARGES FOR SOURCE WATER CHARACTERIZATION AND MANAGEMENT

In this chapter, we discuss the findings from analysis of CSO discharge dynamics by normalizing the scale-related parameters of the events. We were able to develop a stochastic model of CSO load based on mutual characteristics of CSO events. The proposed CSO loading framework can be employed to produce various CSO loading conditions for source water management studies.

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NORMALIZED DYNAMIC BEHAVIOR OF COMBINED SEWER OVERFLOW DISCHARGES FOR SOURCE WATER CHARACTERIZATION AND MANAGEMENT

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ABSTRACT

As one of the major sources of surface water quality impairments, Combined Sewer Overflows (CSOs) are of concern when receiving waters are used for drinking water supplies. Given the large number and variability in CSO discharges and loads, there is a need for a general methodology for estimating discharges for environmental planning and source water protection. Detailed data on CSO flowrates, contaminant concentrations including Total Suspended Solids (TSS), *Escherichia* *coli* (*E. coli*), caffeine (CAF) and acetaminophen (ACE) were used to develop a simple loading model that was then verified using discharge and concentration data from other CSO and stormwater events in the literature. The variability of the parameters within each event was analyzed by normalizing flowrate, concentration and event duration to their respective peak values. The normalized flowrate data indicate that the second decile of the discharge periods was associated with peak flowrates. The dynamic behavior of CSO flowrates can be characterized by a linearly increasing trend and then a logarithmically decreasing trend in terms of normalized values. The samples captured during the first decile of the events were illustrated to be a better representation of peak concentrations of all four contaminants. By analyzing the discharge period in three sections (i.e. 1st decile, 2nd decile and remainder), a semi-probabilistic CSO loading model is proposed for the entire discharge period taking into account the variability of the phenomena. Findings can help water managers and utilities to more efficiently design sampling campaigns with the possibility of capturing the peak raw water concentrations that are critically needed for source water protection planning as well as the operation of drinking water treatment plants.

KEYWORDS

Combined sewer overflows, Total suspended solids, *Escherichia coli*, Wastewater micropollutant, discharge behavior, probabilistic loading.

4.1 Introduction

The discharge of Combined Sewer Overflows (CSOs) leads to the deterioration of receiving water quality because of the presence of microbiological and physico-chemical contaminants in the overflow effluents (Chambers et al., 1997; Marsalek and Rochfort, 2004; Anne-Sophie et al., 2015). The capacity of a sewer system may be reached during or after a rainfall event as the storm waters flow into, mix with sewage and ultimately lead to the discharge of untreated (or partially treated) wastewater into water bodies (Passerat et al., 2011; Jalliffier-Verne et al., 2016). More importantly, CSO discharges are highly variable with regards to event duration, flowrates and contaminant concentrations. Of particular concern for drinking water are peak pathogen concentrations should they exceed the removal capacity of drinking water treatment.

CSO impacts have been relatively well documented with regard to various physical-chemical water quality parameters (e.g., Piro et al., 2012; Kafi et al., 2008; Even et al., 2004). They have been associated with variety of factors including rainfall characteristics (e.g. Yu et al., 2013; Thorndahl and Willems, 2008), drainage area of sewer systems, time of sampling and number of samples (See Madoux-Humery et al., 2013). The microbiological and micropollutant (pharmaceuticals and personal care products)-related CSO studies have mainly focused on a series of sampling campaigns, measuring concentrations, overflow discharges and duration of the event at discharge points/outfalls or in receiving waters (e.g. Fong et al., 2010; Astrom et al., 2009; Kim et al., 2009; McLellan et al., 2007; Arnone and Walling, 2006; Rechenburg et al., 2006; Katayama et al., 2004). However, the dynamic behavior of microbiological and micropollutant contaminants associated with CSO discharges have lacked detailed characterization (Madoux-Humery et al., 2013). Of microbiological concern, CSO discharges without any treatment will instantly deliver high concentrations of fecal pollution in source waters (Marsalek and Rochfort, 2004). On the other hand, the presence of wastewater micropollutants in source waters can provide information on the origins (human versus non-human source) of contamination and persistence in surface waters. For example, caffeine (CAF) and acetaminophen (ACE) have been proposed as markers of domestic sanitary contamination (Guérineau et al., 2014; Madoux-Humery et al., 2013; Sauvé et al., 2012; Benotti and Brownawell, 2007). Wastewater micropollutants in the environment are less a concern for human health, however, they are potentially a concern for aquatic organisms (Jasinska et al., 2015).

Source water protection aims to efficiently prioritize sets of measures to protect the quality of drinking water supplies. Some regulations, as in Québec, Canada (MDDELCC, 2014a) assess the vulnerability of drinking water sources through water quality monitoring. However, routine monitoring might not capture periods of peak concentration in the source waters which are primarily derived from an upstream discharging event, leading to an underestimation of overall contaminant concentration level (Jalliffier-Verne et al., 2016; Madoux-Humery et al., 2016). Therefore, it is essential to characterize the dynamic behavior of discharge-based events such as CSOs or stormwaters to study their potential impacts on downstream drinking water intakes. There are a limited number of analyses of the dynamics of discharged-based events (mostly stormwater and fewer studies of CSOs), which can be classified into three categories of analyzing concentration variations: (1) between events (e.g. Hannouche et al., 2014; McCarthy et al., 2013; Krishnappan et al., 2012), (2) over the course of an event (e.g., Hathaway et al., 2015; Madoux-Humery et al., 2013; Métadier and Bertrand-Krajewski, 2012; McCarthy et al., 2012; Krometis et al., 2007; Selvakumar and Borst, 2006; Gruning and Orth, 2002) and (3) during the "first flush" of stormwater discharges (e.g.,McCarthy, 2009; Park et al., 2010; Gupta and Saul, 1996).

Krometis et al. (2007) characterized stormwater discharge periods into three portions (i.e., rising limb, peak, and recession) based on 1 hour-span before and after the occurrence of peak flow. The study was one of the first attempts in describing the dynamic behavior of microbial contaminants in stormwater. As the definition of these periods are dependent of the discharge duration, the methodology in case of scaled up (longer duration) or scaled down (shorter duration) events are not applicable as they may not fit the definition. Therefore, a simple approach in characterizing the peak periods of events, (peak flow and peak concentration) independent of scale of events have not been introduced so far. In terms of CSO dynamic discharge behavior, a very limited number of studies conducted continuous monitoring of FIB, wastewater micropollutants or pharmaceuticals. Madoux-Humery et al. (2013) considered temporal variability of contaminant concentration during events. However, demonstrating common characteristics in CSO dynamics due to the very variable nature of phenomena has been always considered as a challenging task. This is highly important when it comes to generalizing the knowledge obtained from a limited number of events to other events with different characteristics (ie. duration, flowrate and concentration). To overcome this challenge, normalizing techniques are simple but effective methods for the comparison of events of different scales. Using this technique, Piro et al. (2012) compared the temporal patterns of wet weather flows to those of dry weather. However, the comparisons were simply graphical and did not present any comments on dynamic flowrate behavior. To the best of the authors' knowledge, this treatment of data has not been applied in recognizing CSO discharge behavior in terms of the scale event parameters. These simple analyses are essential for developing predictive stochastic models of CSO discharges, their loads and their impacts on drinking water intakes given the quantification of microbial contaminants by continuous monitoring at every discharge point is not feasible in terms of cost and time (McCarthy et al., 2007).

Estimation of pathogen concentrations in drinking water sources have been feasible employing loading models at a watershed scale (e.g. Dorner et al., 2004; Im et al., 2004; Ferguson et al., 2007). For CSOs, loading models of Total Suspended Solid (TSS) and Chemical Oxygen Demand (COD) (e.g. Métadier and Bertrand-Krajewski, 2012; Lacour et al., 2009; Gruber et al., 2005) or chemical pollutants (e.g. Weyrauch et al., 2010) have been developed. Previous efforts in microbial loading of CSOs have mostly relied on a deterministic approach or a single value estimation of concentration from sources without acknowledging variability of the parameters of the events (e.g. Mahajan et al., 2014). Considering the highly variable nature of the phenomena with regard to overflow, duration and concentration as well as the uncertainty associated in these event parameters, a stochastic approach would be appropriate and well suited to characterize randomly occurring events. The outputs of such models can be in the form of probability distributions, which are more meaningful than single valued answers.

The goals of this study were to: 1) identify the common, scale-independent, underlying dynamic behavior of CSO discharges, 2) develop a semi-probabilistic CSO loading approach for physical (TSS), microbial (*E. coli*) and WWMPs (CAF and ACE) contaminants, 3) apply the model to produce potential CSO loading profiles. The semi-probabilistic model of CSO loading is proposed as a more comprehensive alternative to deterministic loading estimates based on a constant mean value (e.g. Jalliffier-Verne et al., 2016). The outputs of such model can be treated as the inputs of fate and transport models for the estimation of the probability distribution of downstream concentrations and for comparing the potential impacts of various scenarios of CSO discharges.

In this study, the overflow patterns for each portion of the events (i.e. rising limb, peak, falling limb) were investigated and a mathematical approach is proposed as a potential solution for generalizing and quantifying the dynamic behaviors of CSOs. Hence, the periods of peak and recession described by previous studies (See Krometis et al., 2007) is intended to be characterized in terms of time of occurrence regardless of the scale of events.

4.2 Materials and methods

4.2.1 Overflow and stormwater data

Two sets of data were used in this study. The main focus of analysis was based on this first set of data to explore the underlying dynamics of overflows while the second dataset was used for verification purposes. The first set of data included CSO flowrate data, TSS, *E. coli*, CAF and ACE concentrations provided by Madoux-Humery et al. (2013) (See Table 4.1) while the second dataset was extracted from the published literature, where the required information (i.e. primarily discharge hydrographs) could be retrieved. The original data from Madoux-Humery et al. (2013) consisted of intra event sampling of 10 CSO events from two sewersheds (A and B) over a course of a year in the Greater Montreal Area (Table 4.1). Overflow measurements of one event (A3) was excluded from the flow analysis because of technical problems with flowrate measurements. Additionally, a summer storm event (A8) was also removed from the analysis as it was the event with the least precipitation and flowrate and thus was of lesser interest from a contaminant loading perspective. Concentration measurements of TSS, *Escherichia coli* (*E. coli*), CAF and ACE concentrations were included in the analysis from the remaining CSO events. The CSO events occurred as the result of rainfall in summer and fall as well as a mixture of rainfall and snowmelt in late winter and early spring. More details on the sampling methodology, analytical methods, sewer system, locations of the outfalls and site characteristics can be found in Madoux-Humery et al. (2013).

Samples taken during the event A4 were analyzed for *E. coli* concentrations only. Event Mean Concentrations (EMCs) of TSS, *E. coli*, CAF and ACE as well as the parameters reflecting the scale of each event including peak concentrations (C_p), peak flowrate (Q_p), time of peak occurrences (t_{C_p} and t_{Q_p}) and discharge duration (T_{total}) are presented (Table 4.1). Peak concentrations and EMCs of *E. coli*, CAF/ACE varied up to 2 and 1 orders of magnitude among events, respectively. The time of the occurrence of peak concentrations and peak discharges varied among events.

The verification data for discharge rate analysis were obtained from CSO studies published by Rossi et al. (2005), Todeschini et al. (2011), Riechel et al. (2016), Gruber et al. (2005), forming a wide range of events with regards to discharge rate and duration (See Table 4.6. 1). Stormwater hydrograph data published by Krometis et al. (2007) was also obtained to explore the similarity between stormwater events and CSOs in terms of discharge behavior. TSS and *E. coli* concentrations measured over the course of CSO and stormwater events were retrieved from Rossi et al. (2005) and Hathaway et al. (2015), respectively. The secondary datasets are not only to verify findings from analysis data of Madoux-Humery et al. (2013), but also to demonstrate

Table 4.1: Description of scale-related parameters of the studied CSO events for TSS, *E. coli*, CAF and ACE. Event Mean Concentration (EMC), peak concentration (C_p), time of peak concentration (t_{C_p}), peak flow (Q_p), time of peak flow (t_{Q_p}) and total discharge period (T_{total}).

		TSS			*E. coli*			CAF			ACE					
CSO event	Season	EMC (mg/L)	C_p (mg/L)	t_{C_p} (min)	EMC (MPN/100mL)	C_p (MPN/100mL)	t_{C_p} (min)	EMC (ng/L)	C_p (ng/L)	t_{C_p} (min)	EMC (ng/L)	C_p (ng/L)	t_{C_p} (min)	Qp (L/s)	t_{Q_p} (min)	T_{total} (min)
A1	Fall	260.1	348	17	1.70E+06	3.45E+06	8	6650	12176	12	4208	9052	12	653.9	36	312
A2	Fall	88.5	138	48	2.03E+04	6.30+E04	9	7964	27979	27	8673	29118	27	1549.2	108	958
A3	Fall	N/A	588	29	-	2.95E+05	29	-	20336	19	-	22958	14	-	-	346
A4	Fall	-	-	-	1.11E+06	1.99E+06	35	-	-	-	-	-	-	22.7	62	383
A5	Snow melt	243.9	490	96	3.08E+06	7.27E+06	36	9133	11100	55	21621	37849	36	228.0	139	779
A6	Snow melt	265.4	357	45	3.22E+06	6.49E+06	165	1571	1710	14	3636	4598	14	558.2	108	403

Table 4.1: Description of scale-related parameters of the studied CSO events for TSS, *E. coli*, CAF and ACE. Event Mean Concentration (EMC), peak concentration (C_p), time of peak concentration (t_{C_p}), peak flow (Q_p), time of peak flow (t_{Q_p}) and total discharge period (T_{total}) (Cont'd).

CSO event	Season	TSS EMC (mg/L)	TSS C_p (mg/L)	TSS t_{C_p} (min)	*E. coli* EMC (MPN/100mL)	*E. coli* C_p (MPN/100mL)	*E. coli* t_{C_p} (min)	CAF EMC (ng/L)	CAF C_p (ng/L)	CAF t_{C_p} (min)	ACE EMC (ng/L)	ACE C_p (ng/L)	ACE t_{C_p} (min)	Qp (L/s)	t_{Q_p} (min)	T_{total} (min)
A7	Summer	142.7	468	7	1.61E+06	1.54E+07	333	565	4376	2	691	5065	2	3485.1	47	694
A9	Summer	129.5	273	6	7.67E+05	4.61E+06	2	1955	10298	2	543	3230	2	2037.4	24	146
B1	Summer	238.3	754	10	4.56E+05	6.20E+06	10	423	639	10	-	-	-	32.6	39	220

the results would be conclusive to be generalized to other discharge behavior. The methodology of normalizing the scale-related parameters was applied to both data sets.

4.2.2 Statistical methods and normalization techniques

In order to compare events of different scales, and to better characterize the intra-event variability of the scale-related parameters, the concentrations (C_t) of TSS, *E. coli*, CAF and ACE and overflow (Q_t) were normalized to their corresponding peak values (i.e. C_p, Q_p) as well as time elapsed since the beginning of the overflow (t) normalized by the duration of discharge (i.e. T_{total}). The result of the transformation of the variables (i.e. C_t/C_p, Q_t/Q_p and t/T_{total}) forms a uniform scale ranging from 0-1 through which parameters of one event becomes comparable to those of other events. For characterizing probability distributions, the Kolmogorov–Smirnov test (K-S) was used with the Crystal ball (Oracle, Redwood City, USA) and Easyfit (Mathwave Technologies) software packages. The distribution goodness-of-fit, where *p*-value greater than 0.05 (significance level) indicated that the data followed a given distribution.

The normalizing technique was used to characterize the dynamic loading behavior of discharges over the course of CSO events. It was based on the combination of normalized flowrate, normalized concentration and Monte Carlo simulation. The steps were as follows: 1) divide each event into deciles based on normalized time (t/T), 2) obtain a general mathematical description of normalized CSO flowrates (Q_t/Q_p) as a function of normalized time, 3) characterize the variability of normalized concentration (C_t/C_p) and period of peaks within deciles and 4) apply Monte Carlo simulation to estimate normalized loads by randomly selecting t/T and multiplying the normalized flowrate value for t/T by the normalized concentration value, which is randomly selected from the best fit concentration probability distributions. The iterative process for estimating loads by Monte Carlo simulation is illustrated in Figure 4.1: Flowchart of the Monte Carlo simulation process to estimate loads combining deterministic equations of normalized flowrate with probability distributions for concentrations.

4.2.3 Application of the normalized loading model to a CSO in Québec, Canada

The normalized model was used to generate CSO scenarios that discharge into a river upstream of drinking water sources in an urban region in southwestern Québec. CSO data on CSO duration were collected as part of regulatory requirements by the Québec government (MELCC 2014b).

Local data are required to scale up the normalized CSO loading model. These data should include records of duration of CSO discharges, measures of volume of discharges or peak flowrates and

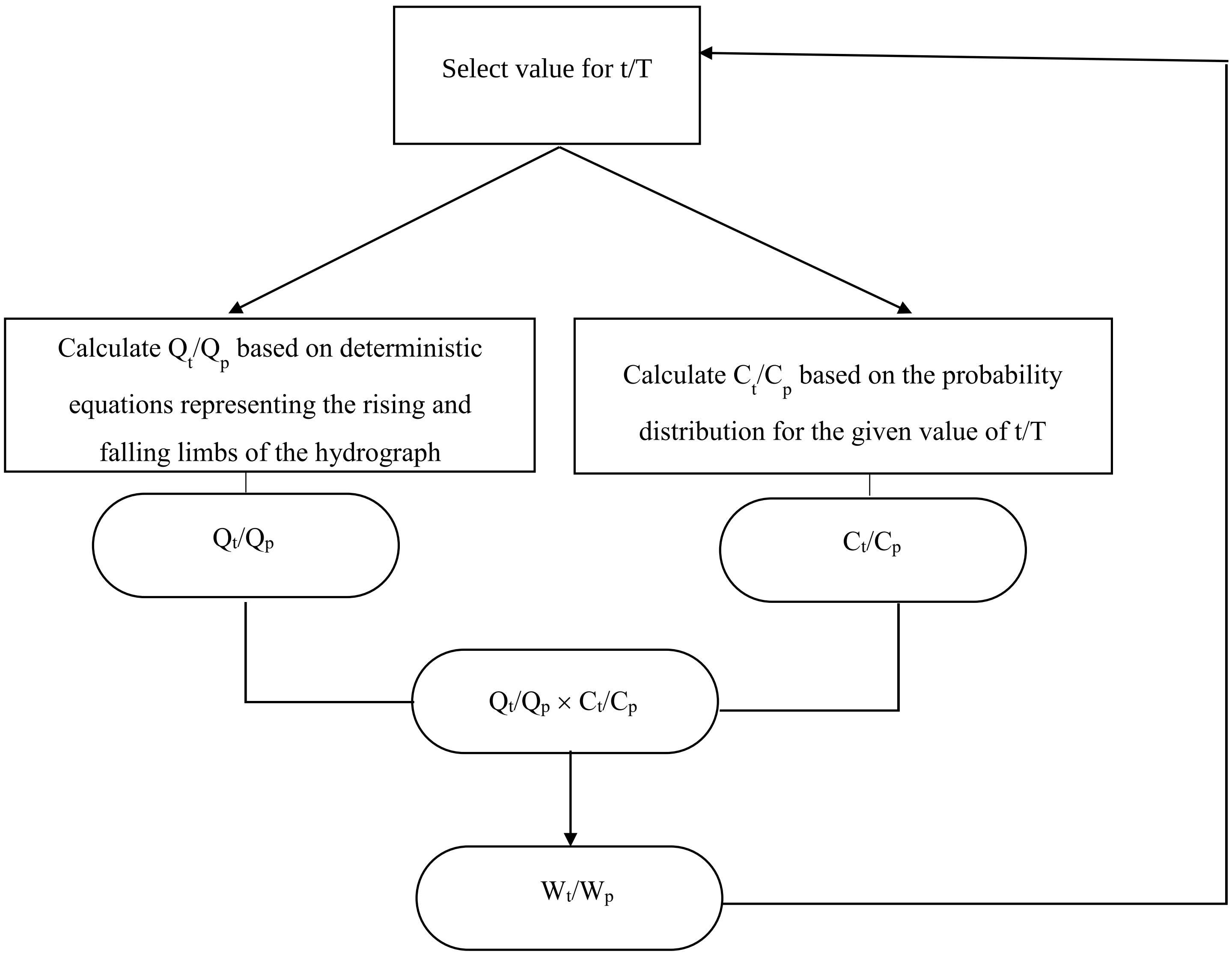

Figure 4.1: Flowchart of the Monte Carlo simulation process to estimate loads combining deterministic equations of normalized flowrate with probability distributions for concentrations.

peak concentrations. For this case study, the discharge duration and volume were provided by a Québec municipality. Concentrations of TSS, *E. coli*, CAF were collected from the sewer network of the municipality and compared with previously published data by Madoux-Humery et al. (2013). Dry and wet-weather concentrations obtained from the case study's sewer network are provided in Table 4.6. 2.

4.3 Results and discussion

4.3.1 Flow Analyses

In order to compare overflow behavior and the time of occurrence of peak flows throughout the discharge period, box and whisker plots of Q_t/Q_p for events A1, A2, A4, A5, A6, A7, A9 and B1 are shown (Figure 4.2). Median values of Q_t/Q_p within the 1st decile of the events were below 0.5 in most cases (those of A7 and A9 were slightly higher,), implying that the peak flows may be less likely to occur during this portion of the discharge period. This was also consistent with the flow dynamics obtained from the second set of literature data (See Figure 4.6. 1). Among all events in the first data sets, peak flows (i.e. Q_t/Q_p=1) typically occurred within the 2nd decile of the discharge period, except events A6 and A7. Event A6 was a result of a mixture of rainfall during a snowmelt event. The impact of the co-occurrence of rain during snowmelt might cause a lag in the peak overflow (peak in the 3rd decile). On the other hand, A7 was an intense summer event with the largest peak flow, the most extreme event in our data sets. Intense CSO discharges, particularly during summer months may potentially lead to an earlier occurrence of peak flowrate, as occurred within the 1st decile of the discharge period in A7. With regards to events gleaned from the literature (second data set), all 5 events had peak flows occurring during the second decile (Figure 4.6. 1), similar to the findings obtained from the first data set. Based upon flowrate analyses, a reasonable choice is to model peak flows as occurring during the 2nd decile. Evidently, it is recognized that short intense storms will increase the likelihood that peak flows will occur earlier and longer events (such as precipitation during snowmelt) may delay the arrival of peak flows. These variations may also be considered in model development, as needed. By using normalization techniques, standardized "model" events can be created for stochastic modeling of loads. While overflows are strongly influenced by processes governing runoff and drainage to sewers and largely driven by precipitation intensity, it is useful to demonstrate when during an event a peak flow will occur.

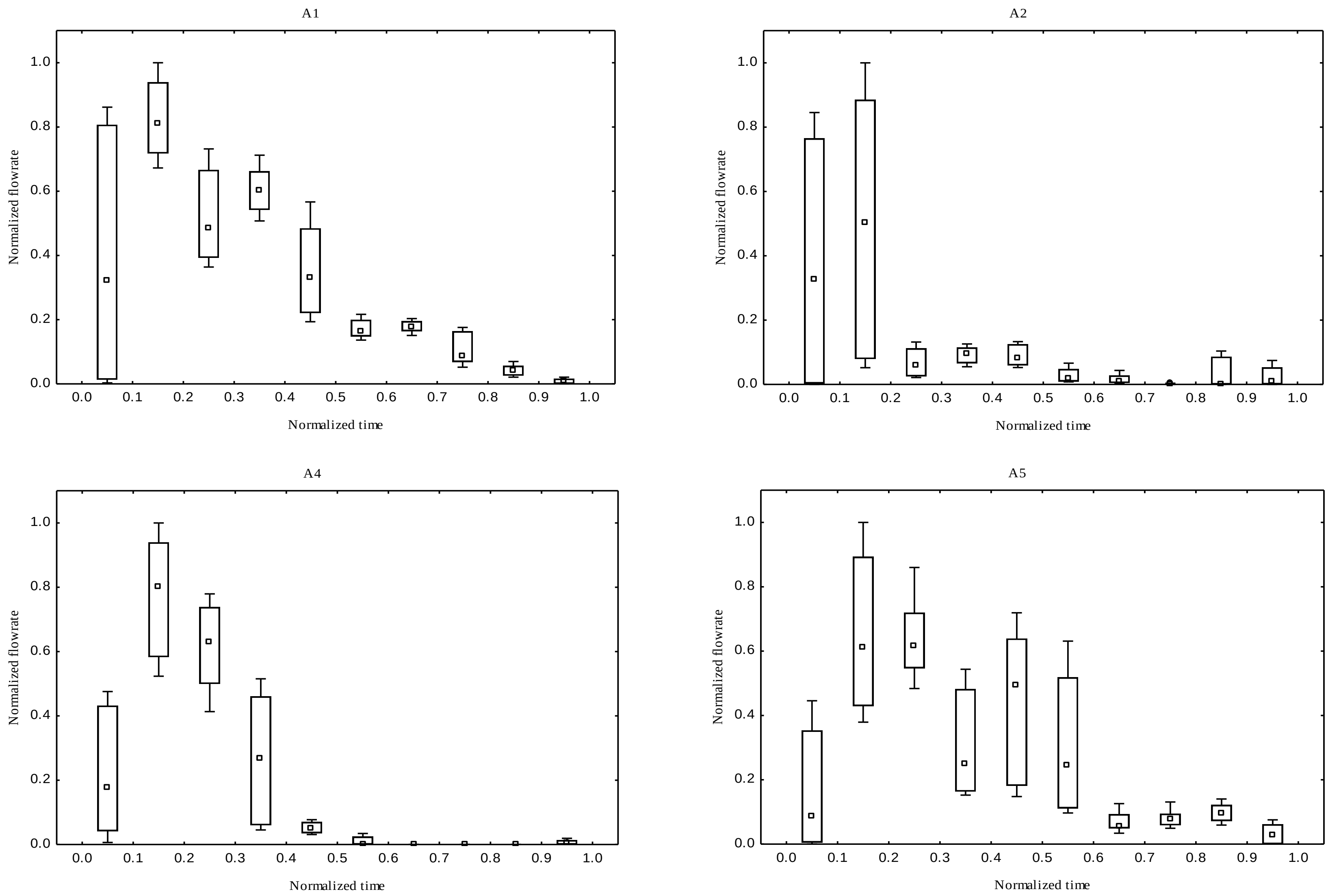

Figure 4.2: Box-plots of normalized flowrates within each decile of the total discharge period. Box plots represent 10th and 90th percentile (box), median values (square in the box) and whiskers show minimum and maximum normalized flowrate values.

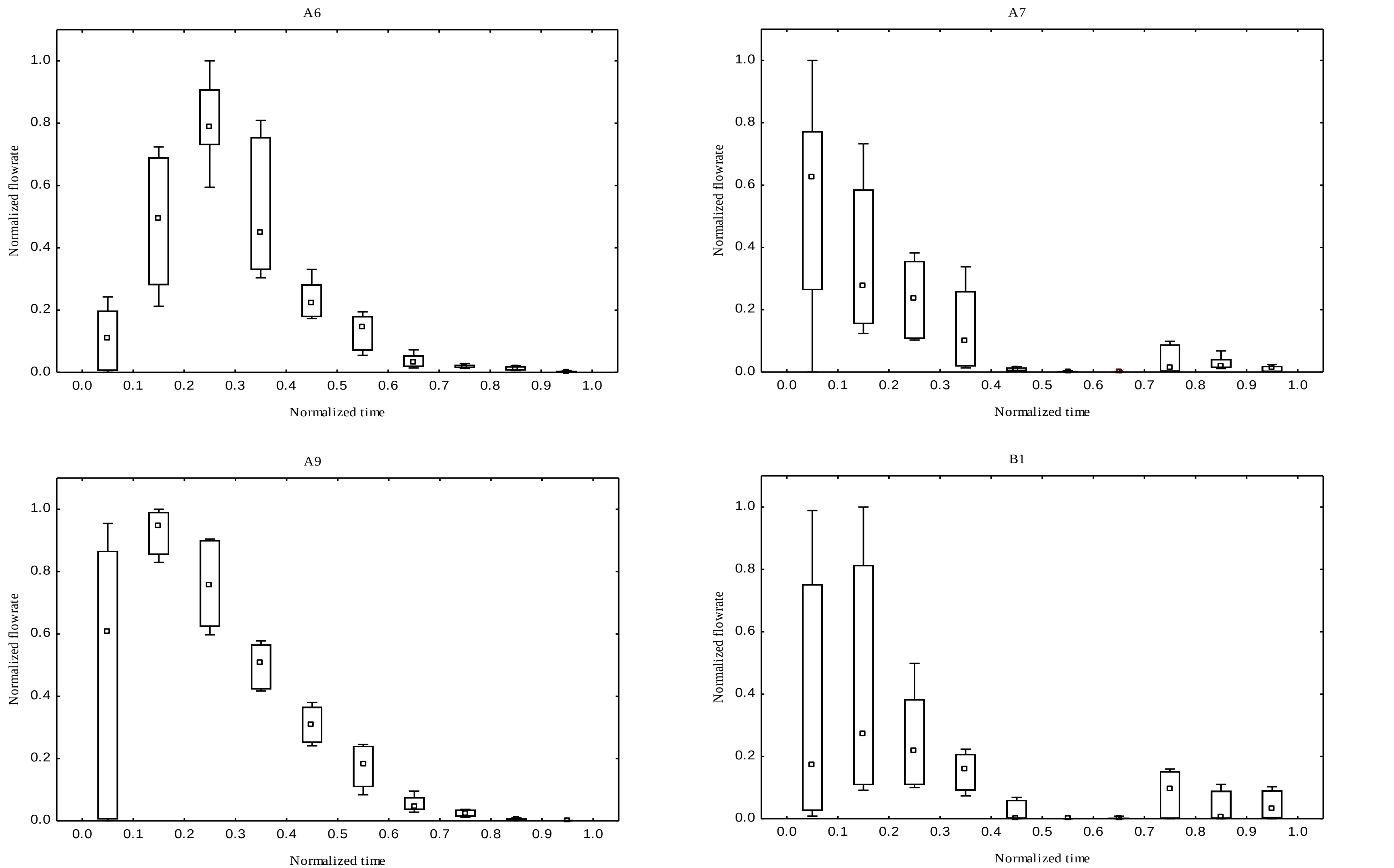

Figure 4.2: Box-plots of normalized flowrates within each decile of the total discharge period. Box plots represent 10^{th} and 90^{th} percentile (box), median values (square in the box) and whiskers show minimum and maximum normalized flowrate values (Cont'd).

The normalized hydrographs for each event are shown in Figure 4.3 where period of increasing trend followed by decreasing trend are observed in each individual event. The expected time of peak overflow , the underlying trends of overflow throughout the entire discharge period (Figure 4.3), and the discharge duration were analyzed in 3 sections: $t/T_{total}<0.1$ (1st decile) and $0.1 \leq t/T_{total}<0.2$ (2nd decile) and $t/T_{total} \geq 0.2$ (remainder). A linear increasing trend was found to be an acceptable model for $t/T_{total}<0.1$, with a peak value reached sometime within $0.1 \leq t/T_{total}<0.2$. Then, the flowrate decreases logarithmically for the remainder of the event $t/T_{total} \geq 0.2$. The linear model for the rising limb in each hydrograph was found to have the best fit with the data (Figure 4.6. 2). Q_t/Q_p was proportional to t/T_{total} (p-value<0.05) for the rising limb in all events, although A7 (extreme event) and B1 events did not display the same degree of linearity within the rising limb. A linear model representing Q_t/Q_p as a function of t/T_{total} for the rising limb was also a good fit for the verification data set (Figure 4.6. 3). Even though a secondary peak overflow (up to $0.7Q_p$) occurred in some events after the occurrence of the initial peak (as seen in A1 and A5), it would not alter the general pattern of overflows inferred from the hydrographs. The presence of a peak during the second decile followed by an overall logarithmic decreasing trend beyond the peak flow was a common characteristic of the overflow hydrograph in all events in both data sets (Figure 4.6. 4 Figure 4.6. 5). Therefore, for CSOs, the dynamic behavior can be characterized as having a linear rising limb and a logarithmic recession, similar to those of stormwater events discussed in Krometis et al. (2007). However, these periods are being defined based on the normalized time of occurrence which can be attributable to events of different scales, filling out the gaps for adaptable definition of periods of rising limb, peak and recession.

To propose a mathematical model to reflect the common characteristics of typical CSO event dynamics, all normalized overflow data of Madoux-Humery et al. (2013) (excluding A6 and A7) were combined. Boxplots of the grouped data representing the 25th, 50th, 75th percentiles and max values of Q_t/Q_p are presented in Figure 4.4 (a). The corresponding scatter plot (with the best trendline fit) for the deciles beyond the peak overflow (i.e. 2nd decile) are available in Figure 4.4 (b). A logarithmically decreasing trend was also found to be a good mathematical description of individual events (Figure 4.6. 4 Figure 4.6. 5). Based on the general pattern observed for occurrence time of peak overflow within the 2nd decile, the proposed model should reflect the same characteristics. The trendlines for the 75th percentile was the best fit with the data. Overall, the

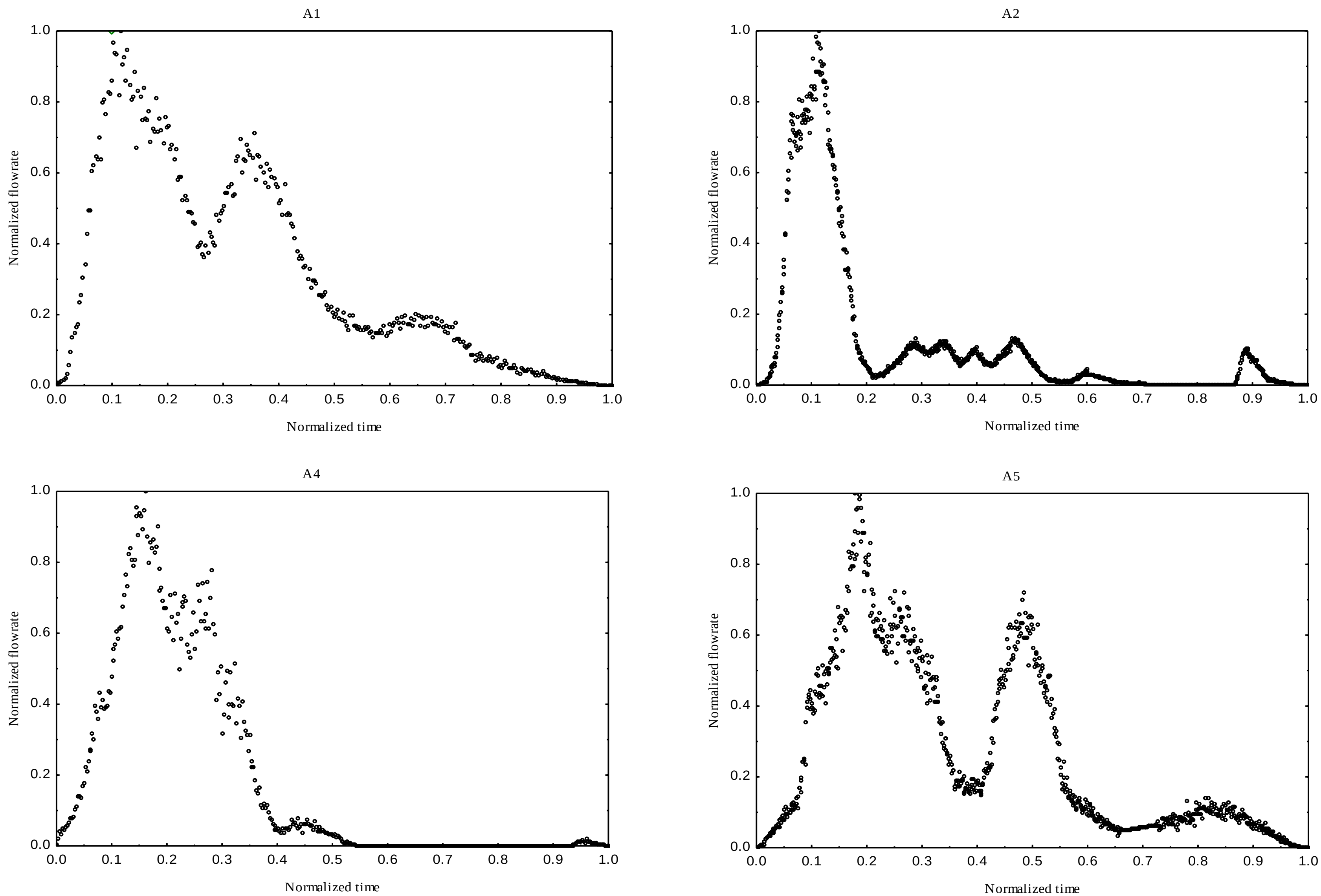

Figure 4.3: Hydrographs of the normalized CSO overflows with regards to normalized discharge duration.

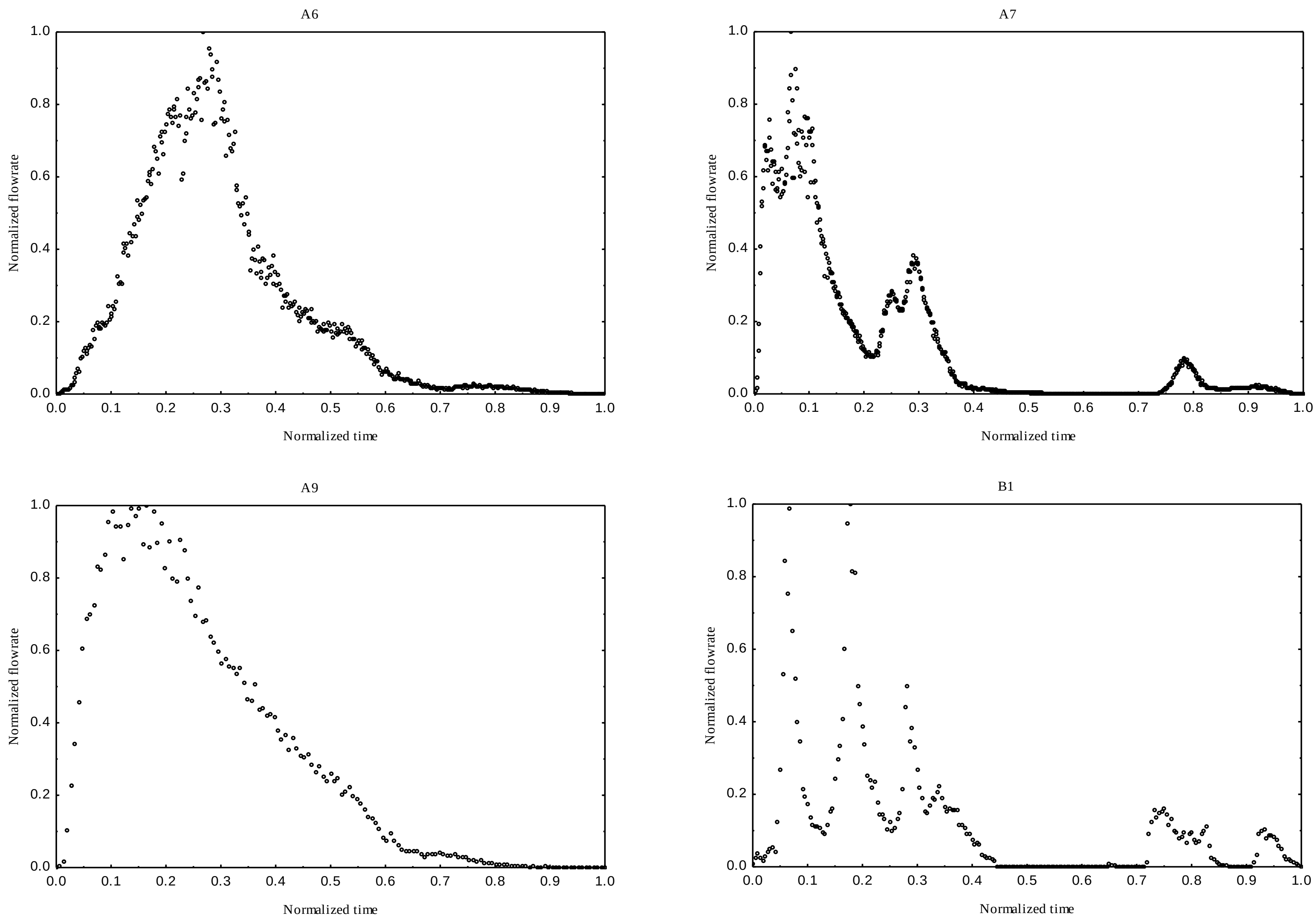

Figure 4.3: Hydrographs of the normalized CSO overflows with regards to normalized discharge duration (cont'd).

correlation for the 75th percentile values were selected to model the flowrate for CSO events. Even though the Q_t/Q_p prediction of this model may potentially overestimate the flowrate in the latter portion of the CSO hydrograph, it can serve as a robust, comprehensive and conservative predictive model of CSO flowrate. In summary, the model of CSO flowrate consists of two terms:

$$Q_t/Q_p = (7.69) \times (t/T) \text{ for } t/T < 0.13 \text{ (rising limb)}$$
$$Q_t/Q_p = -0.5 \times \ln(t/T) - 0.02 \text{ for } t/T \geq 0.13 \text{ (decreasing limb)} \quad (4.1)$$

The proposed model is a mathematical estimation of typical overflow discharge dynamics based on the normalized parameters to be used in CSO modeling applications. For events A6 and A7, which represent extreme conditions, another model representing these types of events would be required (i.e. short duration intense summer storm, and rain during snowmelt). More data should be collected for these types of extreme events, particularly rain on snowmelt because it represents a critical period for drinking water source contamination (Jalliffier-Verne et al., 2017). Overall, the treatment of the data of Madoux-Humery et al. (2013) revealed common discharge characteristics among events. Moreover, the robustness of the proposed method was verified by analysis of the dynamics of other CSO and stormwater events extracted from the literature.

4.3.2 Concentration analyses

Samples gathered during the A4 event were only analyzed for TSS and samples collected during the event B1 were not tested for ACE. The number of samples varied among events, ranging from 8 to 18 samples, which resulted in a total number of 125, 139, 126 and 117 concentration measurements for TSS, *E. coli*, CAF and ACE, respectively. Inter-event variation of TSS, *E. coli*, CAF and ACE concentrations (adapted from Madoux-Humery et al., 2013), (Figure 4.6. 6) illustrate the ranges of contaminant concentrations during each event which can be highly variable and strongly influenced by human patterns within the drainage area (Madoux-Humery et al., 2013). Normalized concentrations of TSS, *E. coli*, CAF and ACE during CSO events were analyzed against their respective normalized time of occurrence (Figure 4.5). Individual analysis of events showed that the TSS peak concentration occurred in the 1st decile for most events (except A5 and A6 whose peaks were in the 2nd decile). The median of normalized TSS concentrations is the highest within the 1st and 2nd deciles (i.e. 0.77 and 0.6, respectively). This was also seen in the data of Rossi et al. (2005), in which the peak and highest median TSS concentration occurred in the 1st

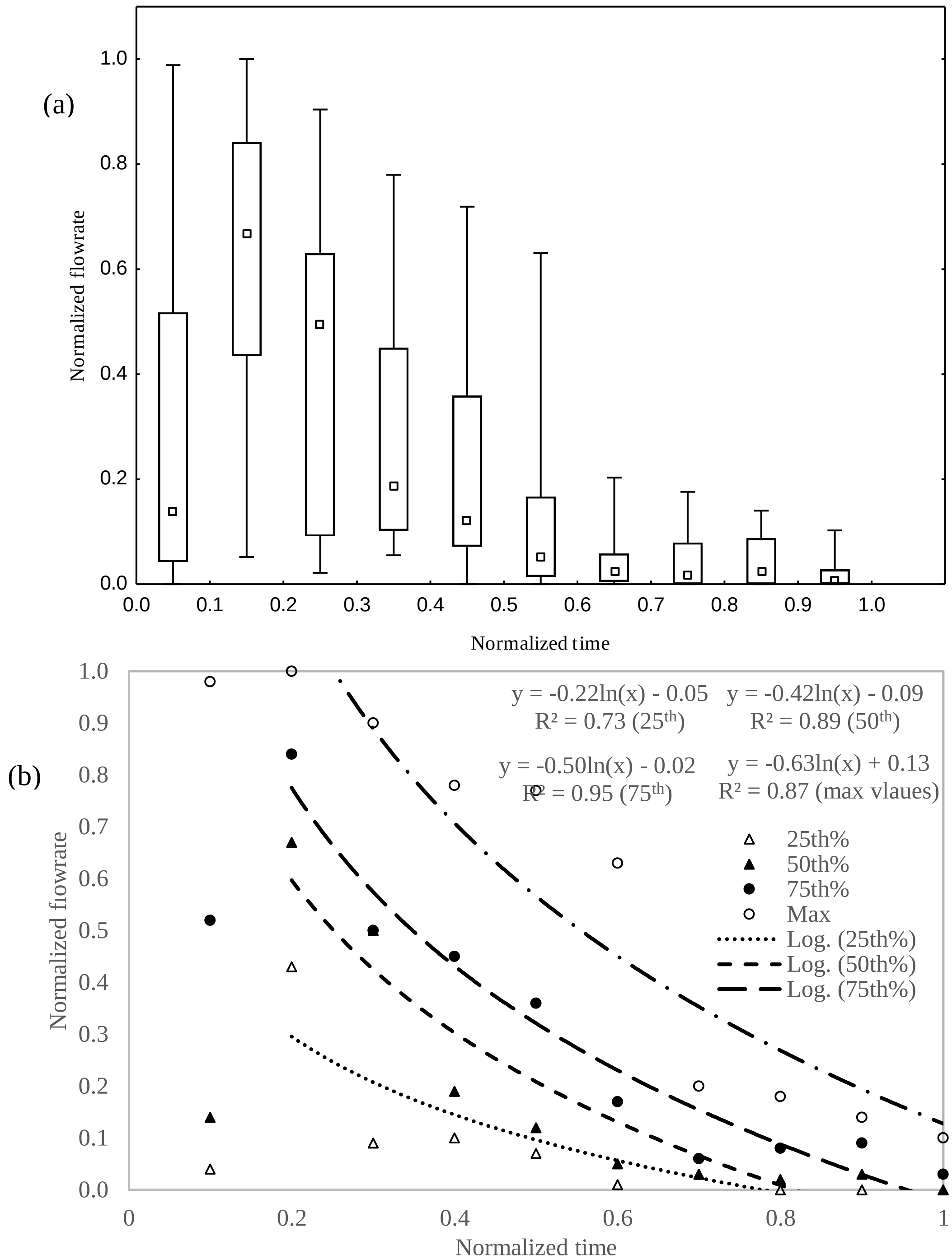

Figure 4.4: (a) Box-plot of normalized flowrates relative to the time of occurrence for all events; representing 25th and 75th percentile (box), median values (square in the box) and whiskers show maximum and minimum values of normalized flow rate, (b) scatter plot of 25th , 50th, 75th percentile and maximum of normalized flowrate data versus normalized discharge duration.

decile (Figure 4.6. 7). For TSS concentrations measured beyond the 2nd decile (Figure 4.5), the respective median values were mostly less than 30% of the peak concentrations implying an important decrease in TSS concentrations from the peak value. This rapid drop from peak concentration was also observed in Rossi et al. (2005) (See Figure 4.6. 7). Periods of high TSS concentration within the initial stages of events are linked to sediment concentrations (McCarthy et al., 2012) and resuspension of sewer deposits (Madoux-Humery et al., 2013). Wet weather discharges of TSS (including CSO and urban stormwater studies) as first flush-driven events has been discussed but there is no consensus with regards to the existence of a first flush for CSOs as high concentrations can often be observed throughout events (e.g. Park et al., 2010; Li et al., 2012; Piro et al., 2012).

For *E. coli*, peak concentrations were observed within the 1st decile of the discharge period for the A1, A2, A3, A4, A5, A9 and B1 events. In fact, events having their peak flows in the 2nd decile, all experienced peak *E. coli* concentration in the 1st decile. For A6 and A7, peaks occurred in the middle of the events (i.e. $0.4<t/T_{total}<0.5$). The median value of normalized *E. coli* is 2 times larger within the 1st decile than in the middle of the event, suggesting peak or near peak concentrations frequently occur within the 1st decile. An analysis of measurements from Hathaway et al. (2015) showed similar results (Figure 4.6. 8) where peak *E. coli* occurred within the 1st decile. From most of the data available, peak *E .coli* concentrations are expected to occur within the 1st decile for a typical CSO event. However, the occurrence of peaks can occur later in the case of extreme events (i.e. A7) or events as a result of snowmelt combined with rainfall (i.e. A6). While McCarthy et al. (2012) concluded that the time of peak *E. coli* concentrations were randomly scattered with regards to the timing of the peak flow, with the larger series of data sets considering normalized flow behavior (i.e. A1, A2, A4, A5, A9 and B1), a common normalized *E. coli* concentration pattern can be observed. This facilitates the potential simulation of downstream impacts of *E. coli* concentrations in relation to their peak or near peak concentrations based on the estimated normalized hydrographs of CSO events.

CAF peak concentrations occurred in the 1st decile for all events except A6. The median normalized concentrations within the 1st decile was the highest among other portions, suggesting the possibility of higher quantity of CAF during this initial period. Occurrence of peak ACE concentrations can be similarly described within the 1st decile for all events except A6 (peak occurred in the 2nd decile).

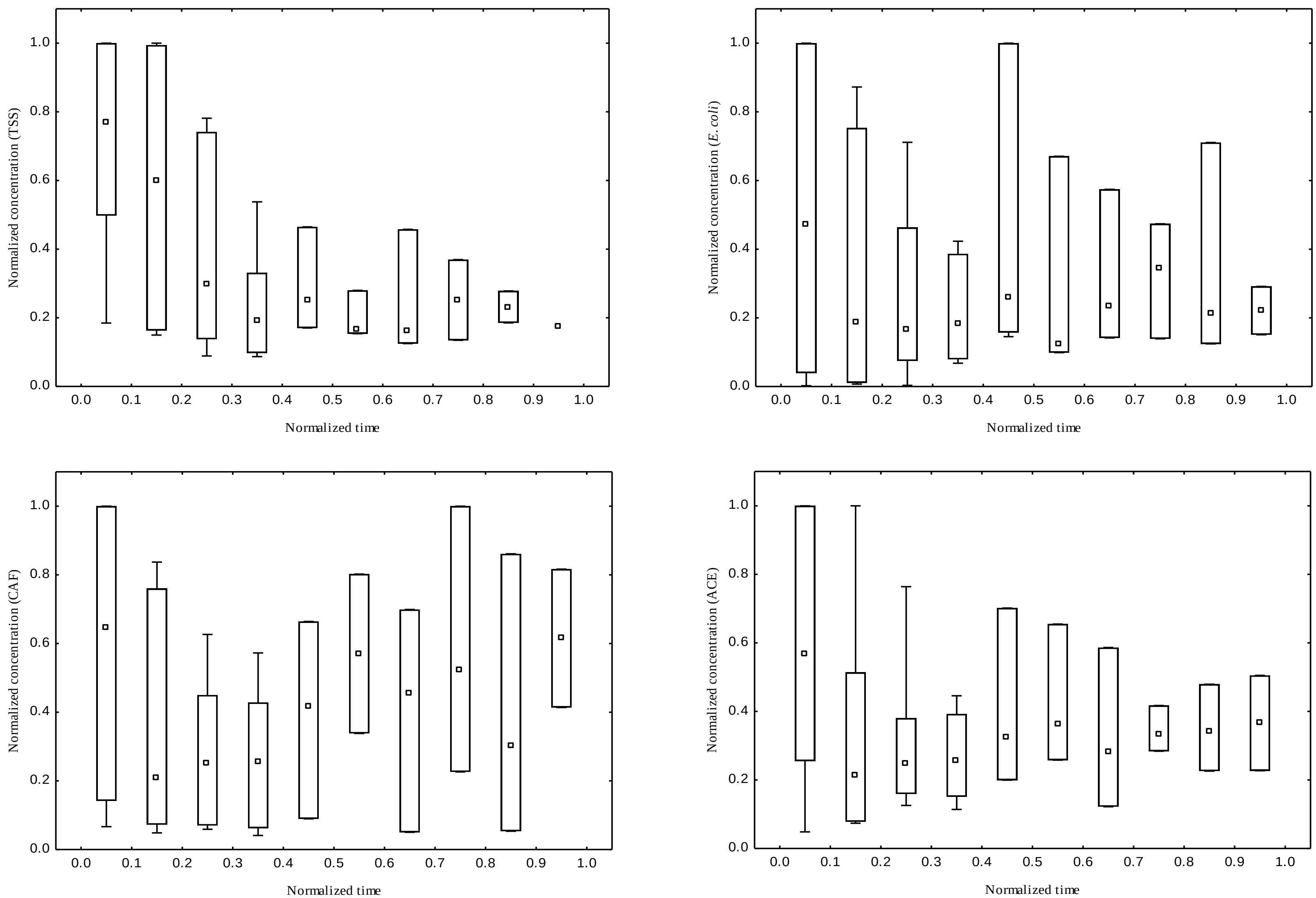

Figure 4.5: Box-plots of normalized TSS, *E. coli*, CAF and ACE concentrations as a function of the normalized time. Box plots represent 10^{th} and 90^{th} percentile (box), median values (square in the box) and whiskers show minimum and maximum concentrations.

The pattern of contaminant concentrations for each decile of CSO events should be considered for modeling CSO discharge events. This is an improvement over the approach used by Jalliffier-Verne et al. (2016) where the underlying assumption was a constant concentration over the duration of the discharge. An alternative, more realistic approach is to consider the 1st decile of a typical CSO as a period of concentrations increasing towards their peak. The concentrations begin decreasing from their peak within the 2nd decile as the flowrate reaches its peak (See Section 4.3.1). The arrival of the peak concentration before the peak flowrate is in accordance with the definition of mass-limited events. During mass-limited events, the mass of contaminant is no longer sufficiently available after being exhausted or is diluted, resulting in concentration drop as flow increases (Tolouei et al., 2019). Various first flush definitions proposed in the literature meet the definition of mass-limited transport processes (Sansalone and Cristina, 2004). CSO events in this study are shown to follow mass-limited patterns. Therefore, the 1st and the 2nd decile of events are critically important for capturing peak flows, concentrations and loads followed by a decreasing pattern for the remaining discharge period. Flow-limited transport processes occur when sufficient contaminant mass is available in the system to be transported throughout the whole discharge period (Piro et al., 2012). Characterizing discharge-based events with regards to two limiting behaviors (i.e. mass or flow-limited transport) are important when designing CSO treatment systems or managing CSOs in real-time as a function of downstream uses.

4.3.3 CSO normalized loading model

Dynamic analysis of flow (Section 4.3.1) and concentration (Section 4.3.2) demonstrated common patterns among events with regards to occurrence time of peak of overflow and contaminant concentrations. The CSO discharge behavior (normalized flowrate) was reasonably characterized by a deterministic model (Eq. 4.1), whereas, contaminant concentration dynamics was best modeled with probability distributions of the first decile, second decile, and remaining portion of the events. The high variability of concentrations means that a stochastic model was more appropriate than a deterministic model. Taking into account the concentration variability throughout the discharge period, the probability distribution of normalized concentration (of TSS and *E. coli*, CAF and ACE) were obtained for three sections of the events, i.e. 1st decile, 2nd decile and the remainder, as presented in Table 4.2 grouping all events with the exception of A6 and A7 as previously described. Normalized concentrations were found to follow a variety of probability distributions for each studied portion from grouped data of the first data set.

Based on the common loading term, which is the multiplication of values of flowrate and concentration, the normalized CSO loading is as defined as:

$$W_t/W_p = Q_t/Q_p \times C_t/C_p \tag{4.2}$$

where W_t is the loading term over the course of an event, W_p is the potential peak loading resulting from the peak flow and peak concentration co-occurring.

In order to obtain a range of CSO loads as a function of elapsed time while considering the underlying characteristics of CSO dynamics, a semi-probabilistic approach is proposed for calculating the term W_t/W_p (Eq. 4.2). In this approach, the deterministic model of the flowrate (i.e. Eq.4.1) was combined with a stochastic sampling procedure from the probability distribution of concentration (Table 4.2) to produce potential loading values for the whole discharge period. Concentration data beyond the 2nd decile was grouped into one overall concentration distribution as “remainder”, and that was assumed for every decile in the remaining portion of the event. Following 5000 iterations for each decile, the range of normalized loading values were obtained and are illustrated in Figure 4.6.

The normalized potential loading values of TSS and CAF contaminant showed an increase from the 1st decile to the 2nd decile followed by a continuous decreasing trend after the 2nd decile. The loading trend of TSS and CAF is similar to the general trend of flowrate observed in Section 4.3.1, which includes the increasing period followed by a decreasing trend. This implies that flowrate drives loading behavior of these two contaminants. In contrast, loading behavior of *E. coli* and ACE were not as strongly influenced by the flowrate dynamics when considering median values, as no sudden increase in loading values was observed from the 1st decile to the 2nd decile. It is noted that the median loading characteristics of *E. coli* and ACE throughout the discharge period do not vary significantly from one decile to another. However, a variation in *E. coli* loading characteristics was observed while comparing values of different statistical descriptions of variability. For example, an increase in loading values within the 2nd decile is noticed for the 95th percentile. This not only indicates the high variability of microbiological loading, but also confirms the robustness

Table 4.2: Characteristics of the probability distribution functions of the normalized concentrations of TSS, *E. coli*, CAF, ACE and normalized flowrate (grouped data).

Parameter	Period	Sample size	Distribution type	Distribution variables	Goodness-of-fit		
					K-S error	Critical *p*-value (significance level of α=0.05)	*p*-value
Normalized TSS	1st decile	34	Gamma	Shape factor=14.79, Scale factor=0.05	0.12	0.22	0.62
	2nd decile	15	Uniform	*a=0, **b=1	0.11	0.34	0.99
	Remainder	40	Gamma	Shape factor=3.1, Scale factor=0.09	0.11	0.21	0.67
Normalized *E. coli*	1st decile	39	Gamma	Shape factor=2.31, Scale factor=0.22	0.12	0.21	0.54
	2nd decile	18	Weibull	Shape factor=0.7, Scale factor=0.29	0.17	0.31	0.62
	Remainder	46	Gamma	Shape factor=2.38, Scale factor=0.09	0.09	0.2	0.82
Normalized CAF	1st decile	34	Uniform	a=0, b=1	0.16	0.22	0.3
	2nd decile	15	Normal	Mean=0.37, ***St-dev=0.29	0.19	0.34	0.57
	Remainder	41	Weibull	Shape factor=1.33, Scale factor=0.31	0.14	0.21	0.35

Tale 4.2: Characteristics of the probability distribution functions of the normalized concentrations of TSS, *E. coli*, CAF, ACE and normalized flowrate (grouped data) (cont'd).

Parameter	Period	Sample size	Distribution type	Distribution variables	Goodness-of-fit		
					K-S error	Critical *p*-value (significance level of α=0.05)	*p*-value
Normalized ACE	1st decile	29	Gamma	Shape factor=4.52, Scale factor=0.13	0.1	0.25	0.9
	2nd decile	12	Gamma	Shape factor=2.53, Scale factor=0.09	0.13	0.38	0.97
	Remainder	37	Normal	Mean=0.25, St-dev=0.08	0.06	0.22	0.98

*lower value, **Higher value, ***Standard deviation

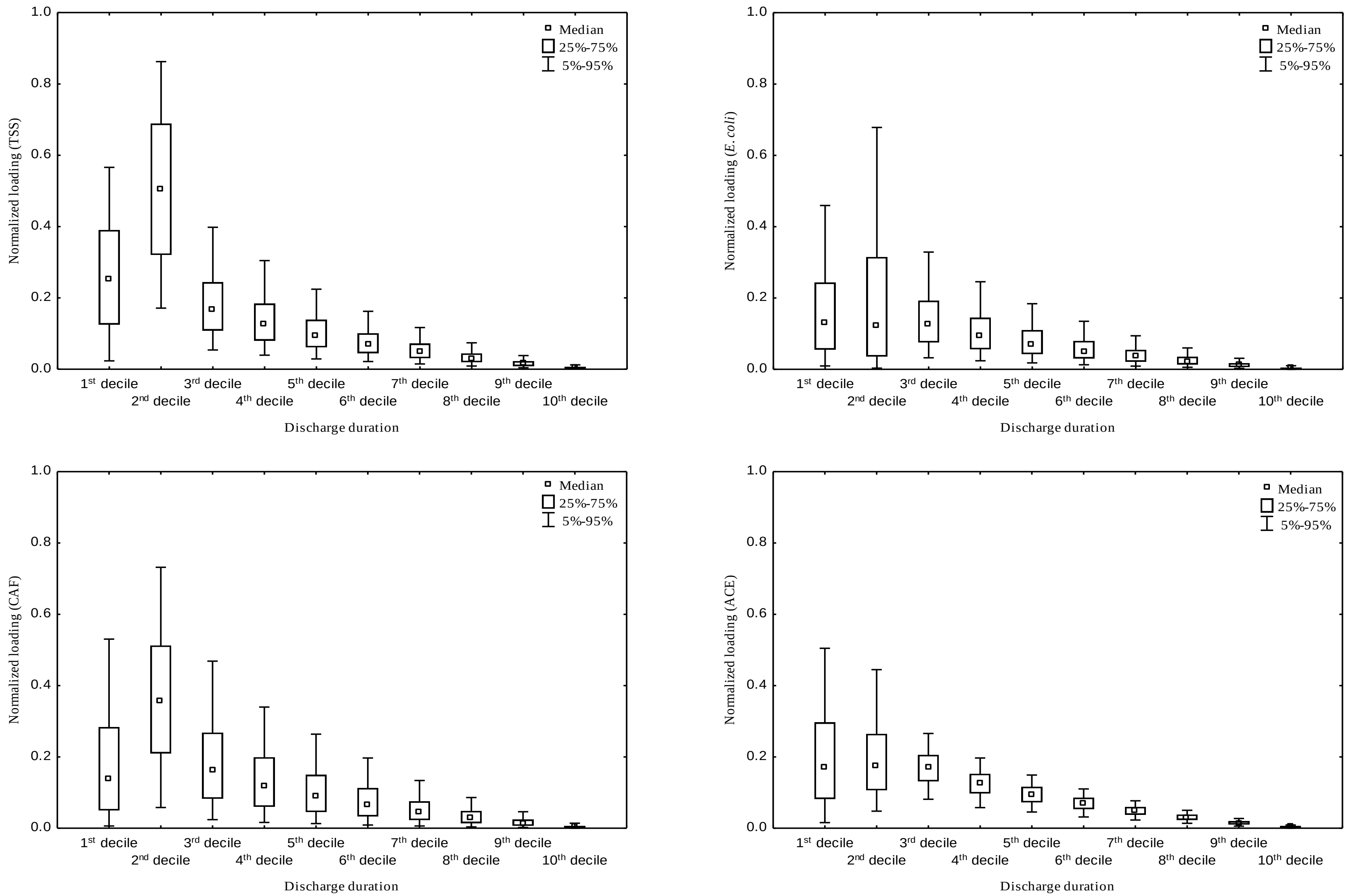

Figure 4.6: Potential normalized loading values of TSS and *E. coli*, CAF and ACE thorough the whole discharge period.

of the present approach in capturing this variability. Therefore, relying on just one range of potential loading may result in inconclusive load estimation (underestimation or overestimation).

Application of the semi-probabilistic CSO loading model reflects the various ranges of potential loading values upon which management strategies should be based. Considering the upper 95th percentile values of loading as the worst-case scenario, the 2nd decile potentially represents the period of highest TSS, *E. coli* and CAF loading rates, even though the peak concentrations were mostly associated with the 1st decile (See Section 4.3.2). The upper 95th percentile loading values of ACE shows the 1st decile of the event as the period of highest loading rate showing a larger influence of peak concentration (in the 1st decile) over the peak flowrate (in the 2nd decile). It should be noted that the measurements of these compounds were on the dissolved phase only. Various processes occur within the sewer system, including resuspension of the particle phase followed by desorption. The desorption behavior mimicking sewer processes was explored in detail by Hajj-Mohamad et al. (2017). The remaining time beyond the 2nd decile does not generally reflect a peak loading period, but loads do remain important throughout events when considering the cumulative effects of CSO discharges.

Loading values within the 2nd decile were observed to be most sporadic as compared to the other deciles for TSS, *E. coli* and CAF while the 1st decile was the most variable loading section for ACE. TSS loads in the remaining deciles are unlikely to exceed half of the peak load (i.e. $W_t/W_p < 0.5$) as the peak is likely to occur in the 1st or 2nd deciles. For *E. coli*, loading $> 0.5W_p$ is expected in the 2nd decile while loads are generally $< 0.5W_p$ in other deciles. Differences in mass loading patterns among contaminants are related to their origins within the sewer network. TSS can be present in stormwater and can accumulate within sewer networks, whereas CAF, ACE are predominantly from sewage. *E. coli* can originate in stormwater and be related to animal presence within the sewer network; however, concentrations in sewage are generally much higher than in stormwater.

4.3.4 Application of CSO normalized loading model

An advantage of the proposed loading model is that it can serve as a tool to compare different CSO scenarios and investigate the corresponding impacts on the receiving waters by adjusting the scale of loading conditions. For example, CSO scenarios can be produced by considering a wide range of loading values representing conditions from median (i.e. from the 50th percentile) to the most extreme scenarios (considering the upper 95th percentile). Moreover, CSO events of any scale in terms of discharge duration, discharge volume or contaminant concentration can be modeled. These data can also help determine the most effective elements of scale-related parameters for attenuating the impacts of CSOs.

The outputs of the semi-probabilistic CSO loading model can be treated as the inputs of a hydrodynamic and water quality model. The scale-related parameters of a CSO event (i.e. T, Q_p and C_p) to be modeled can be determined based the data presented herein, or on other site-specific historical data, or even a series of assumptions for comparative analyses. The timeseries of flowrate and concentration can be generated following the steps in Figure 4.1. An example loading scenario shown in Figure 4.7 is a typical spring CSO event discharging into a river upstream of a drinking water treatment plant. Based on the available data for a CSO event in the case study area, the example CSO duration was estimated to be almost 10 hrs assuming a peak flowrate of 64 L/s and a peak *E. coli* concentration of 1.14E+07 MPN/100mL (90th percentile values considered), for the site, located on a river in Québec, Canada.

One of the important assumptions in the stochastic portion of the loading model related to the concentrations is that temporal correlations within a given decile are not considered. For example, when the load model deterministically estimates the flow, a random sample is obtained for the concentration. The following concentration value for the next time step selected is again randomly drawn from the same distributed and is therefore not correlated to the value from the previous time step. In order to achieve a more realistic loading scenario, moving average values for the loading profiles can be used as shown in Figure 4.7 (c). Various statistics (e.g. median or 95th percentile) from the produced loading profile can be used to investigate the impact of the loads on the receiving water. Various scenarios of CSO events can be produced based on an analysis of the historical CSO discharge duration, typical peak concentration and the volume discharges in course of CSO events for a given system. Using this semi-probabilistic loading approach, the variability of the CSO events can be taken into consideration. Successful application of such approach can ultimately address the needs of municipalities to more efficiently prioritize mitigation policies for these discharge-based phenomena.

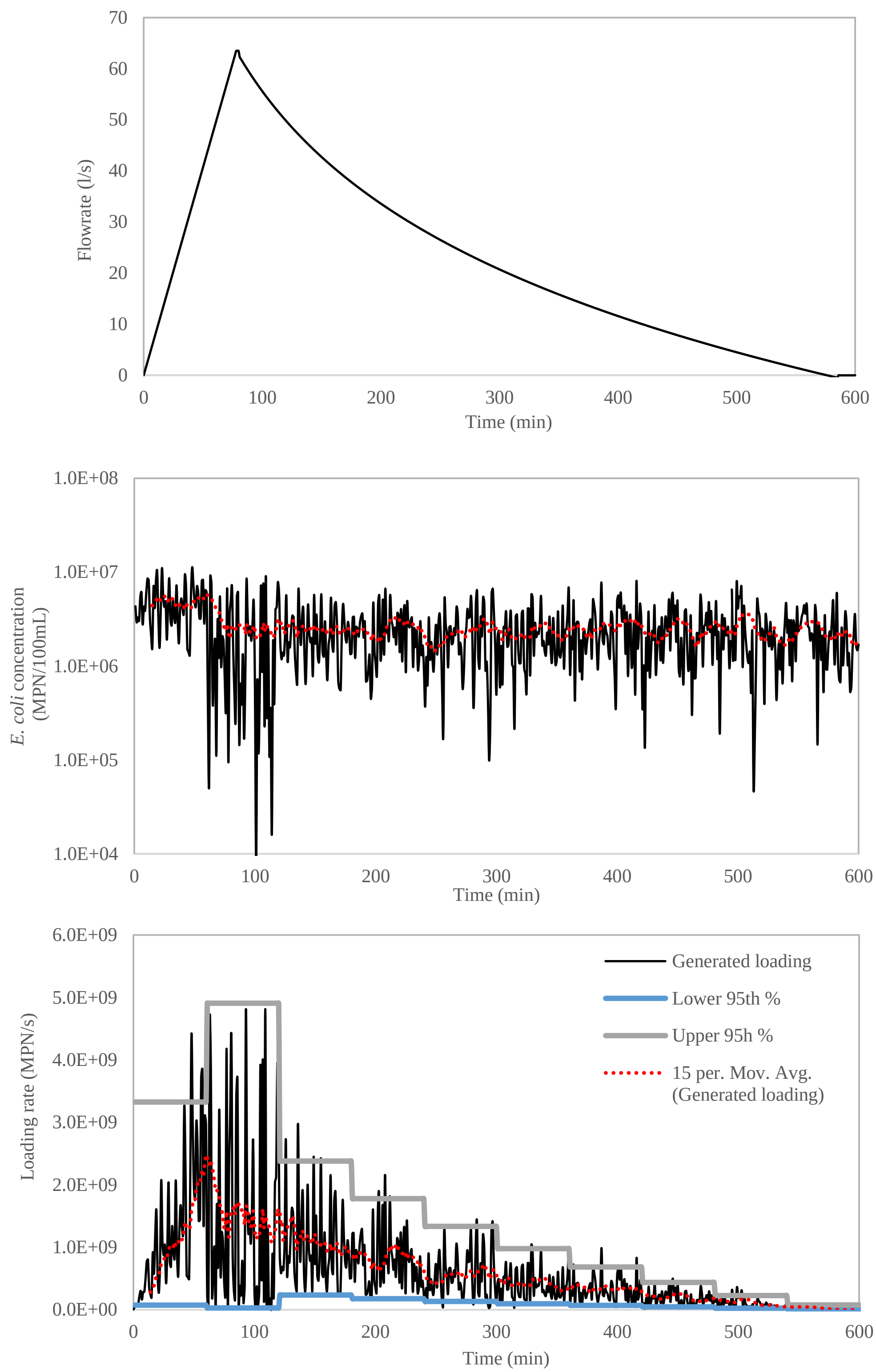

Figure 4.7: CSO loading terms for an example CSO; (a) timeseries of flowrate, (b) timeseries of concentration (red dotted line represents a moving average representing 15 minutes), (c) time series of the generated loading values (red dotted line represents a moving average representing 15 min).

4.4 Conclusions

- A normalizing technique that excluded CSO event scale effects unveiled the inherent common characteristics of CSO loads. Normalized flowrate, concentration and discharge duration data in a uniform scale of 0 to 1 facilitates the analysis of the variability within any portion of the event.
- CSO discharge can be modeled within the entire discharge period using a deterministic model. The increasing trend of normalized flowrate from the initiation of the CSO to its peak can be described by a linear model. The overflow discharges reached their peak flow within the 2^{nd} decile of the event for the majority of observed events. For the decreasing period of the CSO, a logarithmic trend was representative of observed data. Other types of events (e.g., long events during snowmelt, or short high intensity summer events), can be modelled using a normalized technique if sufficient data are available for these specific types of events.
- Unlike flowrates, concentrations are more variable throughout CSO events, meaning that a stochastic rather than deterministic model is needed to simulate concentrations. Peak concentrations occurred within the first two deciles of events. However, high concentrations could be observed throughout events.
- The semi-probabilistic CSO load model for TSS, *E. coli*, CAF and ACE accounts for the variability of the loading values and is an improvement over assuming a fixed value for the loading terms and can be applied to a variety of situations where detailed deterministic models of CSOs are not available.
- Understanding the discharge behavior of the events provides an opportunity to characterize the fluctuations in loads that are needed to estimate downstream peak concentrations, which are important for source water protection.
- The application of the scaled up model will help utilities design more efficient and comprehensive sampling campaigns for capturing peak concentrations at drinking water intakes and evaluate the impact of CSO discharge scenarios on water quality. The application of CSO load models considering the dynamic characteristics of discharges improves impact studies as a range of probable loadings can be analyzed with hydrodynamic and water quality models.

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4.6 Supplementary Materials

Table 4.6. 1: Overflow and concentration verification data.

Type of data	Discharge-based study	Summary	No. data points	Discharge duration (min)	Peak overflow (l/s)	Peak concentration (unit)
Hydrograph data	Krometis et al. (2007)	Stormwater hydrograph read off from Figure 3	46	1444	2668	-
	Rossi et al. (2005)	CSO hydrograph read off from Figure 2	56	180	1875	-
	Todeschini et al. (2011)	CSO hydrograph read off from Figure 5	44	100	556	-
	Riechel et al. (2016)	CSO hydrograph read off from Figure 2	27	120	42	-
	Gruber et al. (2005)	CSO hydrograph read off from Figure 4	26	36	333	-
TSS concentration data	Rossi et al. (2005)	TSS pollutograph read off from Figure 2	36	180	-	559 (mg/l)
E. coli concentration data	Hathaway et al. (2015)	*E. coli* pollutograph read off from Figure 2	10	420	-	1243 (MPN/100mL)

Table 4.6. 2: Concentration measurements obtained from the case study's sewer network in an urban region in southwestern Québec.

	Wet weather (October 2014)			Dry weather (November and December 2014)		
	TSS (mg/L)	*E. coli* (CFU/100ml)	CAF (ng/L)	TSS (mg/L)	*E. coli* (CFU/100ml)	CAF (ng/L)
Location 1	40	>1600000	89275	63	6.50E+06	62303
	64	>1600000	40256	71	3.70E+06	70308
	76	>1600000	54739	92	2.10E+06	49581
	79	>1600000	36599	101	1.10E+06	45822
	62	1.24E+06	36814	125	2.90E+06	32496
	561	1.04E+06	14981	88	2.80E+06	36598
	458	1.18E+06	4599	445	2.00E+06	39378
Location 2	129	5.50E+05	11989	91	1.20E+06	48728
	284	3.90E+05	18002	92	1.80E+06	39924
	107	4.90E+05	20278	88	3.00E+06	55106
	123	2.50E+05	18726	145	3.40E+06	62013
	83	3.60E+05	15528	127	1.50E+06	40286
				135	1.20E+06	49306

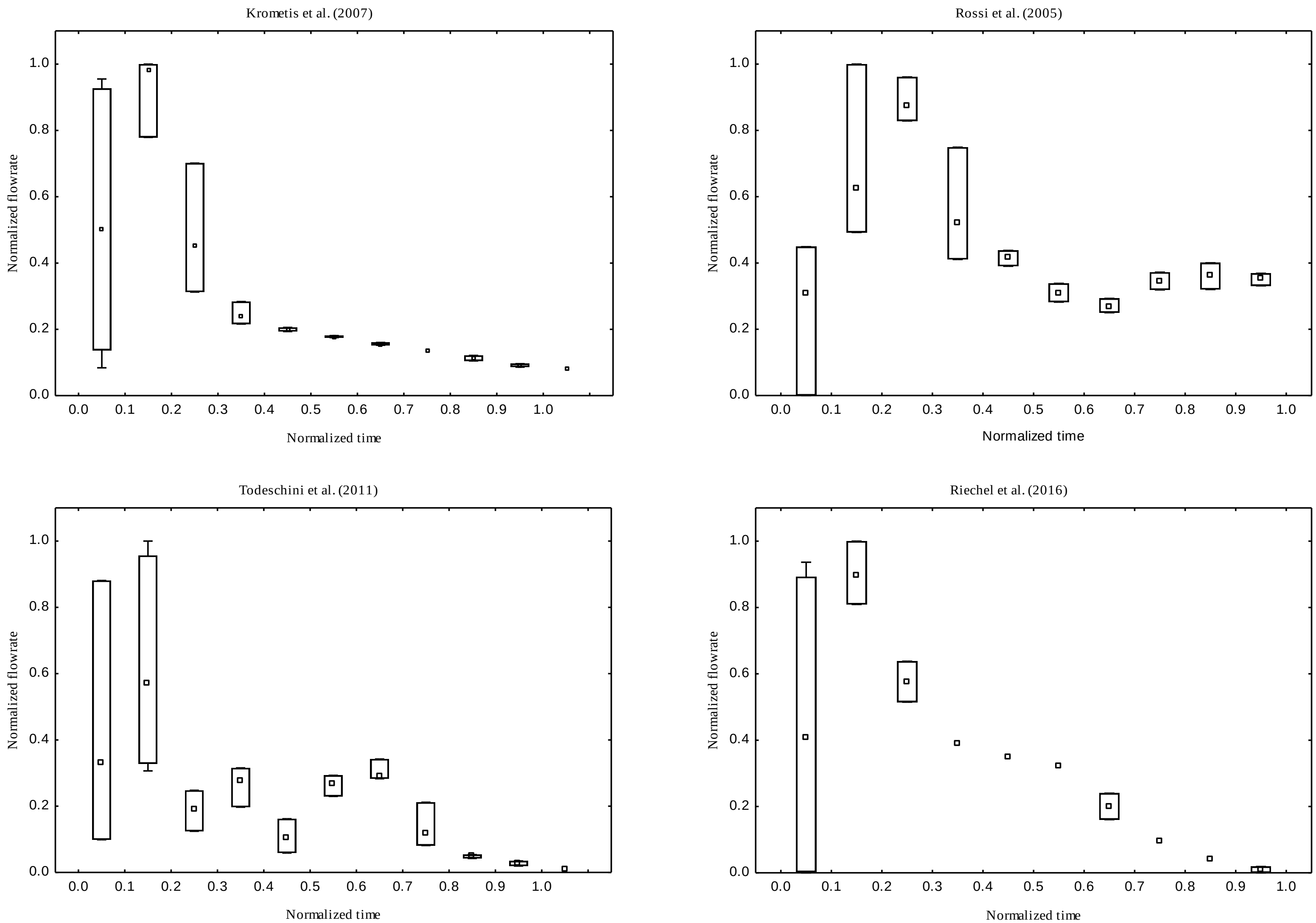

Figure 4.6. 1: Box-plots of normalized overflow rate within each decile of the total discharge period. Box plots represent 10th and 90th percentile (box), median values (square in the box) and whiskers show minimum and maximum normalized flowrate values.

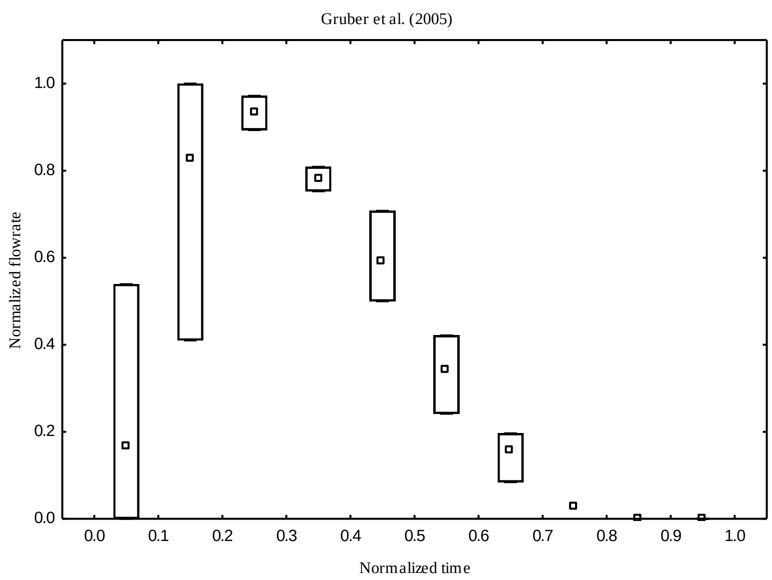

Figure 4.6. 1: Box-plots of normalized overflow rate within each decile of the total discharge period. Box plots represent 10th and 90th percentile (box), median values (square in the box) and whiskers show minimum and maximum normalized flowrate values (cont'd).

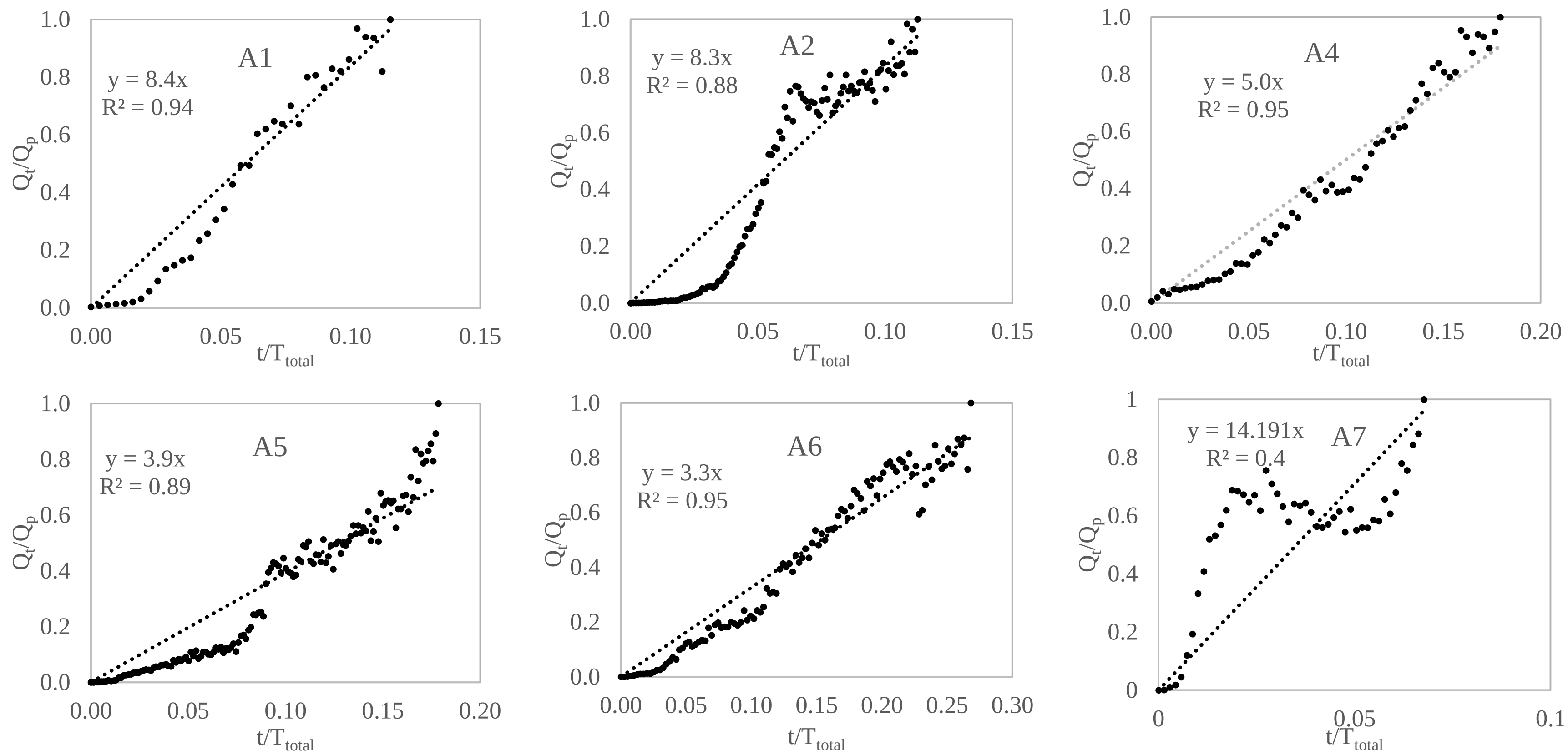

Figure 4.6. 2: Scatter plot of normalized overflow versus normalized discharge duration for the period before the peak flow (first data set from Madoux-Humery et al. (2013)).

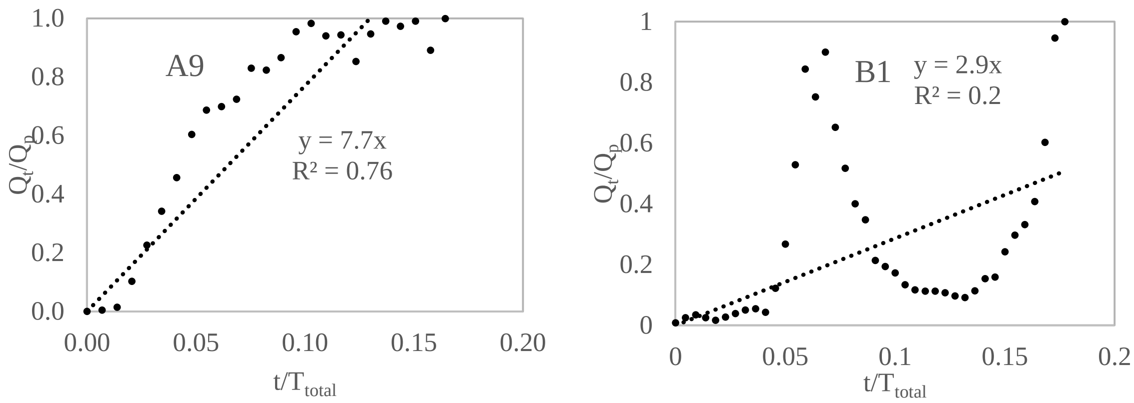

Figure 4.6. 2: Scatter plot of normalized overflow versus normalized discharge duration for the period before the peak flow (first data set from Madoux-Humery et al. (2013)) (cont'd).

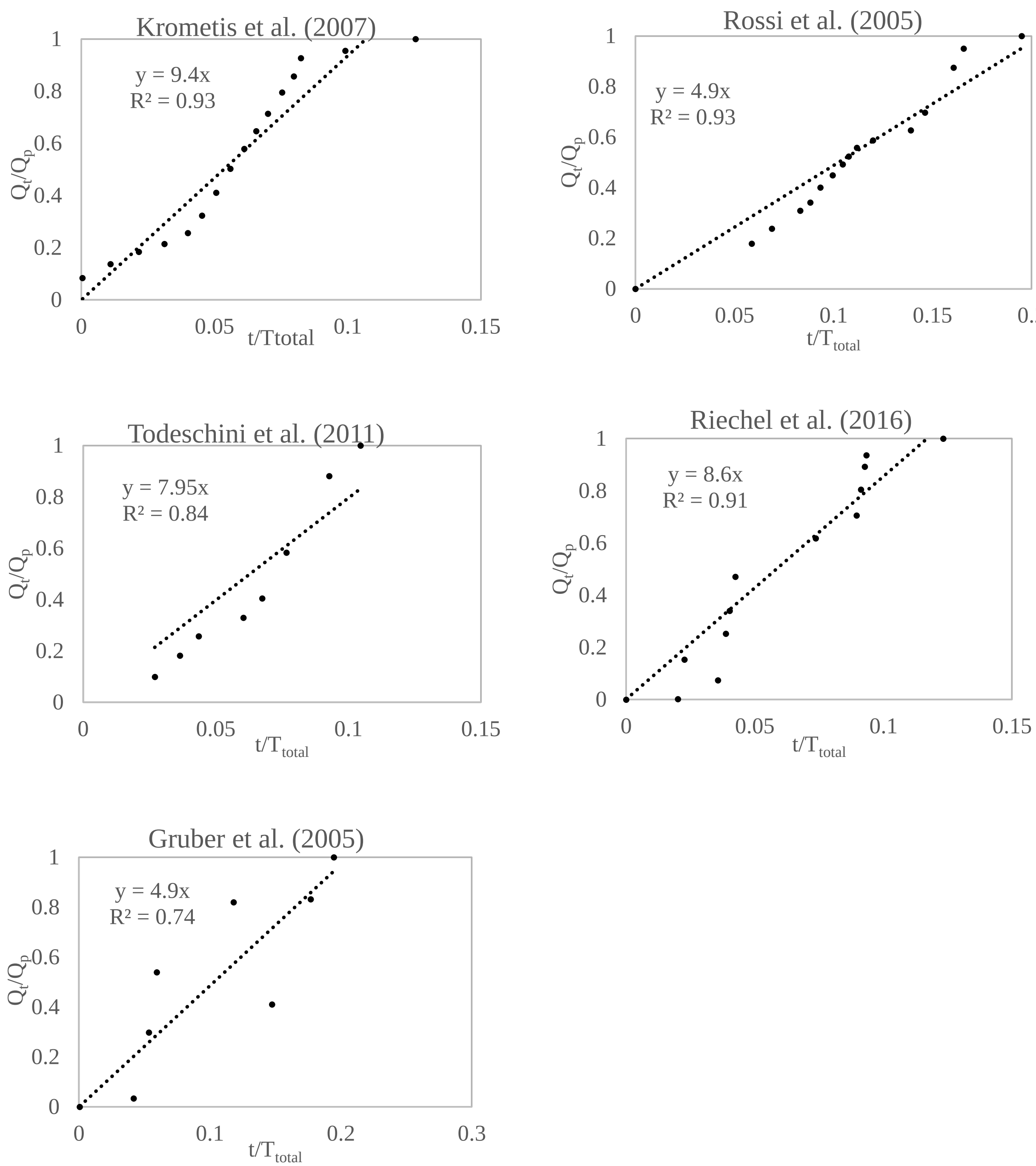

Figure 4.6. 3: Scatter plot of normalized overflow versus normalized discharge duration for the period before the peak flow (verification data set).

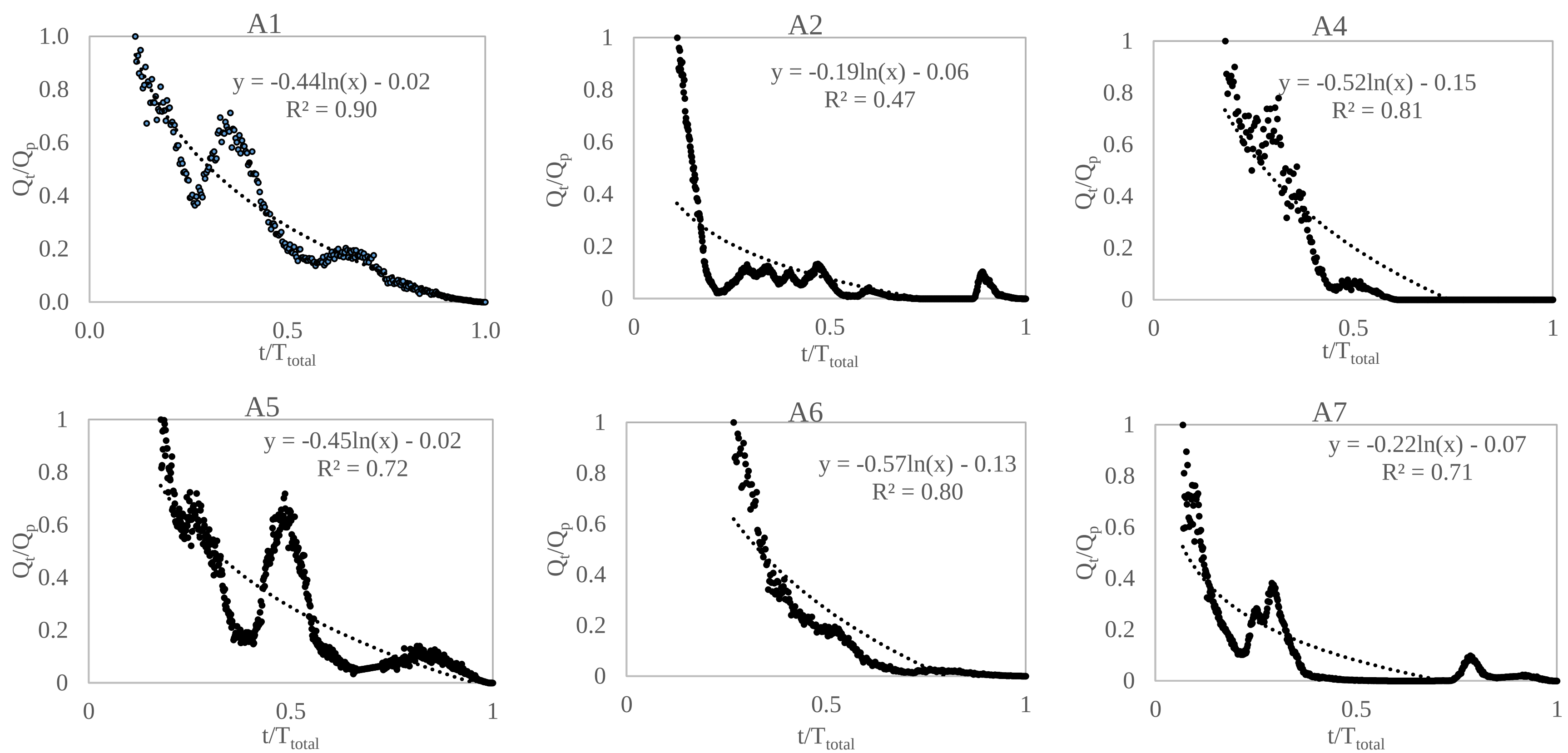

Figure 4.6. 4: Scatter plot of normalized overflow versus normalized discharge duration for the period beyond the peak flow (original data set)

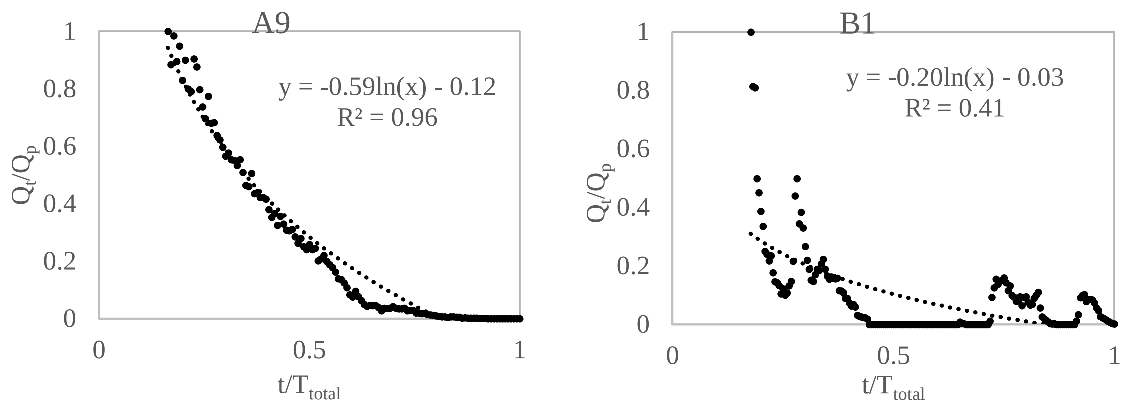

Figure 4.6. 4: Scatter plot of normalized overflow versus normalized discharge duration for the period beyond the peak flow (original data set) (cont'd).

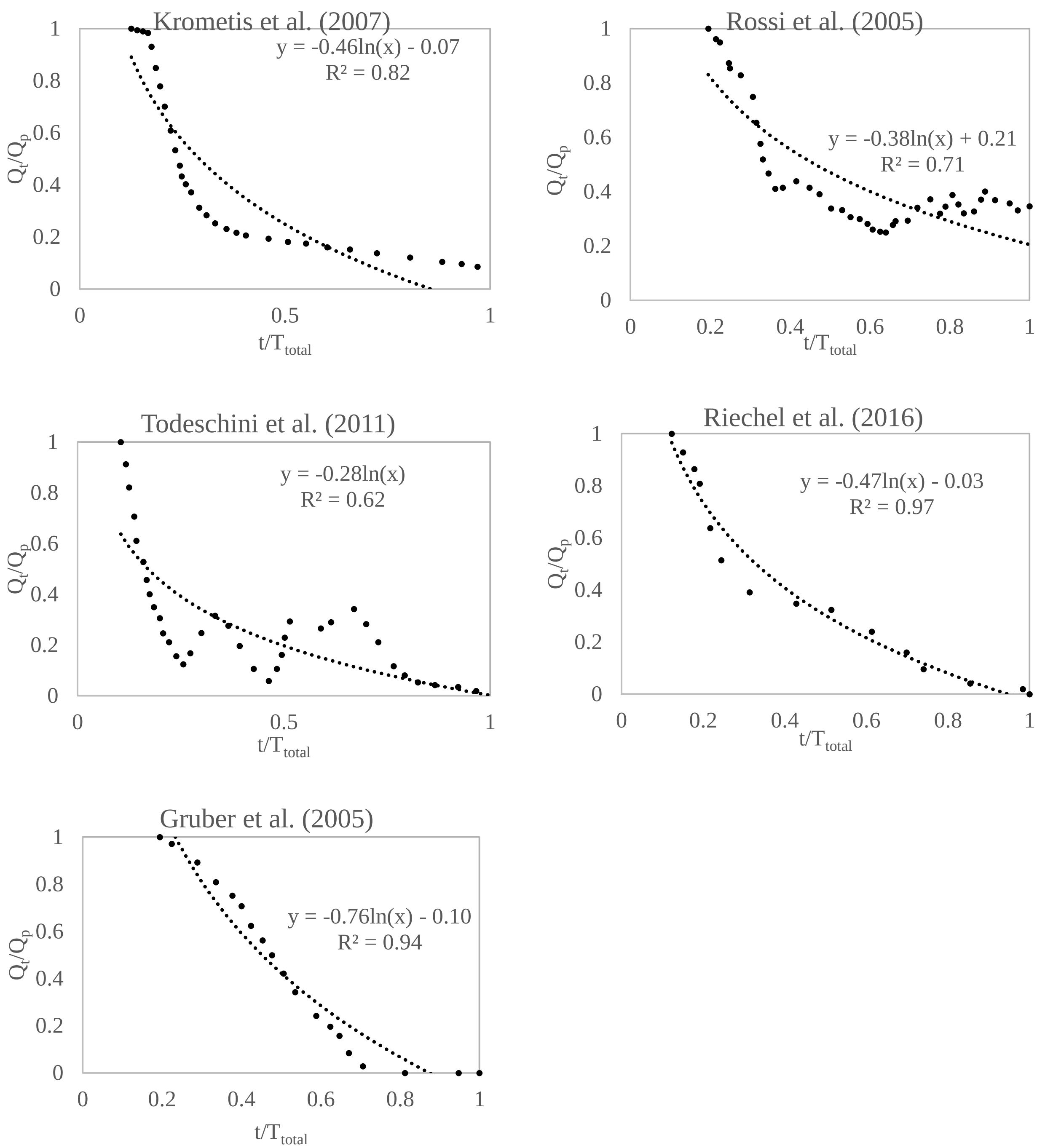

Figure 4.6. 5: Scatter plot of normalized overflow versus normalized discharge duration for the period beyond the peak flow (verification data set).

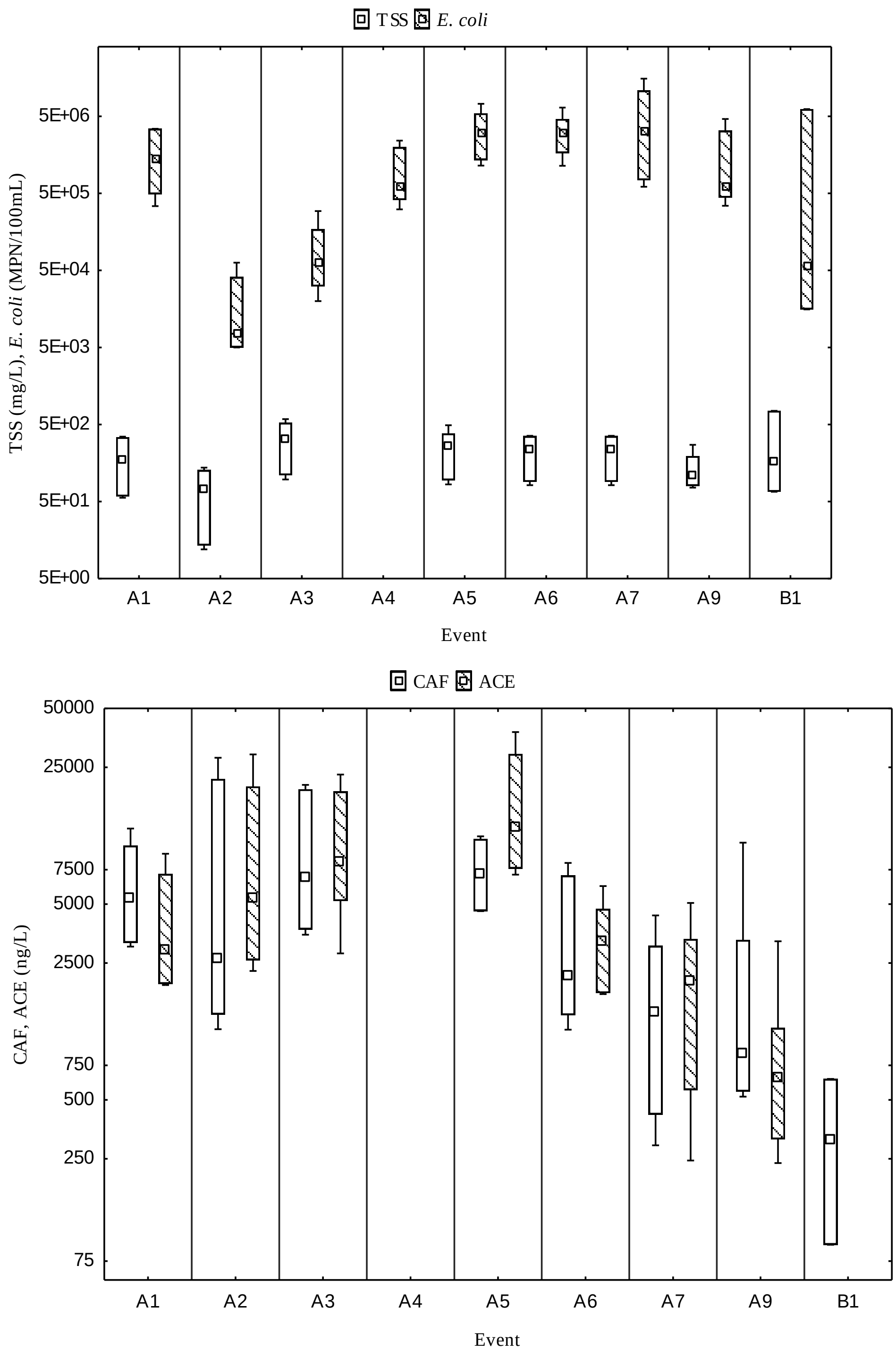

Figure 4.6. 6: Box-plot of TSS and *E. coli* (a), CAF and ACE (b) concentrations in each event, adapted from Madoux-Humery et al. (2013). Box plots represent 10th and 90thpercentile (box), median values (square in the box) and whiskers show minimum and maximum concentration.

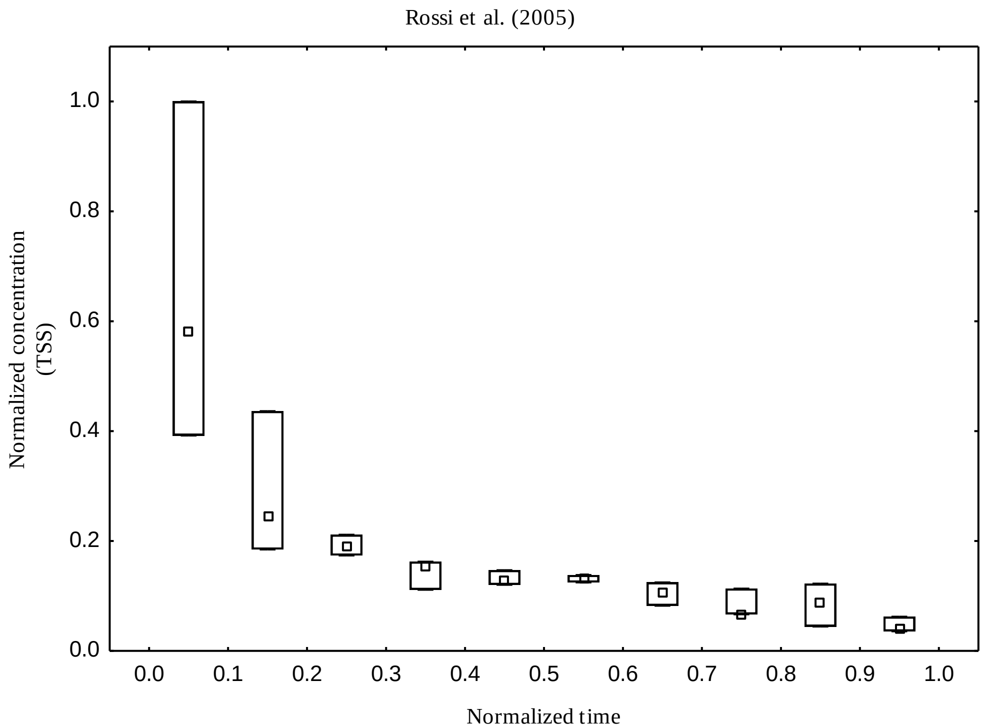

Figure 4.6. 7: Box-plots of normalized TSS concentrations obtained from Rossi et al. (2005) with regard to the normalized time of sampling. Box pot represents 10th and 90th percentile (box), median values (square in the box) and whiskers show minimum and maximum concentration.

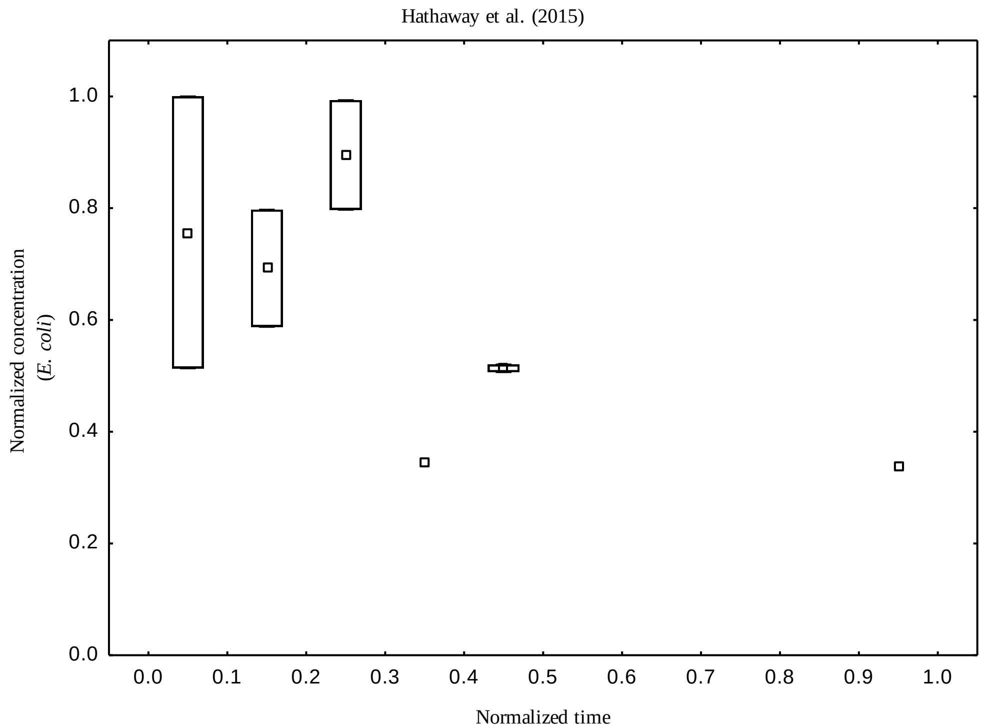

Figure 4.6. 8: Box-plots of normalized *E. coli* concentrations obtained from Hathaway et al. (2015) with regard to the normalized time of sampling. Box pot represents 10th and 90th percentile (box), median values (square in the box) and whiskers show minimum and maximum concentration.

CHAPTER 5 ARTICLE 2: MICROBIAL RISK ASSOCIATED WITH CSOS UPSTREAM OF DRINKING WATER SOURCES IN A TRANSBOUNDARY RIVER USING HYDRODYNAMIC AND WATER QUALITY MODELING

In this chapter, we evaluate the impacts of a series of probable CSO discharges into upstream of a river that is being served as a drinking water source for two municipalities. CSO-associated microbial risk profiles at water intakes were quantified and compared to that of health target. This chapter illustrates the combination of semi-probabilistic CSO load model with a hydrodynamic and water quality model which is then coupled with QMRA.

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MICROBIAL RISK ASSOCIATED WITH CSOS UPSTREAM OF DRINKING WATER SOURCES IN A TRANSBOUNDARY RIVER USING HYDRODYNAMIC AND WATER QUALITY MODELING

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ABSTRACT

Urban source water protection planning requires the characterization of sources of contamination upstream of drinking water intakes. Elevated pathogen concentrations following Combined Sewer Overflows (CSOs) represent a threat to human health. Quantifying peak pathogen concentrations at the intakes of drinking water plants is a challenge due to the variability of CSO occurrences and uncertainties with regards to the fate and transport mechanisms from discharge points to source water supplies. Here, a two-dimensional deterministic hydrodynamic and water quality model is used to study the fluvial contaminant transport and the impacts of the upstream CSO discharges on the downstream concentrations of *Escherichia coli* in the raw water supply of two drinking water plants, located on a large river. CSO dynamic loading characteristics were considered for a variety of discharge. Ranges of *Cryptosporidium* and *E. coli* concentrations based on historical data were used to estimate microbial risk with simulated CSO-induced *E. coli* concentrations and a daily risk target (2.74E0-9 DALY per person per day). During optimal operational performance of the plants, the daily risk target was met (based on the mean concentration during the peak) 80% to 90% of the time. For suboptimal performance of the plants, these values dropped to 40% to 55%. Mean annual microbial risk following CSO discharge events was more dependent on treatment performance rather than the number of CSO occurrences. The effect of CSO-associated short term risk on the mean annual risk is largely dependent on the representativeness of the baseline condition at the intakes, demonstrating the need for more frequent monitoring data at the intakes to reduce the uncertainty of mean concentration estimates. The results of this study will enable water utilities and managers with a tool to investigate the potential alternatives in reducing the microbial risk associated with CSOs.

KEYWORDS

Dynamic CSO loading, *Cryptosporidium*, Event-based QMRA, Source water protection

5.1 Introduction

Microbial threats remain a priority for drinking water treatment (Health Canada, 2017) as they are directly linked to human health (Dienus et al., 2016; WHO, 2017) and are associated with waterborne disease outbreaks (Hrudey et al., 2003). Fecal contamination in urban drinking water supplies following discharges of Combined Sewer Overflows (CSOs) remain an ongoing challenge for water authorities (Madoux-Humery et al., 2013; Marsalek and Rochfort, 2004). Monitoring campaigns of CSOs (e.g. Arnone and Walling, 2006; Katayama et al., 2004; Madoux-Humery et al., 2013) or their receiving waters (such as McLellan et al., 2007; Passerat et al., 2011; Madoux-Humery et al., 2016) have enhanced our general understanding of the contaminant loads, discharged concentrations, intra- and inter event variability. A limited number of studies have implemented Quantitative Microbial Risk Assessment (QMRA) to investigate the short term risk of such discharge-based events (not necessarily CSOs) on drinking water supplies (such as Sokolova et al., 2015; Signor et al., 2007) or on recreational water (such as McBride et al., 2013). While gastrointestinal illnesses were suggested to increase in areas with CSO discharges to a drinking water source (Jagai et al., 2015), CSO- associated microbial risk upon consumption of treated drinking water has not been extensively evaluated.

CSOs and their associated short-term risk are of more complex when considering their variable nature with regards to duration, magnitude of overflows and microbial concentrations (Marsalek and Rochfort, 2004). In Quebec, microbial removal requirements for drinking water treatment plants are based on *Escherichia coli* (*E. coli*) concentrations obtained from weekly or monthly measurements depending on the population served (MDDELCC, 2014). The maximum 12-month moving average concentration (in raw water) over a span of 36 months is calculated and determines the level of removal for *Cryptosporidium*, *Giardia* and virus is required through drinking water treatment. However, routine monitoring is often too infrequent to capture peak periods which are in fact sudden and relatively short (e.g. in a few hours) (Jalliffier-Verne et al., 2017). The risk of waterborne outbreaks may potentially increase during the peak periods (Astrom et al., 2007). Therefore, identifying peaks following CSO events at intakes of drinking water plants is critically needed to characterize microbial risk, given that efficiency of the treatment process may also be variable, but is typically not characterized.

While continuous monitoring of the level of fecal contamination (with the aim of capturing the peak period) had previously not been economically and practically feasible (McCarthy et al., 2007), modeling can be an alternative approach. However, new technologies for continuous monitoring of *E. coli* are becoming commercially available (Burnet et al., 2019), and if combined with modeling, they become powerful tools for source water characterization. The application of fate and transport models of microbial contamination within a water body may target a wide range of objectives such as 1) identification of critical governing fate and transport processes (e.g Hipsey et al., 2004; McCorquodale et al. 2004; Hellweger and Masopust, 2008; Wu et al., 2009; de Brauwere et al., 2014; Rodrigues et al., 2011; Ouattara et al., 2012; Gao et al., 2015), 2) assessment of mitigation measures along with the comparison of the alternatives (e.g. Marchis et al., 2013; Hoyer et al., 2015) and 3) identification of fecal contamination contribution from different sources (e.g.

Passerat et al., 2011; Sokolova et al., 2012; Sokolova et al., 2013). In addition, coupling modeling results with QMRA approaches provides an opportunity to complete monitoring data and characterize the impacts of peak periods in terms of treatment requirements for a given health-based target (e.g. Sokolova et al., 2015).

In many source waters, the probability distributions of *E. coli* concentrations in relation to CSO occurrences is unknown. Measurements at the intakes do not necessarily reflect the periods of highest concentrations as they are regularly taken on a daily, weekly, bi-weekly or even monthly routine basis (e.g. MDDELCC, 2014; USEPA, 2005). Therefore, determining the period and the magnitude of peak concentration caused by discharge events remains a challenge.

The primary objectives of this study were to investigate the microbial risk from CSO discharges in a drinking water source and identify conditions for which health targets are not respected. Firstly, the inter-event variability of CSOs is determined by characterizing the behavior of CSO discharges on a monthly basis while intra-event variability of discharges is described by a semi-probabilistic CSO load model developed previously by Taghipour et al. (2019). Secondly, the impacts of CSO discharges are evaluated using a hydrodynamic and water quality model merged with QMRA. More specifically, this study aims to 1) apply a probabilistic CSO loading model with a hydrodynamic and water quality model for a large river where intakes of drinking water are located downstream of the CSOs, and 2) characterize the peak periods following a CSO discharge event, 3) integrate water quality data from the intakes with CSO occurrences to form a more comprehensive reference data set, 4) acquire the probability distribution of *Cryptosporidium* concentrations in relation to *E. coli* concentrations at the intakes 5) quantify the short-term impacts of CSOs on microbial risk and integrating them into a mean annual risk estimate. Although the results of the modeling framework are specific to the river under study, the approach demonstrates how to establish a relation between very sporadic source of fecal contamination including their impacts and the source water protection strategies. It will also enable evaluation of the adequacy of the mitigation measures for the potential threat to source waters induced by event-based phenomena. A discharged-based QMRA has been applied by a limited number of studies such as McBride et al. (2013) and Sokolova et al. (2015). To the best of our knowledge, this paper is the first to use the discharge-based QMRA and health target for drinking water sources under the impacts of CSOs to associate the number of CSOs to the treatment performance for an acceptable level of microbial risk.

5.2 Methodology

5.2.1 Study site

The study site is an approximately 20 km section of the Ottawa River (also known as *Kitchissippi*), Canada. The watershed area covers approximately 163,000 km^2, with approximately 65% of its territory within the province of Quebec and 35% in the province of Ontario. The river forms the border of two provinces, Quebec and Ontario for most of its length where City A (northern river bank, Quebec side) and City B (southern river bank, Ontario side) are located. Along the studied portion of the river, there are the intakes of 4 municipal drinking water treatment plants. There are two drinking water intakes for each municipality on the section of the studied river: intakes of A1 and A2 for the City A and B1 and B2 for the City B (Figure 5.1).

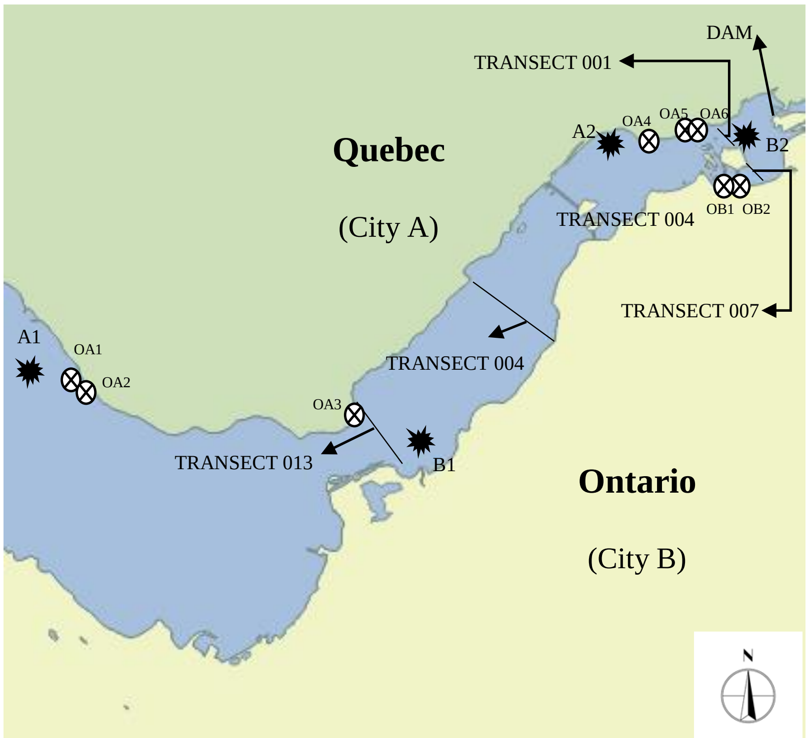


Figure 5.1: Map of the study area showing locations of the transects, CSO discharge points and locations of drinking water intakes.

The intake farthest upstream, A1, is located approximately 5 kilometers downstream of the beginning of the studied section while A2 is almost 2 km from the end of the studied area. B1 and

B2 are distanced (approximately) 7 km from each other. Six hundred meters downstream of B2, there is a dam that regulates the flowrate of the river. The flow and water level are gauged at one hydrometric station within the study area with daily records available since 1960 (Environment Canada, 2015). Monthly-mean river flow ranges from 227 m^3/s to 3720 m^3/s with a mean of 1204 m^3/s. The periods of high flow are during the months of April and May (mean flow 2030 m^3/s and 2060 m^3/s, respectively) while those of low flow are in August and September (mean flow 677 m^3/s and 615 m^3/s, respectively) (See Table 5.6. 1). The study area is not only a source of drinking water in an urban area with CSO outfalls upstream of the intakes, but also involves two different source water protection policies on each side of the river.

5.2.2 Fecal contaminant concentrations

Water management in Canada is a shared responsibility between federal and provincial governments (Cook et al., 2013), whereas municipal governments are typically responsible for providing communities with drinking water. Federal drinking water guidelines (Health Canada 2017) exist; however, each province is entitled to develop and implement its own drinking water treatment-related standards. In Quebec, *E. coli* was chosen to be the indicator of fecal contamination based on which the design of drinking water treatment concerning the required log removal is determined (MDDELCC, 2014). Fecal coliforms were obtained for the A1 and A2 intakes for 3 years starting from 2010 while measurement of *E. coli* concentrations was initiated in 2013 on a weekly basis according to the most updated regulation at the time. In this study, *E. coli* data were interpreted from fecal coliform data assuming the ratio of 0.75 between *E. coli* and fecal coliform concentration (Garcia-Armisen et al., 2007; Jalliffier-Verne et al., 2015) for the period before 2013. *E. coli* concentrations at A1 and A2 are generally low with mean values of 8 and 26 CFU/100mL, respectively. *E. coli* concentrations at these two locations follow a similar pattern throughout the year with months of September and October experiencing higher median concentrations (See Figure 5.6. 1). Measurements of *E. coli* at the intakes on the Ontario side of the river have been conducted for almost 20 years on a daily basis, providing a more complete data set of *E. coli* concentration variation within different periods of time. Median values of *E. coli* measurements at B1 and B2 are 49 (CFU/100mL) and 67 CFU/100mL, respectively. Two periods of higher concentrations are observed at B1 and B2; late spring (i.e. April and May) as well as late summer/early fall (i.e. September and October, similar to A1 and A2) (See Figure 5.6. 1).

Concentrations of *Cryptosporidium* detected at the B1 and B2 intakes are relatively very low (mean value as 5 oocysts/100L). *Cryptosporidium* measurements are conducted once a month by City B. Given that pathogen concentrations in source waters are primarily driven by upstream loading events (Sokolova et al., 2015), infrequent (monthly) sampling of *Cryptosporidium* may be insufficient to capture the concentration variation and fail in detecting hazardous peaks following an event. Therefore, given the lack of a large data set on the background *Cryptosporidium* concentrations on the northern bank, it was decided to focus water quality model development based on the availability of the more comprehensive microbiological data set, i.e. *E. coli*, from both sides of the river. In addition, *E. coli* concentrations in raw water serve as a criteria to design drinking water treatment plants in Quebec (MDDELCC, 2014). Therefore, *E. coli* was selected for calibration and validation of the microbial transport model of CSO outfalls to the drinking water treatment plant intakes.

5.2.3 CSOs in the studied area

There are eight major CSO outfalls located within the study area along both sides that discharge directly into the river. Six out of eight outfalls are managed by City A (OA1 to OA6) and two outfalls are within the jurisdiction of City B (OB1 and OB2) (Figure 5.1). Although there are no municipal wastewater treatment plant discharging effluents to this reach of the river, three out of four intakes (i.e. A2, B1 and B2) are under the potential influence of CSO discharges as they are situated downstream of the outfalls. A1 is not influenced by any CSO outfalls, but it may still be affected by microbial contamination from upstream agricultural activities and local wildlife. A comparison of *E. coli* concentrations (median values) between A1 and A2 as well as B1 and B2, typically shows an increasing trend from upstream to downstream direction, denoting possible influence of CSO occurrences given no other major sources of fecal contamination other than CSOs, stormwater, and possible sewer cross-connections that are common in storm sewersheds (Hajj-Mohamad et al., 2019).

Information on the frequency of CSO occurrences from the Quebec side (6 outfalls) with the duration of the event are provided by City A through a provincial overflow monitoring program (MAMROT, 2018). Rainfall and snowmelt are the two primary triggers of the CSO discharges in the area. Rainfall-caused CSO events (more than 60% of the time) mostly occur from May to October while snowmelt-related discharges (up to 30% of the time) take place in March and April.

On average (over a 5-year period), nearly 78 overflow events per year occur within the area of interest upstream of the intakes that potentially influence the short-term microbial risk at drinking water intakes.

The database of CSO frequency does not include information on the overflow rate, volume or contaminant loads. However, volumes of CSO discharges have been measured by City A at some selected outfalls including OA5. Besides, the duration of CSO events at OA5 have been separately recorded by the City A in each month over a course of 10 years, resulting in characterizing events in terms of their duration. Showing a wide range of variation in duration of discharges, a probability distribution of discharge duration in each month was assigned accordingly (Table 5.6. 2). Based on the available data on volume of discharges within the corresponding discharge duration, a correlation between these two variables was established to estimate overflow volume based on event duration (See Figure 5.6. 2). Using this correlation and probability distribution of discharge duration in each month from March to October, a probability distribution of overflow volumes was estimated for use in simulation scenarios to account for probable impacts of overflow in each month of the year. Outfalls OB1 and OB2 are located in the southern part of intake B2, their discharges do not directly contribute to the level of fecal contamination at B2 and assumed to be negligible compared to the other 6 outfalls.

5.2.4 Numerical model

5.2.4.1 Hydrodynamic model and setup

In order to simulate the water flow, fate, and transport of microbial contamination from discharge sources to drinking water intakes, the two-dimensional hydrodynamic MIKE 21 FM by Danish Hydrodynamic Institute (DHI, 2017) was used. 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. Given the physical characteristics of the river, the number of CSO outfalls, modeling objectives and available data, the 2-D model was deemed to be sufficient for the prediction of the general trends of flow in the river. Although, application of a 3-D model may improve the simulation results in representing the overall processes, the computational demand of such a model in running multiple scenarios would not be practical. The inputs of Mike 21 FM model were mainly hydrometric data (flow and water level) of the river, shoreline and meteorological data. The bathymetry and current data were provided by City B.

The computational domain extended from the downstream dam to 20 km upstream of the dam. The model grid development was based on flexible mesh approach allowing higher resolution of grid in any point of interests resulting the length of triangular grid ranged from 20 m to 100 m (Figure 5.6. 3). Following the development of the grid, the hydrography data of the river was interpolated onto the mesh grid. Based on the availability of hydrometric data that were measured on two different days, the model was set up to simulate two hydrodynamic conditions of the river for calibration and validation purposes. Calibration and validation data were obtained by City B through field investigations conducted in August 2007 and June 2005, respectively. The model was calibrated against current measurement and simulation was performed for the 1-day period. The calibrated model was then validated with current measurement data. A summary of model set up for calibration/validation components is provided in Table 5.1.

5.2.4.2 Microbial water quality model and setup

The Mike 21 Eco lab module (DHI, 2017), as a water quality model was coupled to the validated hydrodynamic model of the river to simulate the dispersion of *E. coli* in the river. By using current distribution as the output of the hydrodynamic model, the Eco Lab module calculates *E. coli* concentrations by considering first order decay rates as the only degradation mechanism. The water quality model of the river was set to simulate a range of river conditions corresponding to *E. coli* concentration measurements at the intakes of B1 and B2. To calibrate and validate the water quality model, the domain was split to include only the lower reaches of the river where B2 would be considered as the upstream of the new domain. Based on daily measurements of *E. coli* at B1 and B2, the water quality model was calibrated and validated by simulating *E. coli* concentrations for a period of 8 days (no CSO events) and for a period of 2 days (with a CSO event), respectively. The *E. coli* decay rate and dispersion coefficient were set in the model so that so that the simulation results (i.e. *E. coli* concentrations) fall within the range of concentrations measured at B2.

Table 5.1: Hydrodynamic and water quality model set up for calibration and validation.

Hydrodynamic model	Calibration	Data set	Water level and current measurements in Aug 2007	
		Upstream boundary condition	River flow, constant	450 (m^3/s)
		No. nodes	10274	
		No. elements	19599	
		Downstream boundary condition	Water Level, constant	5m below model datum
		Simulation period	24 hours	
		initial condition	River flow	0
		Land boundary	normal velocity	0
		Time steps	10 s	
		Bed resistance	Manning number	varying from 0.03 to 0.0125
		Eddy viscosity	Smagorinsky formulation	0.28
	Validation	Data set	Water Level and current measurements, Jun 2005	
		Upstream boundary condition	River flow, constant	950 (m3/s)
		Downstream boundary condition	Water Level, constant	5m below model datum
		Simulation period	24 hours	
		initial condition	River flow	0
		Land boundary	normal velocity	0
		Time steps	10 s	
		Bes resistance	Manning number	varying from 0.03 to 0.0125
		Eddy viscosity	Smagorinsky formulation	0.28

Table 5.1. Hydrodynamic and water quality model set up for calibration and validation (cont'd).

Water quality model	Calibration	Date set	Daily measurements at B1 and B2	
		Upstream Boundary condition	*E. coli* concentration, timeseries	21-29 September 2014
		Downstream boundary condition	Zero gradient	
		Simulation period	192 hours	
		Decay rate	0.22 (/d)	
		Dispersion	1 (m^2/s)	
	Validation	Date set	Daily measurements at B1 and B2	
		Upstream Boundary condition	*E. coli* concentration, timeseries	3-5 September 2014
		Downstream boundary condition	Zero gradient	
		Simulation period	48 hours	
		Decay rate	0.22 (/d)	
		Dispersion	1 (m^2/s)	

5.2.5 Stochastic CSO loading model

The CSO loading model used in this study is based on the approach proposed in Taghipour et al. (2019). The approach generates an *E. coli* loading function that represents common overflow dynamics and variability of the event parameters such as discharge duration and *E. coli* concentration. The approach involves dividing CSO discharge duration into 10 equal portions of time, during which a normalized overflow hydrograph is characterized by a linear increasing trend until reaching to a peak flowrate during the second decile followed by a logarithmically decreasing trend for the remainder of the event. Overflow hydrographs of CSO events are produced, given the total discharge volume and duration. In order to include the variability of *E. coli* concentration during CSO events, probability distribution functions of normalized *E. coli* concentration during the 1st decile, 2nd decile and the remainder of the discharge period were obtained. Time series of *E. coli* concentrations were calculated based on peak *E. coli* concentrations that would typically occur during CSO events as well as selection of random values from the probability distribution functions of normalized *E. coli* concentration depending on the time of occurrence in course of the event which it be molded. Therefore, a CSO hydrograph and time series of *E. coli* concentration (the inputs of Mike 21 and Eco-lab) can be produced for any event by defining a discharge duration, overflow volume as well as typical peak concentration. These data can also be obtained from historical data or outputs of sewershed model simulations (see Pongmala et al., 2015). Based on the available data of CSO events in the studied area on typical overflow, discharge duration and plausible concentrations, microbial loading of CSOs discharging into the river were quantified and incorporated into the hydrodynamic and water quality model.

5.2.5.1 Scenario development

The presence of CSOs upstream of drinking water intakes and their potential fecal loads for a wide range of CSO discharge scenarios were generated based on the monthly characteristics of CSO events within the area. The scenarios were produced to be representative of the potential CSOs considering the variability of discharge duration that is correlated with the volume of discharge, variability of peak *E. coli* concentration and extreme events in each month. The monthly-probability distribution function of CSO discharge volume was calculated for the most frequent outfall, i.e. OA5. There are two assumptions in the scenario development in order to consider the cumulative effects of CSO occurrences in the river: 1) simultaneous occurrence of overflows, and 2) similarity of other overflows to the OA5. Four types of scenarios were developed; scenarios No. 1 to No. 3 were based on the 10^{th}, 50^{th}, 90^{th} percentile of discharge volume along with their corresponding discharge duration (See. Section 5.2.3). Scenario No. 4 corresponds to an event of high discharge volume (90^{th} percentile) within a short period of time that is equivalent to the 10^{th} percentile of discharge period in each month (i.e. extreme event). River flow was selected based on the most probable values in each month for simulations while median *E. coli* concentrations at B1 and B2 (obtained from Figure 5.6. 1) were selected as the monthly background concentration in the river as summarized in Table 5.2.

Peak *E. coli* concentrations reported in Madoux-Humery et al. (2013) were obtained whose 50^{th} percentile (i.e. 4.7E+6 CFU/100mL) and 90^{th} percentile (1.1E+7 CFU/100mL) values were used in the simulations as the peak concentration reference. Details of simulated CSO scenarios are

Table 5.2: River flow and background concentration considered for the scenarios in each month.

Month	River flow (m^3/s) (most probable value)	Estimated background *E. coli* concentration (CFU/100 mL)
March	800	6
April	1416	17
May	1478	44
June	996	29
July	585	24
August	431	44
September	620	64
October	540	87

provided in Table 5.3.

5.2.6 QMRA

Impacts of CSO discharges on drinking water treatment plants were analyzed with regards to the health target. The simulation results under various scenarios of CSO occurrences would provide information on the potential fecal contamination, i.e. concentration of *E. coli* at the downstream intakes. Simulated *E. coli* concentrations are then converted to *Cryptosporidium* using a probability distribution function of the ratio of *E. coli* to *Cryptosporidium* (Figure 5.6. 4). The probability distribution of the ratio of *E. coli* to *Cryptosporidium* was calculated using concentration data of *E. coli* and *Cryptosporidium* measured at drinking water intakes. The ratio includes *E. coli* and *Cryptosporidium* concentration values at the intakes of B1 and B2 and data from 4 similar (large

Table 5.3: Description of the simulated CSO scenarios.

Scenario	No 1			No 2			No 3			No 4		
Peak concentration	1.1E+7 CFU/100mL			4.7E+6 CFU/100mL			1.1E+7 CFU/100mL			1.1E+7 CFU/100mL		
Month	Volume (m^3)	Duration (hr)	Peak overflow rate (l/s)	Volume (m^3)	Duration (hr)	Peak overflow rate (l/s)	Volume (m^3)	Duration (hr)	Peak overflow rate (l/s)	Volume (m^3)	Duration (hr)	Peak overflow rate (l/s)
March	29	0.62	47	319	5.4	59	812	12.6	65	812	1.6	522
April	9	0.22	41	238	4.1	58	794	12.3	65	794	0.6	1348
May	14	0.31	44	81	1.6	52	481	7.8	62	481	0.45	1071
June	110	2.1	53	354	5.9	60	744	11.6	64	744	0.64	1173
July	15	0.34	44	119	2.2	54	447	7.3	61	447	0.42	1075
August	26	0.57	47	174	3.1	56	578	9.2	63	578	0.48	1212
September	24	0.53	46	157	2.9	55	515	8.3	62	515	0.48	1062
October	28	0.6	47	183	3.3	56	609	9.7	63	609	0.52	1164

river flowrate, urban contaminant sources) drinking water intakes in large rivers (Sylvestre et al., 2018). There are important assumptions with using an *E. coli* to *Cryptosporidium* ratio. For example, the infectivity/viability of *Cryptosporidium* was not considered (Lalancette et al., 2012; Swaffer et al., 2018). Also, recovery data were not available and a conservative assumption of 30% for each sample was considered as suggested in Petterson et al. (2015). These assumptions may result in an overestimation of the produced risk profiles. Having been estimated the potential *Cryptosporidium* concentration at the intakes, the DALY (Disability Adjusted Life Year) risk was calculated as (WHO, 2017):

$$P_{inf,daily} = C \times LR \times V \times r \tag{5.1}$$

$$P_{inf,annual} = 1 - \prod_{i=1}^{n} \left(1 - P_{inf,daily}\right)_i \tag{5.2}$$

$$DALY\ RISK_{annual} = \left(P_{inf,annual}\right) \times \left({P_{ill}}/{P_{inf}}\right) \times Disease\ Burden\ Factor \tag{5.3}$$

Where:

- C is estimated *Cryptosporidium* concentration in source water (oocyst/L).
- LR is the treatment removal of treatment unit, including 3 log removal (0.001) and 4 log removal (0.0001) depending on performance of the units
- V is the exposure volume (L), the volume of unboiled tab water is assumed to be 1 L/day per person (WHO, 2017)
- r is infectivity, the probability of infection of the host organ by a single microorganism is assumed to be 0.2 for *Cryptosporidium* (WHO, 2017)
- $P_{inf,\ daily}$ is the probability of infection per person per day
- n is the number of exposures, (the number of days in a year, i.e. 365)
- $P_{inf,\ annual}$ is the probability of infection per person per year
- ${P_{ill}}/{P_{inf}}$ is the conditional probability of illness following infection, is assumed to be 0.7 for *Cryptosporidium* (WHO, 2017)
- *Disease Burden Factor* is the DALY weighting is assumed to be 0.0015 for *Cryptosporidium* per case of illness (WHO, 2017)

In order to calculate the individual risk of events on the yearly probability of one more infections, Equation (5.2) can be expanded as (Medema et al., 2006):

$$P_{inf,annual} = 1 - \left(1 - P_{inf,daily\,(event)}\right)^t \prod_{i=1}^{n} \left(1 - P_{inf,daily}\right)_i \tag{5.4}$$

where $P_{inf,\ daily\ (event)}$ is the probability of infection caused by an event and t is the number of days during a year having that event occurred. In this study, t is considered the number of CSO discharges that are expected or permitted to occur (i.e. 14 events per year).

CSO related *Cryptosporidium* concentrations at the intakes are influenced by the variable nature of events in terms of overflows, discharge duration and ratio of the pathogen to the fecal indicator. Therefore, the magnitude of the risk fluctuates over a course of time, e.g. one year, for which a stochastic sampling should be considered to include the variability. Monte Carlo simulations have been used for randomly selection of stochastic variables while considering the range and likelihood of possible values. In this study, the distribution of $P_{inf,\ daily}$ can be estimated by repeating the Monte Carlo simulation 10000 times.

5.2.7 Characterization of the CSO-induced peak periods and risk calculations

Simulated periods of peak concentrations at the intakes following CSO events are characterized by two parameters: 1) an arithmetic mean of *E. coli* concentration values over the course of a 24-hour period starting from the moment the plume of contamination reaches the intakes, and 2), the time of arrival of plume to the intake from the beginning of the CSO discharge, defined as the time lag. QMRA analyses based on the average concentration during the peak period may provide more realistic results representing the average condition of the raw water supply during that time. The health target of 1 micro DALY per person per annum is converted to the daily equivalence (2.73E-9) DALY per person per day. Although, respecting the daily target requirement is stricter than the annual target (Sokolova et al., 2015), waterborne disease outbreaks are reported to be linked to shorter periods of elevated risk. Therefore, QMRA for a shorter reference period (e.g. daily) may provide a better understanding and guidance for control measures and mitigations (Signor and Ashbolt, 2009) in the case of adverse elevated risk caused by discharge-based events. On the other hand, two treatment performance scenarios were also considered; 4 log removal (as the normal operating conditions) and 3 log removal (for underperformance conditions) according to the regulatory requirements that are set out by the MDDELCC (2014). The latter condition may represent the periods during which treatment processes may not necessarily provide designed removal efficiency.

5.3 Results and discussion

5.3.1 Model calibration and validation

5.3.1.1 Hydrodynamic model

The transient hydrodynamic model was simulated until outputs reached steady state (i.e. constant boundary condition) for both periods of calibration and validation datasets. Steady state conditions were achieved at hour 12 of a 24-hour simulation time. The depth-averaged velocity field was obtained for each calibration and verification period (Figure 5.6. 5). The model was calibrated (Figure 5.2) and validated (Figure 5.3) by comparing results of model simulations against measured depth-averaged velocity provided by City B data for different sections of the river. Based on the calibration results, the hydrodynamic model could capture general trends in the velocity distribution across Transects 001 and 007 (shown Figure 5.1). The model estimation of the current near the southern bank of Transect 001 was somewhat underestimated but sufficiently accurate to predict peak flow in the centre of the river. Model predictions of the river flow of Transect 007 are well matched with measurements. Moreover, results of the hydrodynamic model of the river are in a good agreement with the stationary point measurements near the intake B2 (i.e. less than 15% discrepancy). Following calibration of the hydrodynamic model, it was then used to simulate the flow regime in Jun 2005 for validation. Current measurements along Transects 004 (upstream of intake A2) and 013 (upstream of intake B1) were compared with the model results. While the hydrodynamic model can adequately capture the flow regime along Transect 004, it slightly overestimated the current velocity in the center. However, it successfully predicted the flow patterns across the river along Transect 013.

Considering the scope of this study, the extent of the river modeled and the accuracy required, the developed hydrodynamic model provided a reliable prediction of the general river hydraulics for water quality modeling.

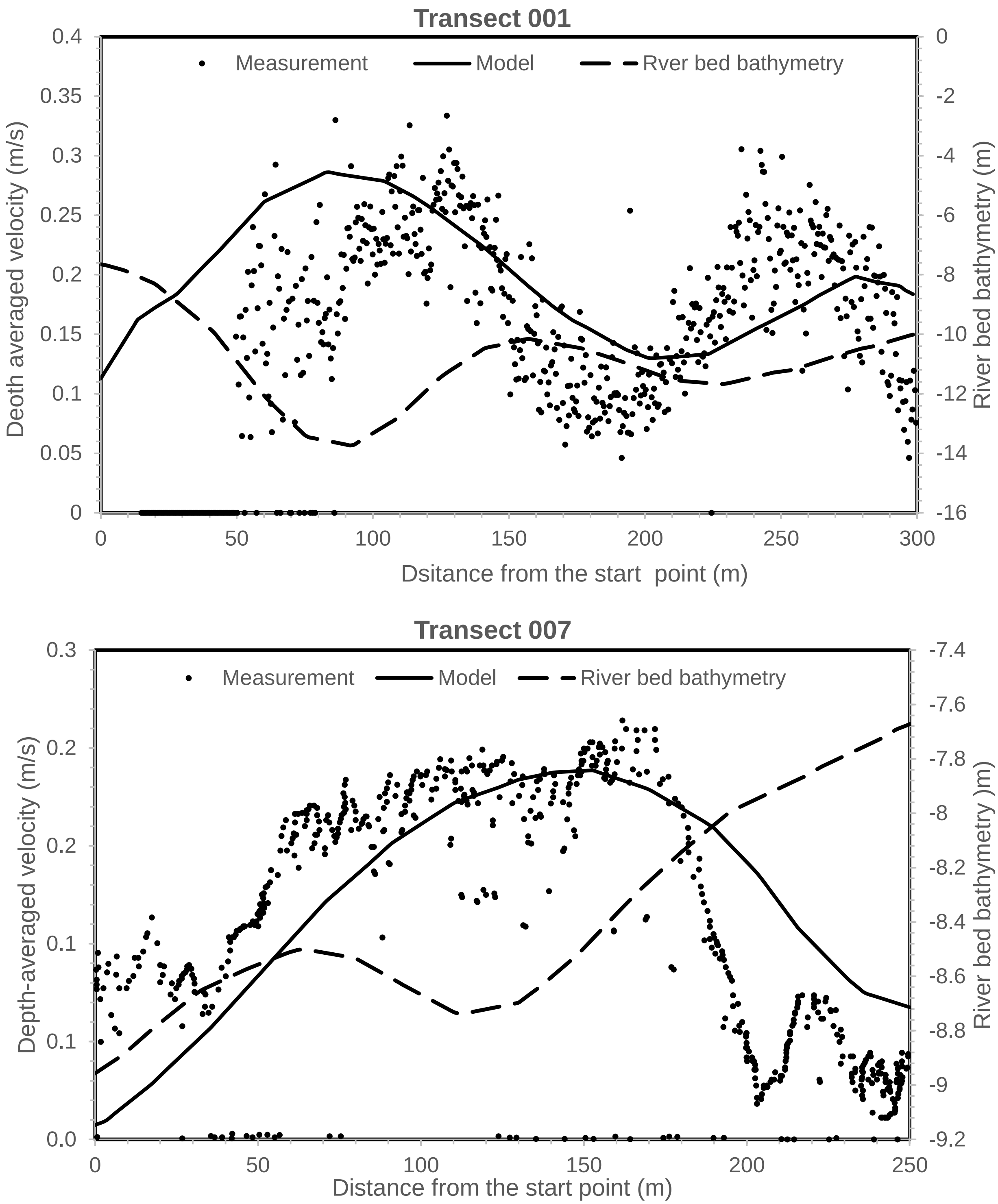


Figure 5.2: Hydrodynamic model results compared with current measurements (calibration).

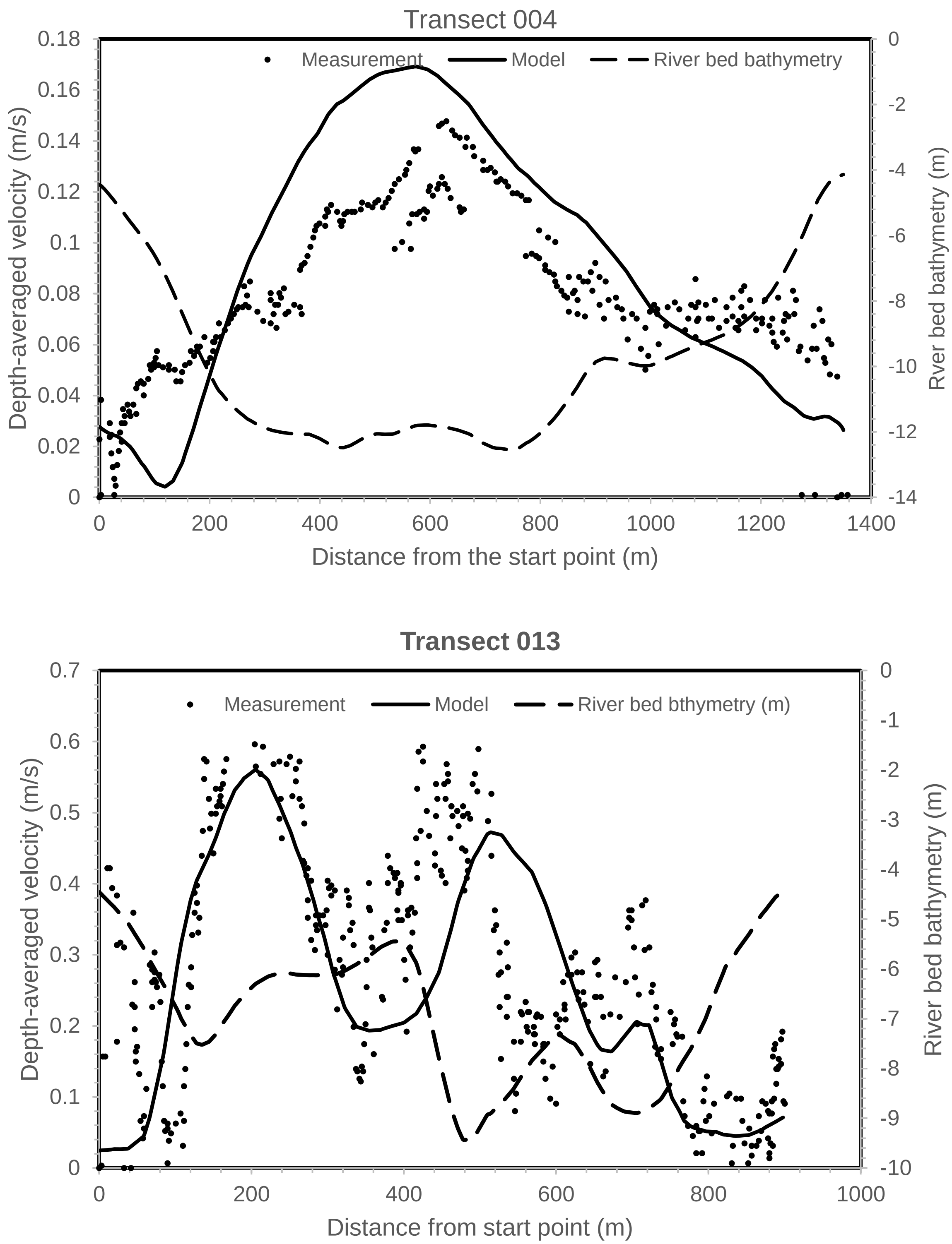


Figure 5.3: Hydrodynamic model results compared with current measurements (validation).

5.3.1.2 Water Quality model

Eco lab sub-module of Mike 21 was coupled with the calibrated and validated flow model to simulate fate and transport of *E. coli* discharged from CSO outfalls. The *E. coli* decay rate and dispersion were the dominant processes in the water quality model. Different values of decay and dispersion parameters within ranges recommended by the literature were adjusted to find the best agreement between the model results and measurements. The decay rate is less influential on the overall removal process of *E. coli* in the water column for cases with short travel times (e.g., order of hours) from discharge point to the point of interest (Jalliffier-Verne et al., 2017). However, the *E. coli* decay rate is often considered as an important parameter in fecal contamination transport studies (e.g. Jonsson and Agerberg, 2015; Dienus et al., 2016). The horizontal dispersion is defined in the model described by the dispersion coefficient. The model was set up to simulate a range of conditions representing low to high dispersion conditions. As goodness of fit for *E. coli* modeling has been considered on an order of magnitude level as they are variable on a logarithmic scale (Dorner et al., 2006), it was found that the model results will show a better agreement with the measurements (i.e. within an order of magnitude) when the decay rate and dispersion coefficient constant were set to 0.22/d and 1 m^2/s, respectively (Figure 5.4). The values set for the water quality model calibration are within the range of reported values of decay rate (See Sokolova et al., 2013) and dispersion coefficient (See Aghababaei et al., 2017; Etemad-Shahidi and Taghipour, 2012). The water quality model performance in estimating the *E. coli* concentrations (shown in Figure 5.4) demonstrated a reasonable capacity of the model to predict fluvial contaminant transport associated with CSO discharges.

5.3.2 Simulation of CSO scenarios

Simulation results showed that B1 is not strongly affected by the upstream CSO discharges while A2 and B2 potentially are. Therefore, the B1 intake is excluded from further discussion. *E. coli* concentrations at the A2 and B2 drinking water intakes resulting from CSO discharges were estimated by taking into account the dynamic behavior of CSO loading events. The results pertaining to the occurrence of the peak periods at each intake is provided (Table 5.4). A higher range of peak concentrations at A2 occurs in March and April when background concentrations of *E. coli* in the river are relatively low, but locally driven events such as precipitation during snowmelt lead to important loads from the sewer networks. The B2 intake also demonstrated a

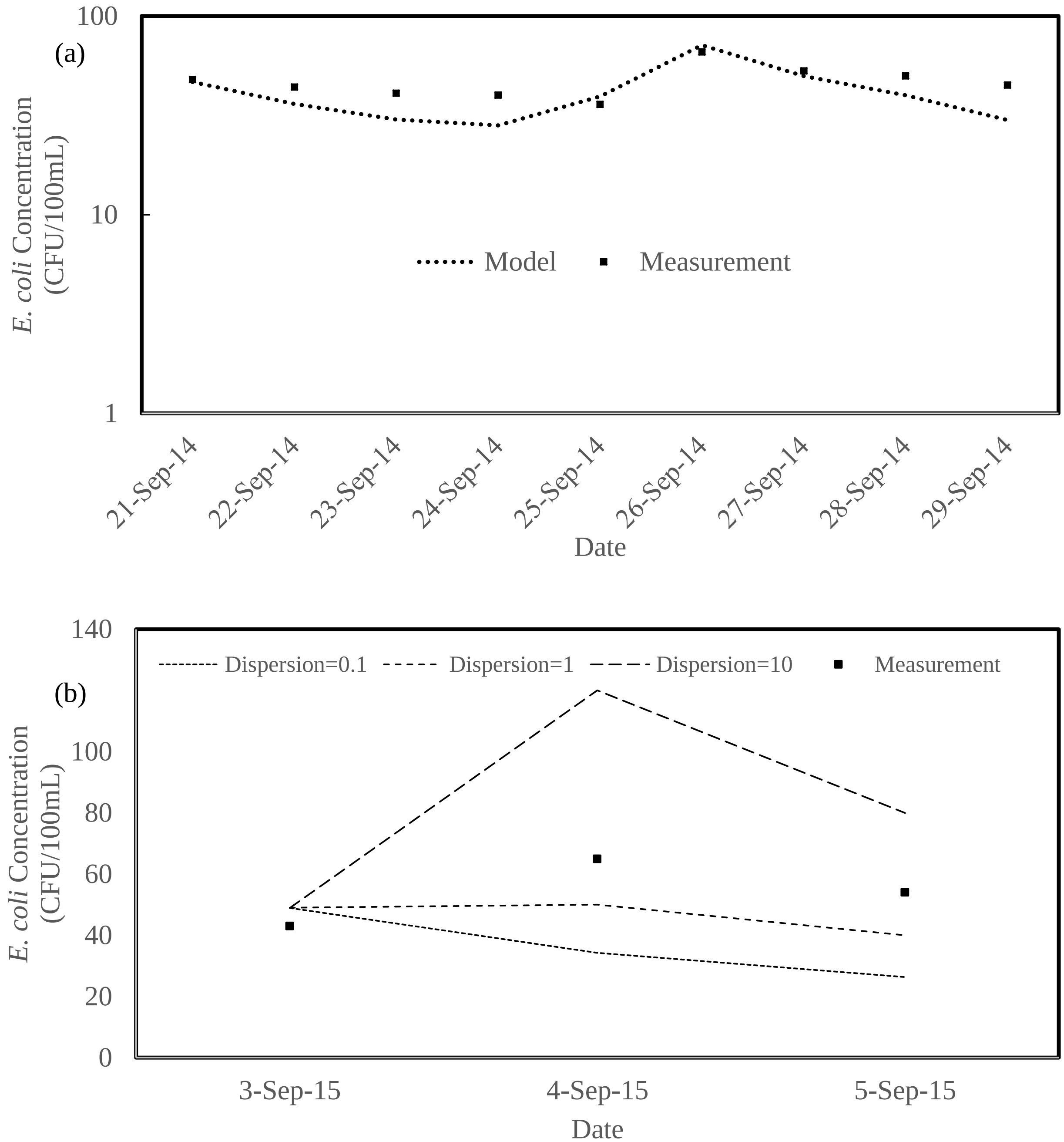


Figure 5.4: Water quality model results compared with *E. coli* concentrations at B2; (a) period with no CSO events, (b) period with a CSO event.

higher range of CSO-induced concentrations in the months of August, September, and October during which a lower river flow is observed. Similarly, higher concentration values are also observed in the measurement data at the intakes within these months (Figure 5.6. 1). Measured concentrations at the drinking water intakes are related to the discharges of CSOs, stormwater, the presence of migratory birds in addition to processes such as dispersion and inactivation. As shown in Table 5.4 peak concentrations are typically higher at A2 than at B2. This is related to the location of the A2 intake, which is longitudinally downstream of the outfalls (on the same river bank), while B2 is located approximately across from the outfalls (on an island across from the river bank). The time of peak concentration is also a flow-dependent parameter, which ranges from a couple of hours to almost half a day (for A2) following the events. Due to the proximity of CSO outfalls (i.e. OA4 to OA6) to B2, the peak concentration at B2 usually happens within 1 to 4 hours after the discharge. The plumes of contamination discharged by a CSO event (i.e. scenario 4 in March) has been illustrated for the moment it reached the intakes A2 and B2 (Figure 5.6. 6) as an example simulation result. Mean *E. coli* concentrations during the peak period from simulation at the intakes of A2 and B2 follow Gamma distribution functions (Figure 5.6. 7). Peak concentrations vary up to two and three orders of magnitude throughout the simulation months at B2 and A2, respectively.

Application of the hydrodynamic and water quality model provides the characterization of the period of peak *E. coli* concentrations in the source of drinking water under potential CSO events by quantifying the magnitude of the loading conditions, estimating the peak value, and determining the time for peak concentrations to reach the intakes. Nonetheless, uncertainties of the modelling results must be considered. A detailed analysis of CSO water quality measurement uncertainties and hydrodynamic modelling uncertainties are provided by Madoux-Humery et al. (2013) and Jalliffier-Verne et al. (2017). The largest uncertainties are associated with CSO concentrations and loads given that concentrations that can vary over several orders of magnitude and are more variable in time. The modeling results can also be used as complementary information to include the short-term microbiological impacts of CSOs. Periods of peak concentration are critically important to water managers to ensure the treatment process will reduce the contamination to an acceptable level. The information will also help water managers efficiently operate drinking water treatment plants considering the upstream discharging events while knowing a typical travel time of contamination plume or a range of expected microbial concentration occurring at the intake.

5.3.3 QMRA results

Having obtained the probability distribution functions of *E. coli* concentrations at the A2 and B2 intakes and the ratio between *Cryptosporidium* and *E. coli* (See Figure 5.6. 4), the potential ranges of *Cryptosporidium* concentrations could be estimated and used as the inputs for QMRA. The CSO associated microbial risk profiles under two treatment conditions were analyzed for the A2 and B2 intakes (Figure 5.5) along with an illustration of the risk calculated based on the routine regulatory measurements at the intakes (Figure 5.6. 8). The risk profile for an operating condition of 4 log removal calculated from the mean concentration, showed that A2 and B2 satisfy the daily target of 2.74E-9 DALY per person per day 80 % and 90 % of the time, respectively. If the operating condition of 3 log removal occurs, the daily target for A2 and B2 is only met 40 and 55% of the time, respectively. One log removal deficiency (i.e. 3 log versus 4 log removal) could double or triple the number of times the daily target is being breached. However, the effect of this violation of the daily target on the overall annual risk should be evaluated to see if it can alter the annual risk profile while considering CSOs events, leading to describing CSO-related risk in terms of long-term risk.

The CSO-based risk to the consumers is dependent on the number of CSO events that may potentially occur in a given year (simultaneous occurrence of discharges at the six CSO outfalls in this study). The more CSOs discharge to the river, the more frequent the peak periods will occur, during which the microbial risk is higher. Mean annual risk of drinking water at A2 and B2 were calculated with the associated risk of CSOs integrated in the annual risk estimate. Using the mean value of the daily risk calculated from direct measurements at the intakes, the mean value of daily risk as a result of CSOs and the number of potential CSOs (i.e. from 1 up to 60 hypothetical events) in Equation 5.4, the mean annual risk for a year including days with CSOs was calculated (Figure 5.6). Risks were evaluated for the two performance conditions of 3 and 4 log removal efficiency. We found that the mean annual risk at A2 under normal treatment performance (4 log removal) consistently meets the health target throughout a year, regardless of number of events. However, this will change should there be 1 log lower removal in the plant, in which health target is not respected at all, even for a year with no CSO events. Hence, the mean annual microbial risk is more dependent on the treatment performance of the plant rather than on the number of CSO events per year. Similar to the A2 intake, the risk related to the consumption of treated water from the plant B2 uninterruptedly complies with the health target throughout the year. For the lower

Table 5.4: *E. coli* simulation results for the A2 and B2 drinking water intakes.

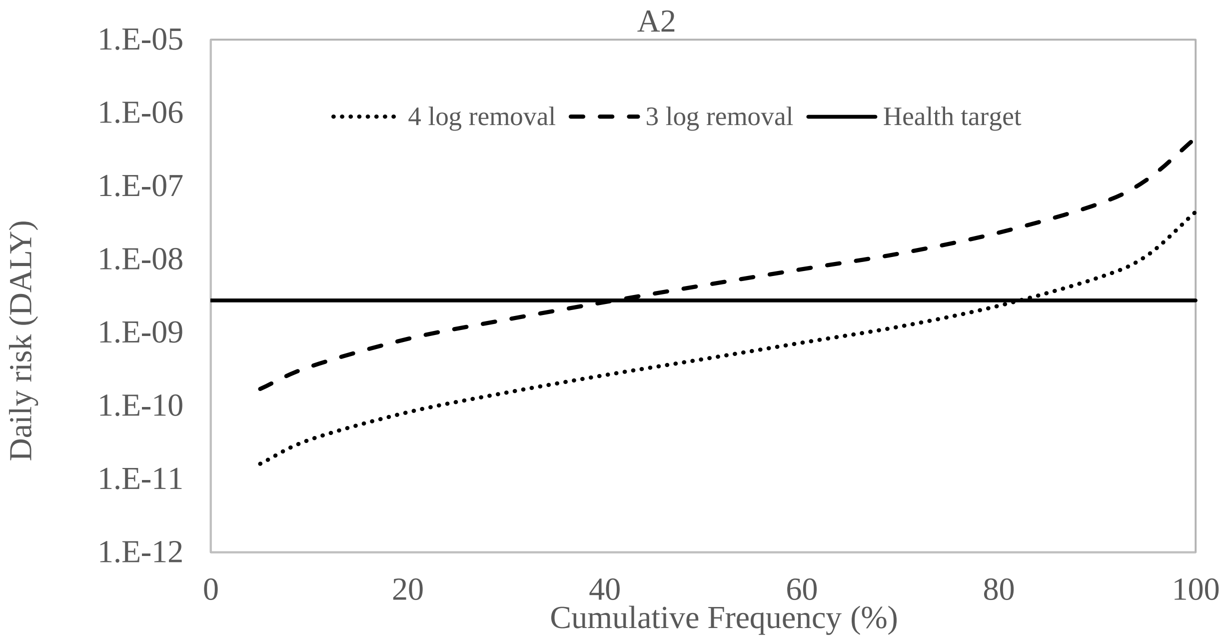
	Peak concentrations (CFU/100mL) (min-max)		24-hr averaged concentration (CFU/100mL) (min-max)		Time lag (hr, min) (min)-(max)	
Month	A2	B2	A2	B2	A2	B2
March	(72-2491)	(17-411)	(20-300)	(8-70)	(5,0)-(7,10)	(1,10)-(3,20)
April	(39-1680)	(19-119)	(18-194)	(18-33)	(3,40)-(5,20)	(0,50)-(2,40)
May	(59-855)	(49-99)	(34-113)	(38-42)	(4,10)-(5,20)	(0,40)-(2,10)
June	(129-1003)	(39-259)	(31-240)	(17-43)	(7,20)-(9,20)	(1,0)-(3,0)
July	(44-346)	(51-572)	(26-172)	(16-68)	(9,0)-(10,40)	(1,20)-(3,0)
August	(192-210)	(102-955)	(118-138)	(31-143)	(10,50)-(12,30)	(1,40)-(3,20)
September	(93-1214)	(71-675)	(41-227)	(42-106)	(6,10)-(8,10)	(1,20)-(3,0)
October	(122-985)	(110-1140)	(85-375)	(76-209)	(8,20)-(10,40)	(1,30)-(4,10)

performance in the plant B2, the health target is not respected.

There is not much difference between the risk profiles of "no event" conditions and those of "CSO events included" at both intakes for mean concentration risk profiles as seen in Figure 5.6. The mean concentrations used for estimating the background concentrations at the drinking water treatment plants did not distinguish days with wet weather flows and CSOs and days without. Although the risk profile does not significantly increase as a result of CSOs, it could be useful to confirm these results with event-based sampling at the drinking water treatment intake to determine how mean concentrations are influenced by the peaks. As the annual risk is driven by the mean and 3 log removal does not provide sufficient removal, it is critical to estimate mean baseline conditions more precisely. This means higher frequency raw water quality sampling, event-based sampling of peaks and treatment removal efficiency to reduce uncertainties of the estimate of the mean.

The duration of peak concentrations at the intakes could play an important role in determining the ultimate risk level. Depending on the length of peak periods from hours to days or weeks, the 24-h mean concentration value may vary. The longer the duration of the peak period, the higher the average concentration will be, which results in a higher risk level. The duration of peak concentrations has received less attention in the literature with regard to its impact on microbial risk. In this study, microbial risk results were obtained from simulations with peaks lasting up to 2 days (in some scenarios). With a longer peak duration, the mean concentration increases and would lead towards higher risk values.

CSO discharges and plant removal efficiencies are important elements of urban source water protection strategies. Microbial risk assessment results (daily and annually) can be used to prioritize mitigation measures and optimize sampling at the drinking water intakes to ensure that the influence of peak concentrations on mean concentrations are well characterized to reduce uncertainties associated with the mean value that is used for estimating annual risks.



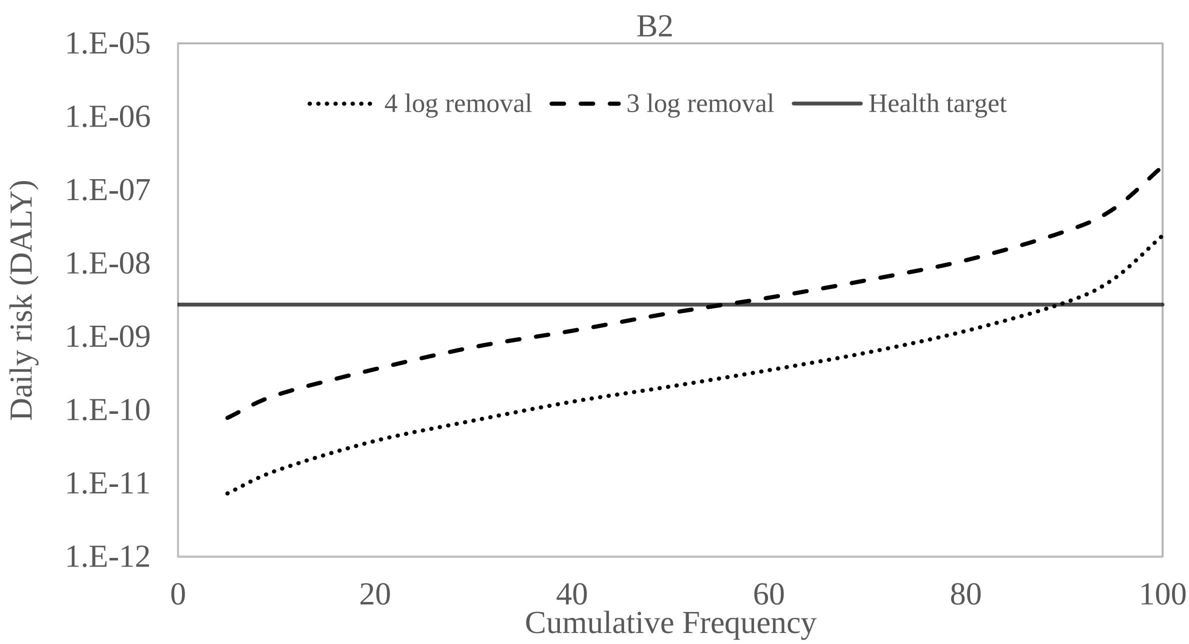
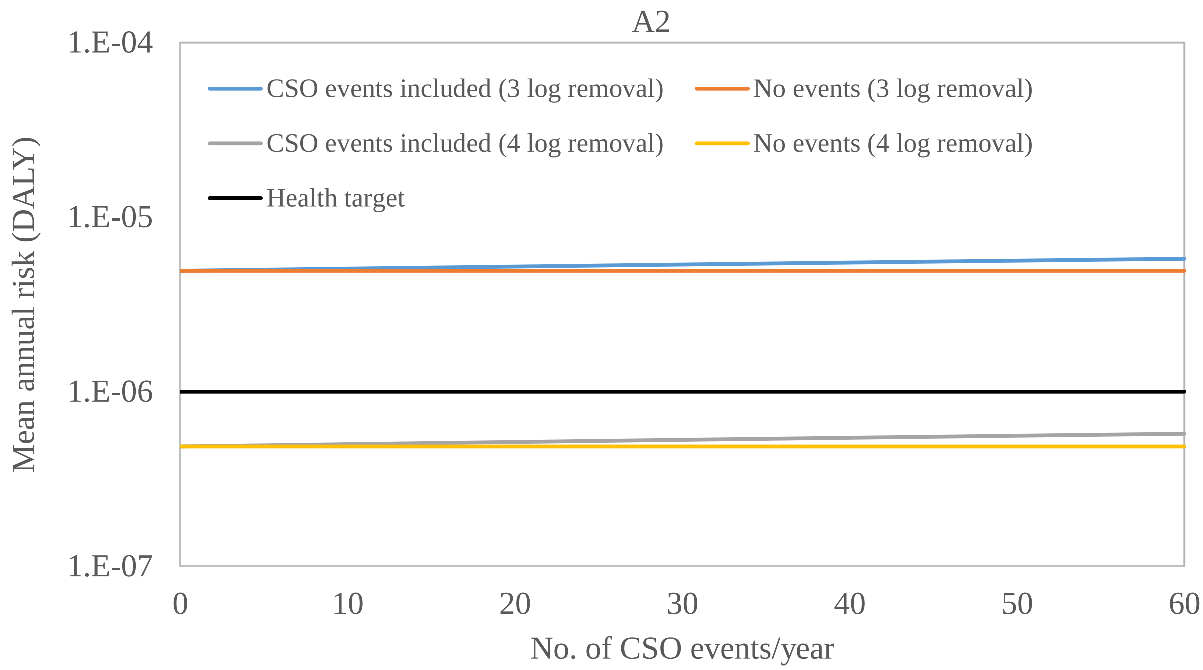


Figure 5.5: Risk profiles for consumption of drinking water following CSO events.



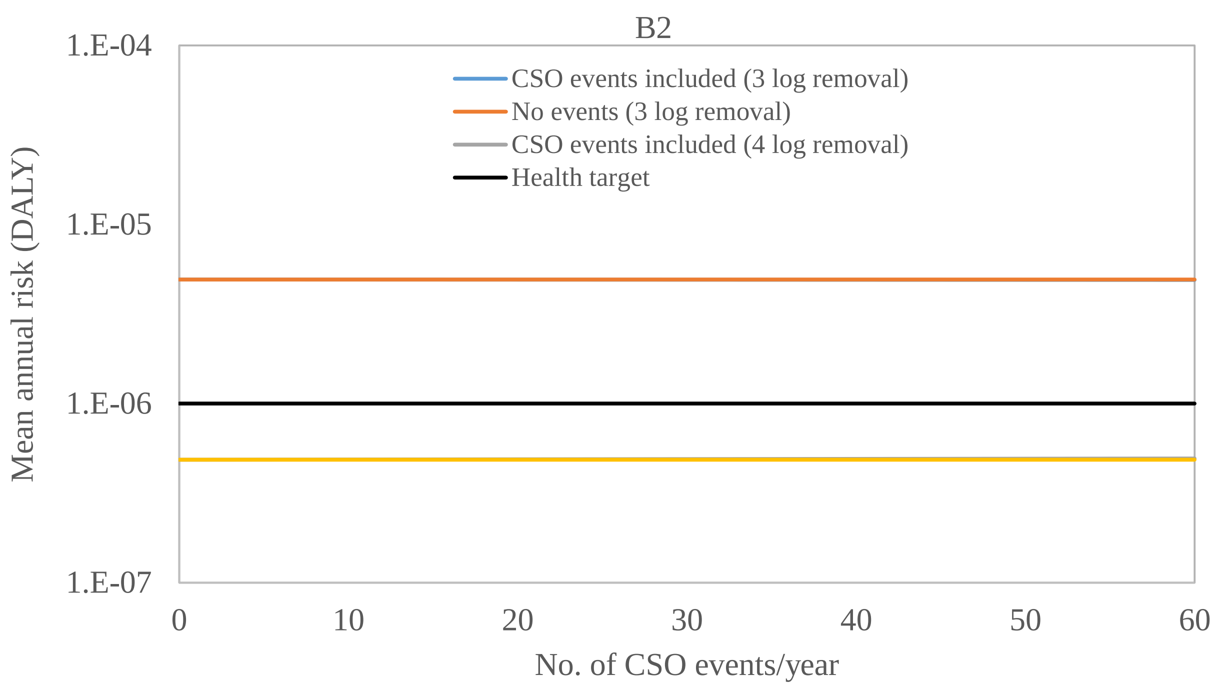


Figure 5.6: Mean annual risk of CSOs based on the number of occurrences and the treatment performance. For the B2 intake, the number of CSO events does not change the mean annual risk and it is identical to the mean annual risk based on log removal.

5.4 Conclusion

The methodology developed for this study demonstrates how we can quantify short term discharge-based sources of microbial contamination and evaluate their corresponding microbial risk to downstream drinking water treatment plants. The results of this study can be employed in source water protection mitigation strategies when it comes to: 1) prioritizing CSO events to be controlled based on the risk to consumers and 2) decision-making (for example, issuing boil water advisories) for the drinking water treatment plant in the event of suboptimal treatment. The results can be summarized as:

- The various CSO loading scenarios and river hydrodynamic conditions simulated showed that peak concentrations arrived at drinking water treatment plants within a few hours depending on the location of the drinking water intake.
- Using hydrodynamic and water quality modeling results with QMRA enables us to assess the risk from a series of realistic CSO discharge scenarios while taking into account the variability of the events in terms of discharge volume, discharge duration and river flow conditions.
- A comparison of daily DALY risk as a result of CSO occurrences between two treatment performance conditions confirmed that 4 log removal performance would adequately respect the daily target for the studied plants. Should lower removal conditions occur, the compliance with the health target was reduced to half of the time as compared to the condition of 4 log removal.
- The treatment efficiency of the plants plays more importance role in determining the CSO-associated short and long-term risk as compared to the number events per year. The mean annual risk of the CSO events do not exceed the mean annual health target defined in Canada, for all potential number of events, as long as the treatment performance of 4 log removal is maintained. However, the annual health target is not met with reduced treatment performance (i.e. 3 log removal).
- Integration of the short-terms risk (i.e. daily) into long-term risk (annual) depends on the quality of available data measured at intakes to represent comprehensive baseline conditions. The annual risk profile is dominated by the mean background concentrations measured at the drinking water intakes. Thus, it is important to reduce the uncertainty of

the mean concentrations that could be strongly influenced by peak values. Thus, higher frequency monitoring and monitoring during peak events is important for characterizing mean concentrations and the resulting microbial risk.

- Applying a fate and transport model with a health-target microbial risk assessment is useful for determining the impact of CSOs on source of drinking waters. The approach could be extended to determine the cumulative impacts of other sources of microbial threats that could occur in addition to CSOs. The results demonstrated that the annual risk is driven by the mean concentrations and not necessarily the number of CSOs that occur in a given year. Therefore, in addition to CSO control, source water protection should also focus on other sources of microbial contamination that are related to higher mean *E. coli* and pathogen concentrations at the drinking water intakes. Examples of such sources of contamination may include waterfowl, cross-connected storm sewers, and stormwater discharges.

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5.6 Supplementary Materials

Table 5.6. 1: River flow statistics based on daily records.

Month	River flow (m^3/s)				
	Valid N	Mean	Minimum	Maximum	Std.Dev.
Jan	1737	1229	498	2200	311
Feb	1559	1212	547	2810	269
Mar	1719	1271	538	3360	400
Apr	1680	2061	648	4740	784
May	1736	2028	359	5060	914
Jun	1680	1292	383	3330	539
Jul	1767	886	348	2600	380
Aug	1767	677	242	1890	267
Sep	1710	616	165	2150	232
Oct	1767	840	259	2560	411
Nov	1710	1145	367	2760	483
Dec	1767	1261	494	3480	435

Table 5.6. 2: Characteristics of the probability distribution functions of the CSO discharge duration in each.

Month	Sample size	Distribution type	Distribution variables	Goodness-of-fit		
				K-S error	Critical *p*-value (significance level α=0.05)	*p*-value
March	46	Exponential	λ=0.07	0.09	0.2	0.83
April	60	Weibull	Scale factor=16, Shape factor =0.7	0.16	0.17	0.20
May	42	Lognormal	Mean=6, St-dev=16.81	0.15	0.21	0.63
June	61	Lognormal	Mean=13, St-dev=17.22	0.08	0.17	0.89
July	50	Lognormal	Mean=8.67, St-dev=26	0.13	0.19	0.31
August	54	Lognormal	Mean=9.28, St-dev=21.40	0.10	0.18	0.67
September	48	Lognormal	Mean=9.28, St-dev=21.40	0.09	0.19	0.82
October	50	Lognormal	Mean=9.28, St-dev=21.40	0.09	0.18	0.85

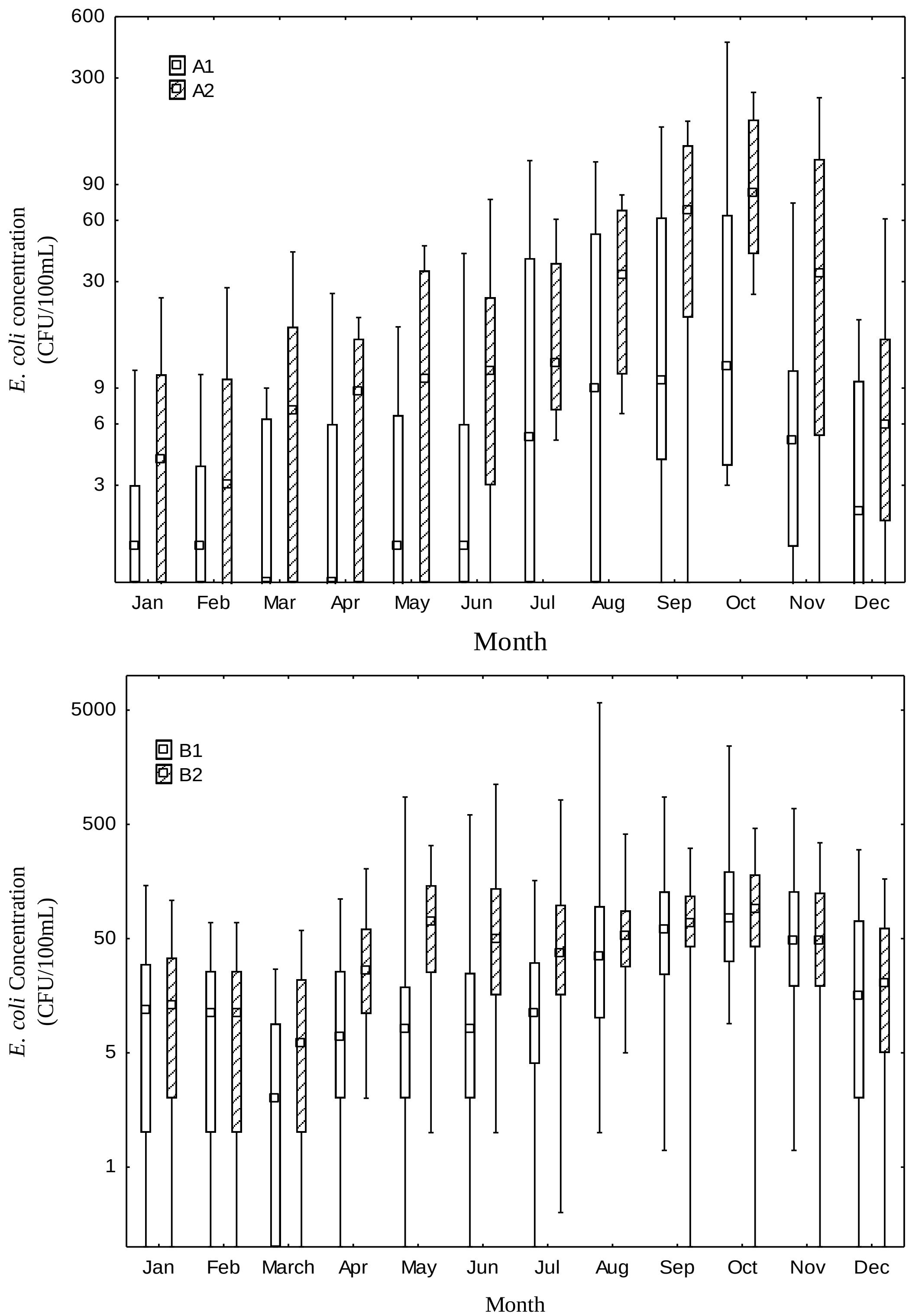


Figure 5.6. 1: Monthly *E. coli* concentrations. Box plots represent 10th and 90th percentile (box), median values (square in the box) and whiskers show minimum and maximum.

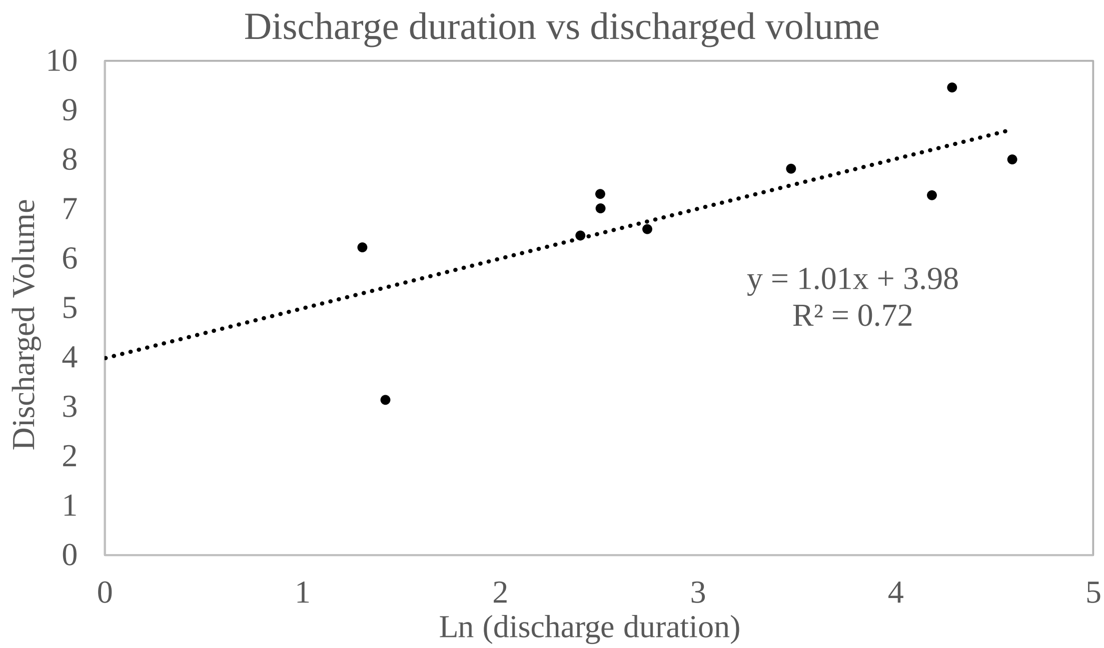


Figure 5.6. 2: Correlation between discharge duration (hr) and discharged volume (m^3) of CSOs at OA5.

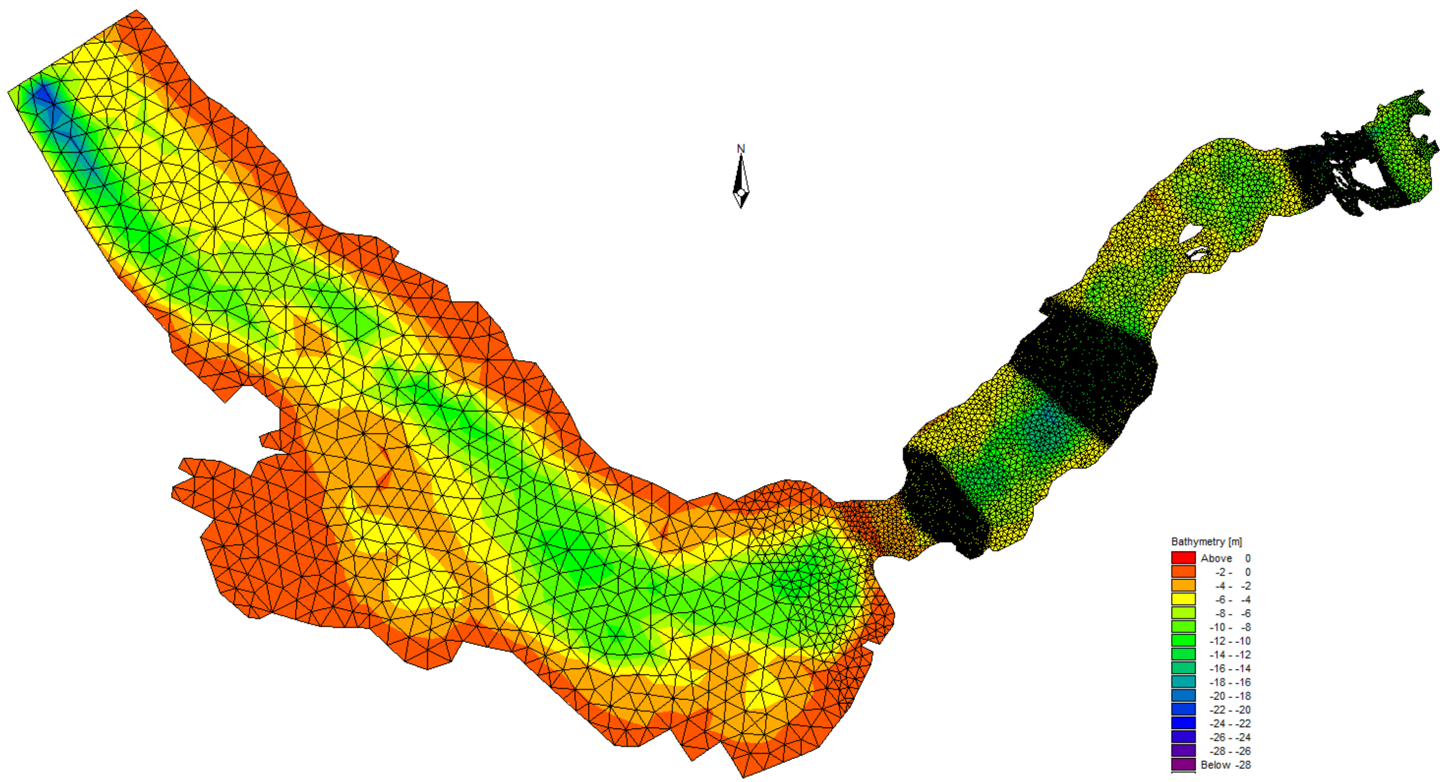


Figure 5.6. 3: River bathymetry and model grid of the studied area.

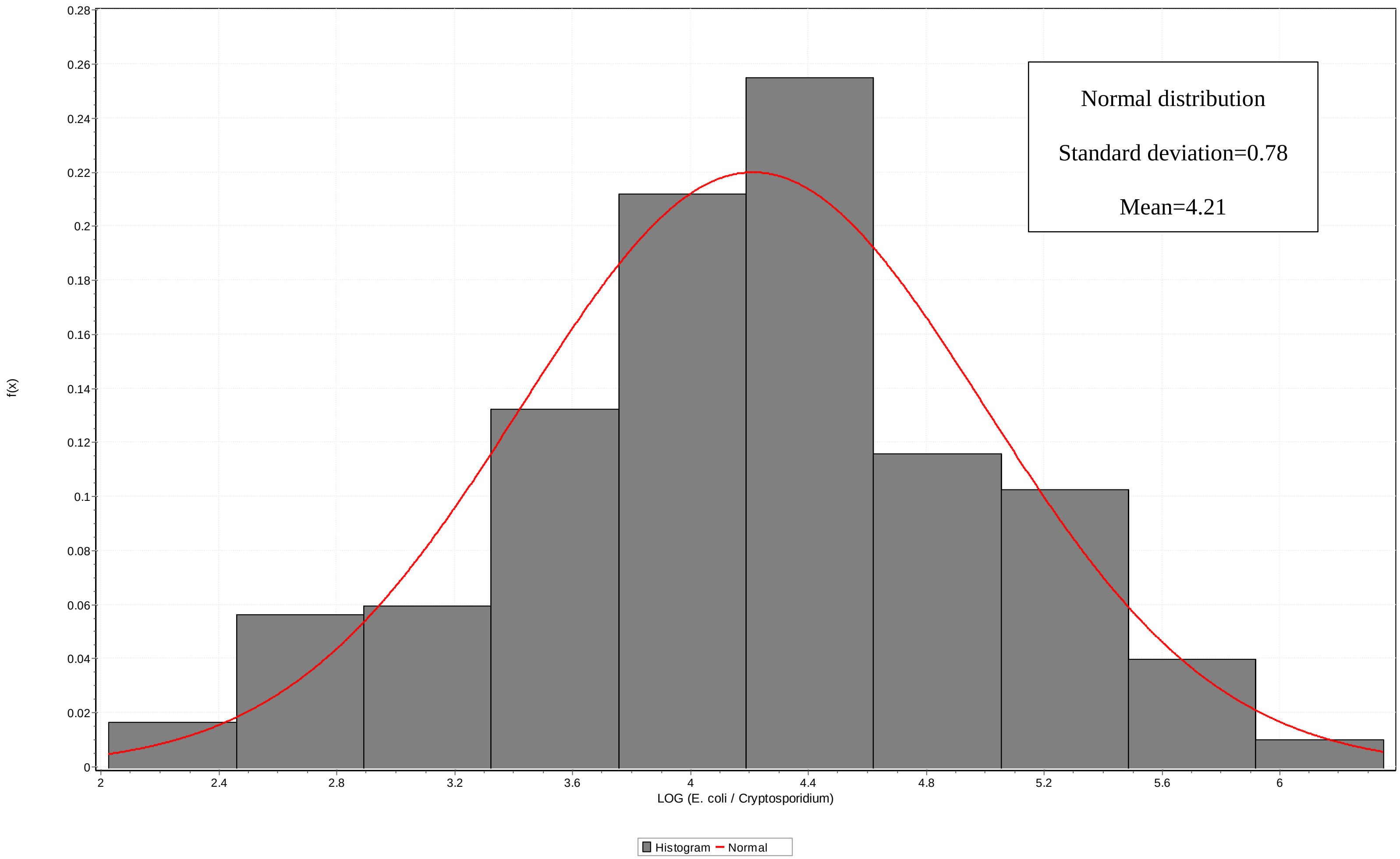


Figure 5.6. 4: Probability distribution function of the ratio between *E. coli* concentration and the corresponding *Cryptosporidium* concentration from paired data.

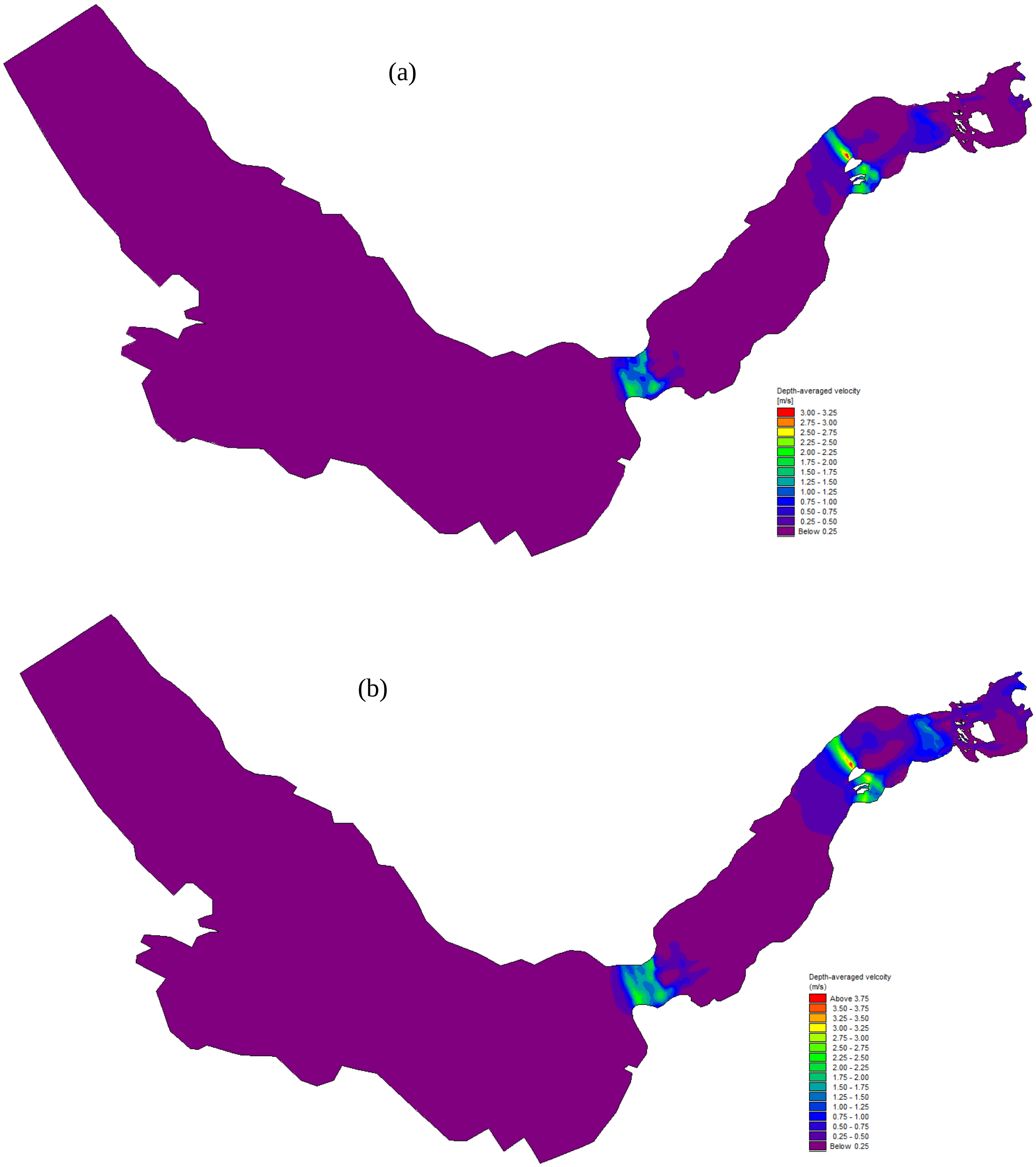
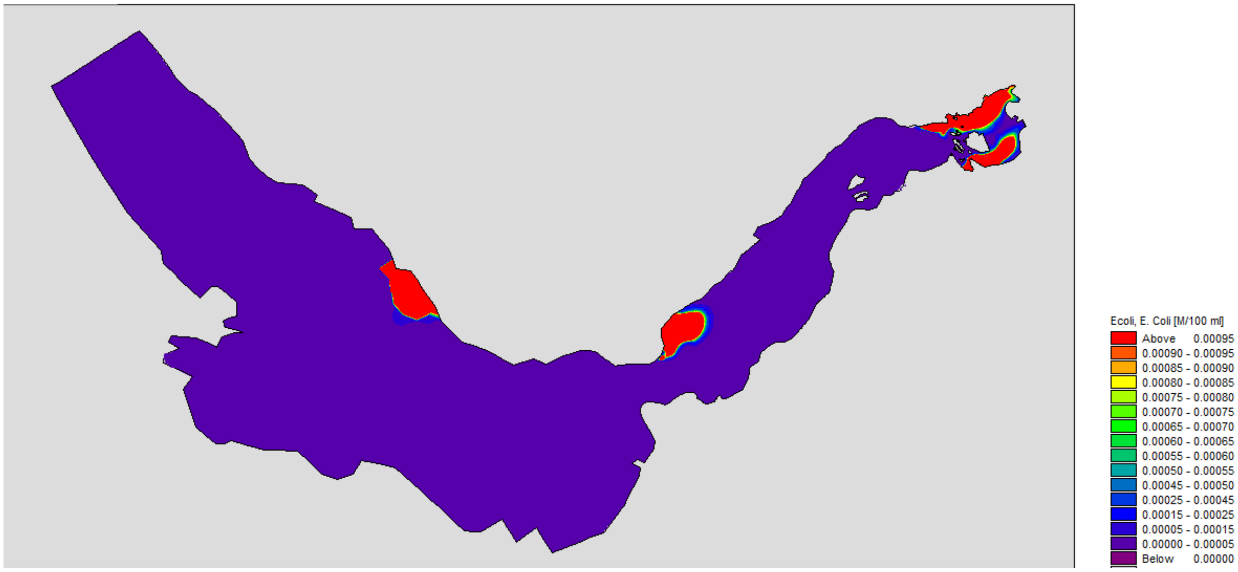


Figure 5.6. 5: Depth-averaged velocity field for calibration (a) and validation (b) periods.

(a)



(b)

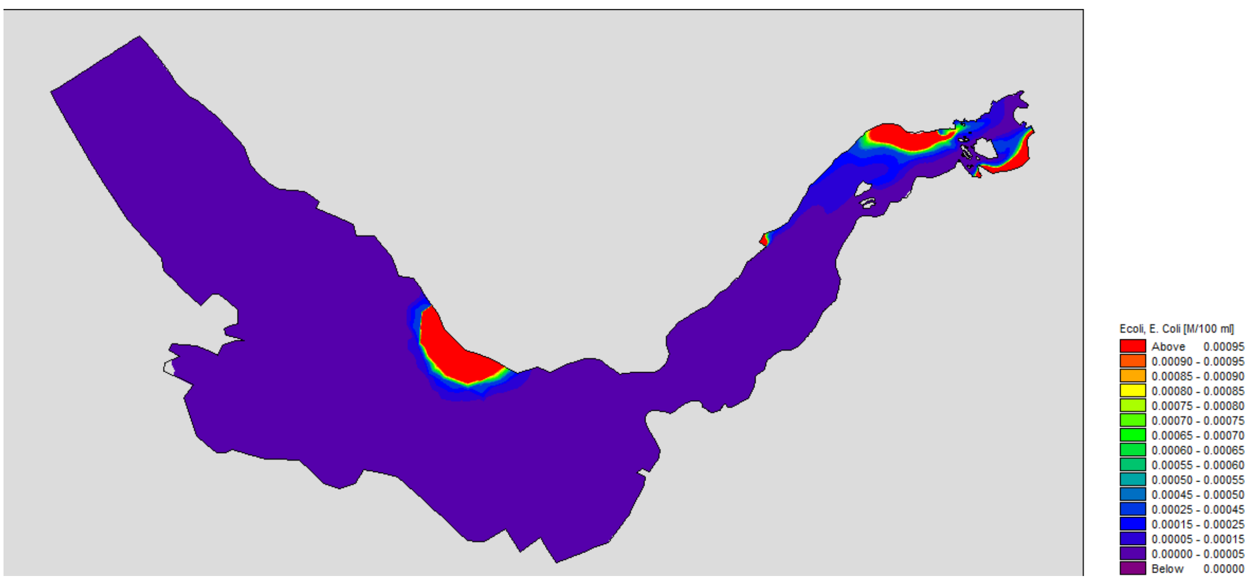


Figure 5.6. 6: Illustration of simulation of CSO plumes (scenario No. 4 in March) reaching the drinking water intakes for a 48-hour simulation time: a) reaching B2 after 1.3 hours, b) reaching A2 after 5.8 hours. *E. coli* unit expressed in million (M)/100mL.

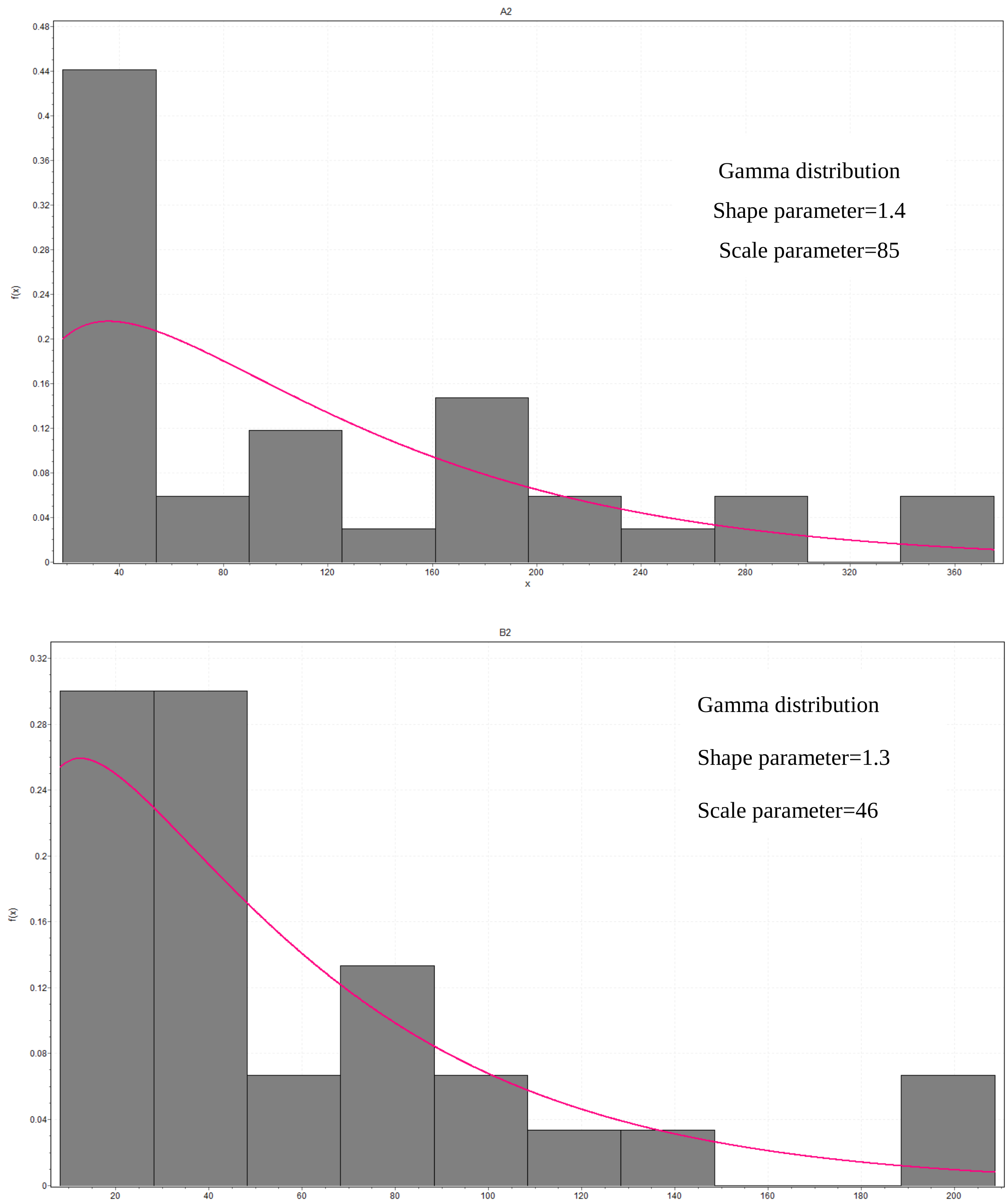
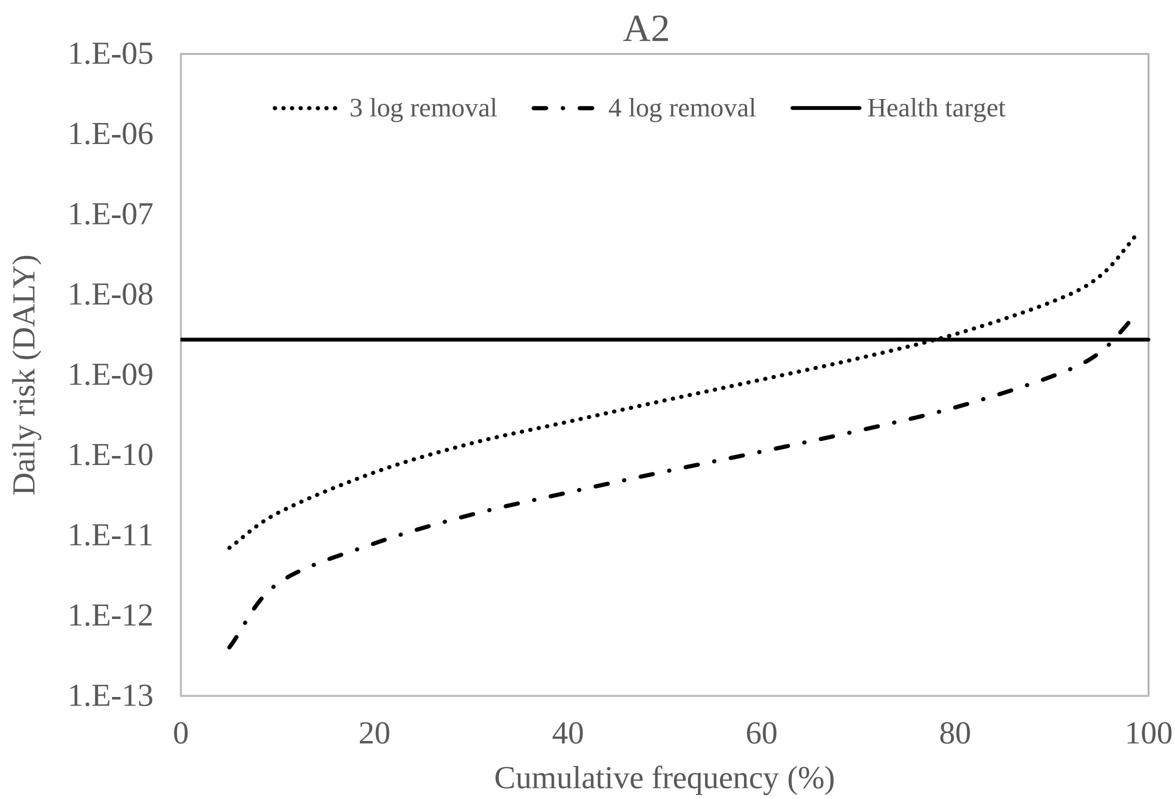


Figure 5.6. 7: Probability distribution function of *E. coli* concentrations (mean).



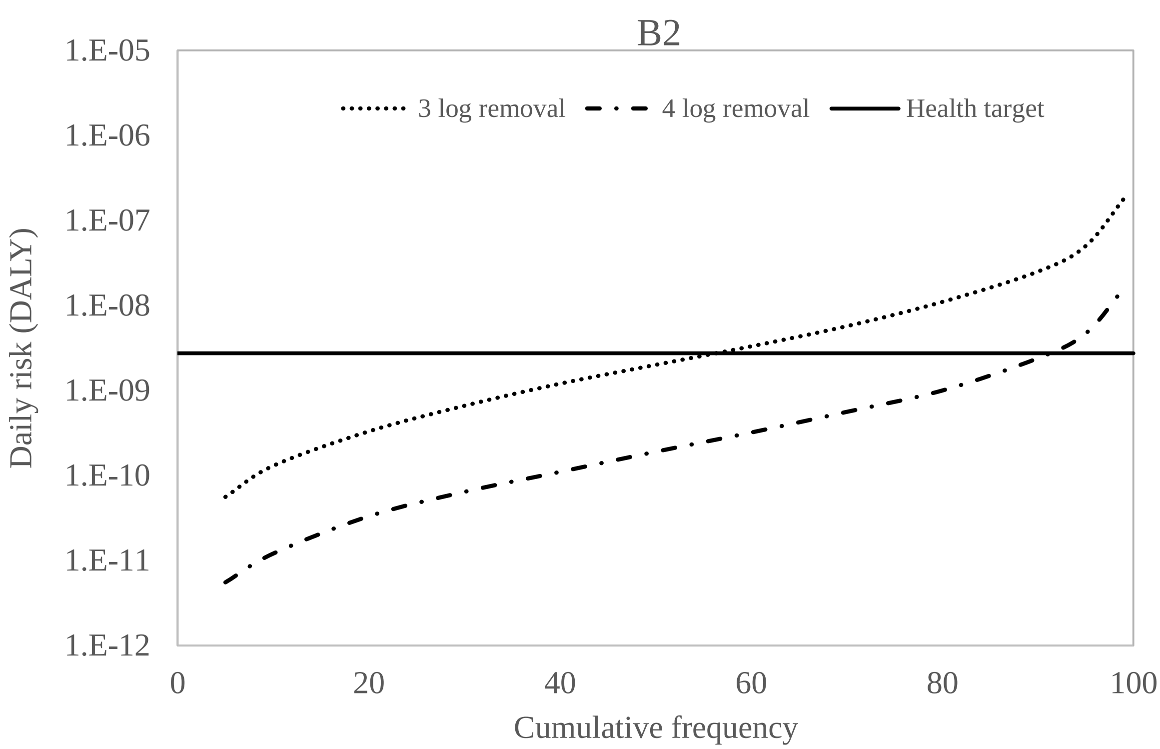


Figure 5.6. 8: Risk profiles based on the regular measurements at the intake.

CHAPTER 6 A COMPARISON OF MICROBIAL VULNERABILITY AND THREAT ASSESSMENT PRACTICES FOR DRINKING WATER INTAKES IN QUEBEC AND ONTARIO, CANADA

This chapter reviews the components in the vulnerability and threat assessment of drinking water intakes currently conducted in Quebec and Ontario concerning the microbial contamination. It also points out the advantage of including QMRA-based analysis in ranking of threats to sources considering the treatment requirements they may impose to treatment chains for respecting a specific health target.

A COMPARISON OF MICROBIAL VULNERABILITY AND THREAT ASSESSMENT PRACTICES FOR DRINKING WATER INTAKES IN QUEBEC AND ONTARIO, CANADA

ABSTRACT

Source Water Protection (SWP) is regulated by the provincial governments and local authorities in Canada, leading to a variety of approaches for characterizing threats to drinking water. Drinking water intake vulnerability and threat assessments are the primary components of SWP currently conducted in two Canadian provinces, Ontario and Quebec. This paper discusses the key differences between the elements of vulnerability and threat assessments for microbial contaminants in each of the two provinces. Considering drinking water intakes of two municipalities in Quebec and Ontario, each located on different sides of a transboundary river as a case study, the two provincial approaches were compared. The vulnerability classification of Quebec's intakes to microbial contaminant is directly related to the concentration of *E. coli* at the drinking water intake while the concept of vulnerability in Ontario is more generally applied and is related to physical and hydraulic characteristics of zones around an intake. Quebec's threat characterization considers the severity and frequency of a threat, resulting in six levels of threat. Ontario's approach uses the location of the threat with a 3-level threat classification. In order to evaluate the two provinces' threat assessment frameworks in addressing the short-term impacts of

discharge-based events, a series of combined sewer overflow discharge scenarios upstream of the 2 intakes were simulated along with log removal requirements for meeting specific microbial risk health targets. Unlike Ontario's' threat assessment approach, Quebec's approach provides an opportunity to investigate the effectiveness of risk reduction strategies such as adjustment of frequency of events or weakening the severity of the associated impacts. In both provincial approaches, available drinking water treatment does not explicitly modulate the importance of threats. Threats were classified at the same risk level while there can be a difference of up to 1 log removal requirement. For a more comprehensive threat classification, it is suggested to assess the threats according to their associated treatment requirements while quantifying the magnitude of the microbiological impacts and the frequency of the events rather than qualitatively-based classification of the events.

KEYWORDS

Source water protection, water resources, event-based analysis, log-removal requirement.

6.1 Introduction

Surface waters are commonly used as sources of drinking water and can receive contamination from a variety of activities and their discharges. Examples include agricultural and urban sources of contamination (such as livestock waste, runoff from pasture land, sewage effluents, Combined Sewer Overflows (CSOs), urban surface runoff and stormwaters) (Ferguson et al., 2003; Dorner et al., 2004; Gerba and Smith Jr, 2005; Dechesne and Soyeux, 2007). Pathogenic microorganisms (bacteria, protozoa and viruses) have long been a concern for drinking water treatment as even low concentrations can contaminate the water sources (Ferguson et al., 2003). While public health and human-related concerns are linked with the microbiological quality of drinking water sources worldwide (Sato et al., 2013; Dunn et al. 2014a), governments and water authorities have implemented specific measures to address the microbiological-related concerns through risk evaluation and management strategies (WHO, 2017; USEPA 2005). For example, in Canada, microbial risks are recognized as the most significant risks in establishing drinking water guidelines (Health Canada, 2017). In order to ensure the quality of drinking water sources, a multiple-barrier approach consists of policies, activities and plans to prevent/control contamination from the source to the tap is recommended (Ivey et al. 2006). Source Water Protection (SWP), commonly known as the first barrier, addresses the quality of raw water prior to drinking water treatment (Hrudey et al., 2003).

SWP plans and policies in Canada are primarily the responsibility of local and provincial authorities or ministries while the federal government has comparatively limited water-related obligations (Cook et al., 2013). Municipalities in Canada are primarily responsible for providing safe drinking water to their residents. Lacking an obligatory 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.

Canadian water quality guidelines have been employed differently by various provinces, in some cases they remain guidelines, whereas in other provinces they become legally binding standards (Cook et al., 2013). Development of various water quality standards across Canadian provinces with regards to water quality parameters and their legal enforcement level remains voluntary with regards to provincial decision-making (Dunn et al., 2014b). For microbial contamination in particular, methodologies for microbial testing of drinking waters in three Canadian provinces (i.e. Ontario, Quebec and British Columbia) were shown to have some common aspects, but were different with regards to parameters and values used in water quality standards, types of water samples, frequency of testing and specification of the system size (Cook et al., 2013). Moreover, different approaches (conducted in Ontario and British Columbia) for risk assessment of microbiological water quality parameters is another example of non-uniform water regulatory frameworks in Canada (Dunn et al., 2014a).

It is therefore under the authority of the provincial governments in Canada to develop their own strategies for the protection of their source waters. In Ontario, the Clean Water Act (Ontario, 2006) was promulgated to ensure safe drinking water supplies in response to the waterborne disease outbreak in Walkerton, Ontario (O'Connor, 2002). The law requires local municipalities to adopt a unique SWP framework to develop science-based and locally-driven plans on a watershed scale to safeguard their sources of drinking water. The Clean Water Act mandates the production of an assessment report for drinking water sources every 5 years, a key requirement upon which source water protection policies are founded. The assessment report must include information such as watershed characteristics, location of the drinking water sources, quantity and quality of source waters, vulnerability of source waters to contamination and potential threats to water quality and quantity of source waters. The vulnerability of drinking water intakes in Ontario is determined by the hydraulic and physical characteristics of the waterbody where intakes are located regardless of contamination type. In the assessment of threats to water quality in Ontario's approach, it is the combination of the vulnerability score that is assigned to the areas where potential threats are situated and the type of threats (i.e .chemical, or microbiological). Quebec has recently implemented its own SWP approach (MDDELCC, 2014) which directs every municipality in Quebec serving drinking water to more than 500 people to produce a report detailing the vulnerabilities of their drinking water intakes. SWP elements required by the Quebec government are dependent on the vulnerability assessment of drinking water supplies that are based in part on raw and treated water quality and an inventory of threats with the potential to affect water quality and quantity. An assessment report must be provided to the Minister of the Environment every 5 years. Before the introduction of the Quebec regulation, a handful of studies examined the vulnerability of drinking water systems in rural regions (Cool et al., 2010), to cyanobacteria (Carriere et al., 2010) or to low water levels (Carriere et al., 2007).

The present study is the first to employ Quebec's vulnerability assessment guidebook for drinking water intakes. 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.

In the literature, the importance of events that lead to the periods of peak microbial contaminant concentrations at the intakes and their corresponding impacts on drinking water treatment performance is well recognized (Jalliffier-Verne et al. 2015; Sokolova et al., 2015; Hamouda et al., 2016). The question arises as to whether the regulatory vulnerability and threat assessments will adequately capture these short-term impacts of discharge-based events like CSOs. Under the current regulation that requires water quality measurement at intakes (Quebec's approach), it is likely that peak *E. coli* concentrations will be missed during or following a CSO event. It becomes a greater concern given that microbiological treatment requirements of drinking water are determined based on the mean values of *E. coli* concentrations (MDDELCC, 2014), and not the peaks, which indeed, could lead to an underestimation of risks if routine analysis misses peak events. As a result, peak concentrations may not be sufficiently treated and potentially increase the risk of infection upon consumption by the users. If peak concentrations of microbiological contamination are not properly addressed in the measurement protocols to be included in the vulnerability assessment or threat assessment procedures, the human-related health risk may be underestimated. Quantitative Microbial Risk Assessment (QMRA) is an effective tool to investigate risk of waterborne disease and has been widely reported for drinking surface water supplies (such as Sokolova et al., 2015; Dunn et al., 2014; Xiao et al., 2013). Therefore, a method of estimating a range of potential microbial impacts caused by CSO events at the intakes is still of demand to be included in the vulnerability and threat assessments. To do so, a model of fate and transport of contaminant within the water body can be suitable tool to simulate the potential conditions following an event.

The Ottawa River that separates Ontario from Québec in the Outaouais Region provides an opportunity to compare the Ontario and Québec SWP approaches for vulnerability and threat assessments. Four drinking water intakes are located in close proximity, and theoretically should have similar threats and vulnerabilities according to both Québec and Ontario approaches. The aim of this study is to compare the approaches for vulnerability and threat assessments for drinking water intakes located in the same region, but in two different provinces. In this study, Quebec's framework for vulnerability of intakes to microorganism has been employed for all four intakes within the studied area. In addition, threats (i.e. occurrence of CSOs) to two of the intakes were classified according to Quebec's and Ontario's approaches, separately. It is also of interest to show how threat assessment criteria of both approaches can include the potential microbiological-related impacts of upstream CSOs. Therefore, a series of CSO occurrences were simulated and their impacts were characterized in terms of the respective log removal requirements at drinking water intakes according to which the threat classification approaches can be improved.

6.2 Methods and Materials

6.2.1 Study area

The study area is the part of a large river in the Outaouais region, Canada. The river dissects two Canadian provinces; Ontario and Quebec. The City of A from Quebec and the City of B from Ontario are located on the northern and southern banks of the river. This water body is the source of drinking water for both municipalities as each city has two intakes for their drinking water treatment plants, shown in Figure 6.1.

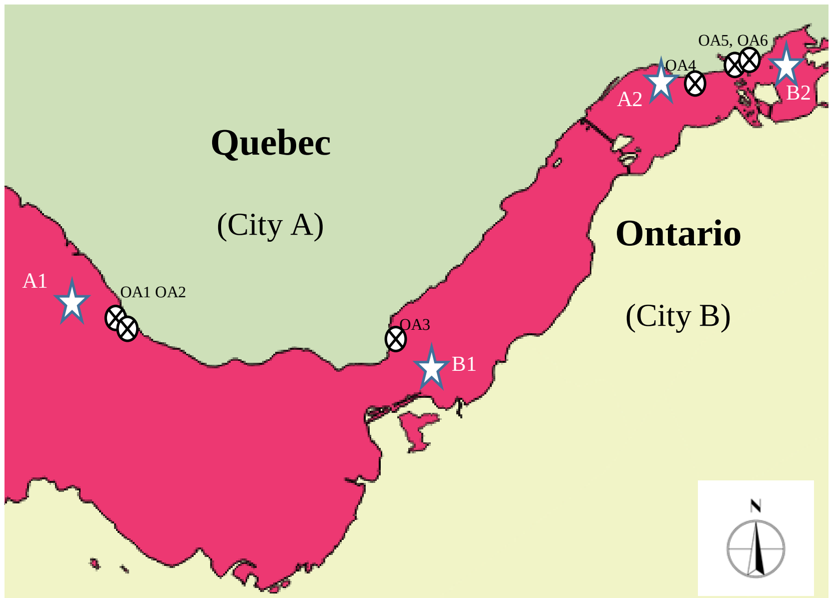


Figure 6.1: Locations of intakes and CSOs in the study area.

Intakes A1 (the most upstream) and A2 are the Quebec-side utilities whereas B1 and B2 (the most downstream) supply drinking water to the Ontario side. Considering the source of drinking water for the two municipalities, the river water quality is not only of high importance to ensure a secure treatment process, but also of great concern as there are urban CSOs upstream of these intakes. As seen in Figure 6.1, there are CSO outfalls along Quebec side (OA1 to OA6) that may potentially discharge untreated water directly into the river. The number of discharge events at OA1 to OA6 were provided (Table 6.1) for a 5-year period (from 2009 to 2013). The characteristics of this section of the river surrounded by the urban environment where four intakes of drinking water intakes are located provides such a platform to explore the application of the vulnerability and threat assessment practices, particularly when it comes to different policies for one body of water given the existence of the CSOs as potential source of microbiological contamination.

Table 6.1: Frequency of discharges at each outfall from 2009 to 2013.

Outfall	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

A2 have been provided to us by the City A. Prior to monitoring *E. coli*, fecal coliforms were measured until 2013. Since then, weekly *E. coli* measurement has been put into practice, based on which the microbiological treatment requirement at the treatment plant is defined (MDDELCC, 2014). City of B also provided water quality data including daily measurements of *E. coli* at their two intakes. *E. coli* concentrations were estimated form fecal coliform concentrations assuming the ratio of 0.75 (Lalancette et al., 2014; Jalliffier-Verne et al., 2015) for the period with no *E. coli* measurements. The range of *E. coli* concentrations for the 5-year period is shown in Figure 6.2. Downstream from the A1 to B2 intakes, the mean median *E. coli* concentrations in raw waters increase denoting the higher number of sources in the river where the density of urban activities is higher. *E. coli* concentrations may vary from 1 to 3 orders of magnitude at the drinking water intakes.

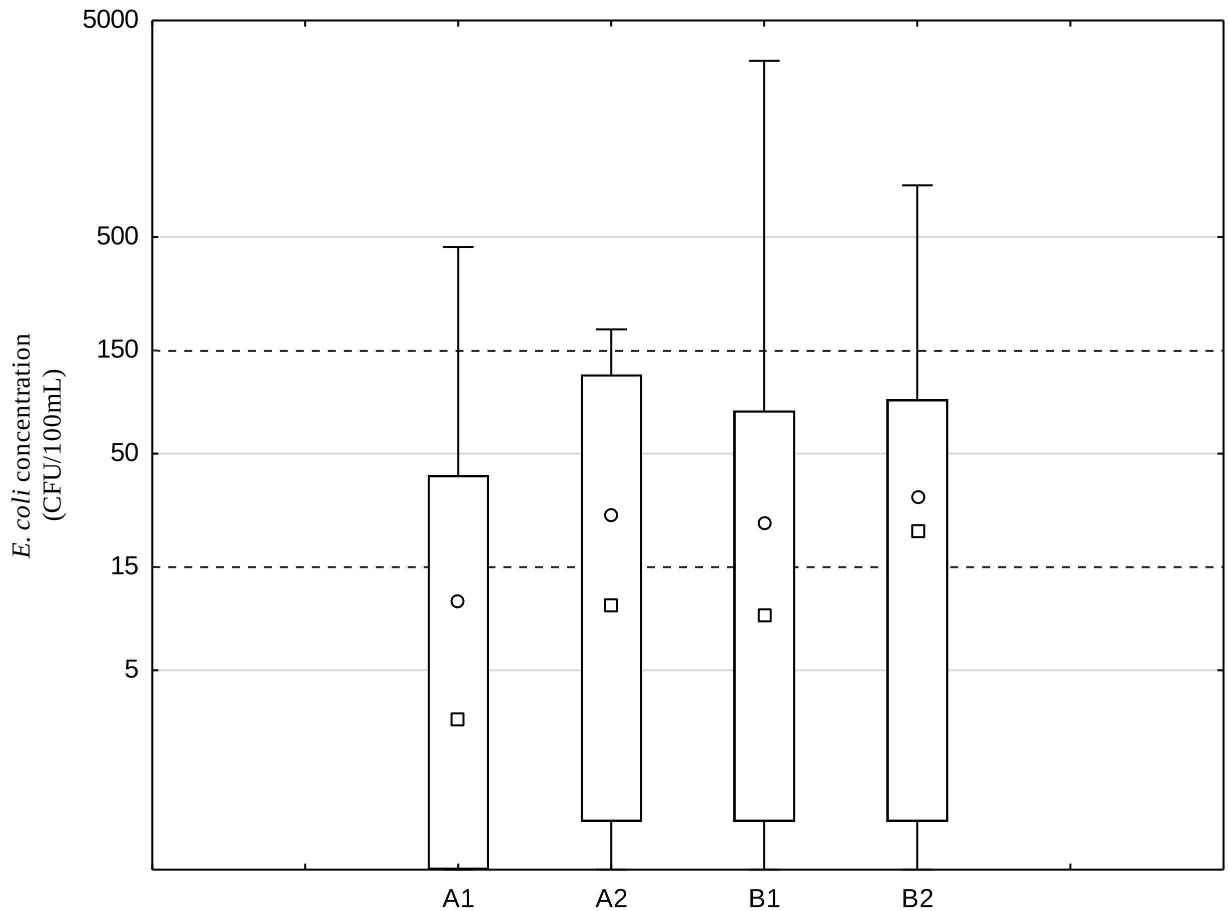


Figure 6.2: *E. coli* concentrations for 5 years (2012-2016). Box plots represent 5th and 95th percentile (box), median values (square in the box), mean values (circle in the box) and whiskers show minimum and maximum.

6.2.2 Application of Québec's vulnerability as well as Quebec's and Ontario's threat assessments

A detailed explanation of Ontario and Quebec's vulnerability and threat assessment methodologies is provided in sections 6.6.1 and 6.6.2. Ontario's vulnerability assessment is a mandatory step-by-step process through which the areas (of a drinking water intake) vulnerable to contamination are determined based on the physical and hydrodynamic conditions of the intakes regardless of the contamination type (See Table 6.6. 1). The vulnerable area is assigned a vulnerability score from 1-10; the higher the score is, the more vulnerable the area will be (Table 6.6. 2). The vulnerability score will be applied to evaluate the risk of a threat within an Intake Protection Zone (IPZ). In this approach, it is the area surrounding the intake that is given a score, and not the intake itself unlike Quebec's approach. Quebec's vulnerability assessment of the drinking water intake relies heavily on the water quality measurements at the intakes. There are 6 vulnerability indicators (including vulnerability-to-microorganism criteria) against each of which, vulnerability of an intake is assessed. The concentration-based comparison of microorganisms (*E. coli*) measured at the intakes of drinking water sources forms the basis in this approach to assign different vulnerability classes of being low, medium and high (Table 6.6. 3).

Another component of the assessment report following the vulnerability assessment of source waters is the threat assessment (or risk potential analysis) in which potential sources of contamination or activities are identified and ranked with a level of risk. Threat assessment is critical for the prioritization and mitigation of the contaminant sources of concern. The Ontario's approach typically relies on recognizing drinking water issues within the IPZs that contribute to modification of the quality and quantity of water. Then the current or potential activities/conditions that are or would be worsening the problem are considered as threats to drinking water quality and quantity followed by a level of threat assignment. In Ontario's approach, there is a list of 22 pre-described activities considered as threats among which storage, application and discharge of chemicals or pathogenic materials have been addressed in Ontario regulation 287/07 (Clean Water Act, 2006). Depending on the vulnerability scoring of areas around the intake where the threat is/would be located, the level of threat is determined (Table 6.6. 4). Ontario threat assessment is directly dependent on the vulnerability assessment of IPZs and the position of a threat within those areas. On the other hand, Quebec's threat assessment approach is based on a more qualitative technique where the level of threat is defined by the magnitude of impacts of an activity/a condition (i.e. severity) and its frequency/probability of occurrence (Table 6.6. 5). Unlike Ontario's threat assessment, Quebec's approach, being independent of vulnerability assessment, considers the nature of the threat in terms of magnitude of negative effects as well frequency of the phenomena. The framework requires a more detailed characterization of the threat in vicinity of the drinking water intakes even though it is based on qualitative definition of the terms. The focus of this study is on the microbial water quality threats.

6.2.3 Hydrodynamic and water quality model of the river and CSO scenarios

The previously developed hydrodynamic and water quality model of the river (Mike 21 FM coupled with sub-module Eco-lab, DHI, (2017)) (Chapter 5 as Taghipour et al., (2019a)) was used in this study. The potential impacts of CSO discharges on the treatment requirements of the downstream drinking water intakes were investigated using the model results combined with QMRA. The 2D model is capable of simulating general characteristics of the river flow. The microbiological impacts from CSOs (as a threat by definition) in terms of removal requirements for drinking water treatment are calculated and compared with the results of conventional threat assessment methods proposed by the two provinces. In order to evaluate the potential impacts of CSO at the downstream intakes of drinking water treatment plants, a series of discharge-based scenarios were developed. The primary objective of the scenarios was to include a CSO event which potentially would be considered as an extreme event, i.e. high volume of overflow within a short period of discharge for a given month (from March to Oct). The dynamic behavior of the CSOs with regard to overflow and the *E. coli* concentration have been taken into account using previously developed CSO loading model in Chapter 4 (Taghipour et al., 2019b). Two intakes of drinking water were studied, one from Quebec (A2) and one from Ontario (B2). The contribution of the upstream CSO outfalls to *E. coli* concentrations at the intakes were simulated individually for each month.

6.2.4 QMRA

Having identified a range of potential peak periods at the intakes as a result of CSO occurrences, the level of treatment required to meet the health target of 1E-06 DALY per person per annum was calculated for each intake, based on the QMRA approach introduced by (WHO, 2017). The details of QMRA approach used in this study is provided in Chapter 5. A series of probable CSO events in each month from March to October were considered and the resulting peak period at the intake was identified using a 24-h arithmetic mean value of the concentration during CSO related peak periods at the intake. The probability distributions of the ratio of *E. coli* to *Cryptosporidium* and *E. coli* to *Giardia* were obtained from the literature and used in the analysis (Figure 6.6. 1).

6.3 Results and discussion

6.3.1 Quebec's vulnerability assessment of the intakes

Quebec's vulnerability approach was applied to characterize the drinking water intakes located along the river with regards to vulnerability to microorganisms using the median or 95th percentile value as classification criteria for vulnerability to microorganisms. The results of the analysis are given in Table 6.2.

Table 6.2: Results of vulnerability (to microorganism) analysis of four intakes of the study area (Quebec approach).

	Intakes	**A1**	**A2**	**B1**	**B2**
Method 1	Median (CFU/100mL)	3	10	9	22
	95^{th} % (CFU/100mL)	40	116	79	89
	Vulnerability to microorganisms	Low	Low	Low	Medium
Method 2	Vulnerability to microorganisms	High	High	High	High

Based on Method 1 of Québec's approach (See Table 6.6. 3), the vulnerability of intakes A1, A2 and B1 are determined to be low while that of B2 is classified as medium. Based on the weekly raw water sampling for *E. coli* in the intakes of A1 and A2, the median or 95^{th} percentile values of concentration of *E. coli* may not be as conclusively indicative of *E. coli* concentrations as those obtained from daily measurements (i.e. at B1 and B2). Therefore, vulnerability analysis of an intake may be more uncertain if the sampling frequency fails to capture daily or short term variation. This is even more pronounced in case of a CSO event which delivers a considerable amount of waste containing microbiological contamination (Madoux-Humery et al., 2013) during a short period of time. The higher sampling frequency at the intakes from Ontario provides a more robust estimate of the period of higher *E. coli* concentrations at the intakes.

In Method 2 of the vulnerability assessment (Table 6.6. 3), all four intakes are categorized as highly vulnerable to microorganisms, as a result 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 i and intermediate areas. Method 1 and 2 provide different results because of the potential contributions from the urban environment including the presence of CSO discharges. Unlike Method 1, Method 2 descriptively highlights the importance of these sources in the vicinity of the intakes. As discussed before, the Ontario vulnerability assessment is not related to the intake concentration measurements and is generally applied to delineate the IPZs.

6.3.2 Quebec's and Ontario's threat assessment of the intakes

The threat assessment (microbiological contamination) was conducted for the intakes of A2 and B2 within the study area according to the approaches developed by Quebec and Ontario (See Table 6.6. 4 and Table 6.6. 5). CSO outfalls upstream of the A2 and B2 intakes have been identified and evaluated individually with regards to their frequency of occurrence as well as severity of the phenomena as introduced in the Quebec threat assessment framework. For the threat assessment based on the Ontario's approach, vulnerable IPZs of the City B were already delineated by the City B and provided to us where, the IPZs of A2 could also be determined. The results of the threat assessment are provided in Table 6.3 with a list of threats (CSO outfalls) within the protection zones of both intakes. As seen, threats to A2 are three outfalls (i.e. OA1, OA2 and OA3) all located within the intermediate zone, upstream of the intake. The level of threat to the intake A2 was determined to be very high, high and very high for OA1, OA2 and OA3, respectively where the difference in frequency resulted in different classification of the threats. The Ontario approach merely considers the location of a threat within the IPZs, the closer a threat to the intake is, the higher potential risk that threat will be. Therefore, OA1 and OA2 are grouped as moderate threats while OA3 is recognized as a significant threat. The frequency of the occurrences of these threats are not taken into account in Ontario's approach while that of Quebec's distinguishes between the threats by considering the historical or potential records of the threat activity. For example, there is one level of risk difference (i.e. very high to high) between the threat OA1 and OA3 just because of the former is more frequent than the latter given that they are of "catastrophic" nature within the classification system. Therefore, frequency of the CSOs is the reason for two classes of the threat. However, OA1 and OA3 are both considered as a similar threat in Ontario approach. Quebec threat assessment method would provide a platform to investigate the effectiveness of mitigation strategies to scale down the potential risk of threats to a desired level. For example, installing

Table 6.3: Result of threat assessment of intakes A2 and B2 according to Ontario's and Quebec's approaches.

Intake	Threat	Potential risk						
		Quebec's approach			Ontario's approach			
		Severity	Frequency	Risk	Area Vulnerability factor	Source Vulnerability factor	Vulnerability score	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**

Table 6.3: Result of threat assessment of intakes A2 and B2 according to Ontario's and Quebec's approaches (cont'd).

Intake	Threat	Potential risk						
		Quebec's approach			Ontario's approach			
		Severity	Frequency	Risk	Area Vulnerability factor	Source Vulnerability factor	Vulnerability score	Risk
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**

in-place treatment equipment to lower the severity of the threat or reducing the frequency of the discharges could result in attenuating threat-related impacts. However, the evaluation of such mitigation strategies in Ontario's approach can be challenging as the influencing parameters of the threat level are merely based on the location of the threat and hydrodynamic and transport process in the waterbody.

An analysis of threats to B2 includes the other CSOs (i.e. OA4, OA5 and OA6) in addition to the ones considered for A2. Threat of OA1, OA2 and OA3 to B2 (by Quebec's method) are still defined as very high, high and very high, respectively, even though they are located within the outer protection zone of the intake B2 (See intake classification proposed by Quebec, Table 6.6. 1). It is also interesting to note that the role of severity of the activity is more pronounced than the frequency of the event in the threat assessment proposed by Quebec (unlike threats of OA1 and OA3 to A2). For example, OA4 and OA5 are shown to occur more frequently than the OA6; however they are all being classified as very high threat to the intake B2 because they are of catastrophic severity, implying it is more effective to lower the severity of the activity rather than the frequency of the event to reduce the risk level of the threat. Therefore, the role of frequency and severity of a threat in determining the associated risk level may vary from one threat to another. A comprehensive threat classification should be based on a more quantitative approach 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. Ontario's approach defined OA1, OA2 and OA3 as moderate threat to B2 with one risk level being downgraded for OA3 compared to corresponding risk level at A2 due to its longer distance to the B2.

Threat classification for these three outfalls resulted from the two approaches are not consistent while being characterized as high to very high on one hand (Quebec approach) and assigned as moderate (Ontario approach) on the other hand. However, threat classification for the three downstream CSOs (i.e. OA4, OA5 and OA6) by the two approaches yield similar results, i.e. labeled as very high (by Quebec's method) or significant (by Ontario's method) due to their proximity to the intake B2 (within the IPZ2). Therefore, the threat assessment proposed by the two methodologies not only are incompatible but also variable in terms of risk classification, even for a unique source of drinking water body.

6.3.3 Event-based analysis of threat

E. coli as microbiological contaminants at the intakes from upstream CSOs were simulated using a hydrodynamic and water quality model of the river (Taghipour et al. 2019a). Probability distributions of *Cryptosporidium* and *Giardia* from historical data were used to relate *E. coli* concentrations to potential parasite concentrations. The river model simulation provides estimates of the severity of the threat (i.e. CSO) while frequency of occurrence of was considered in the microbial risk calculation. The log removal level of such microbiological contamination in order to meet the annual health target is not constant and is dependent on pathogen concentrations at the intakes. A range of log removal requirement is illustrated (Figure 6.3) considering variability of pathogen concentrations. The negative values correspond to reduction of concentration in the treatment. Depending on the location of the outfalls as well as averaged number of CSOs per year, the water treatment requirement ranged significantly in both plants, implying different microbiological contribution of the CSOs. At A2, the treatment criteria to cope with the annual health target (i.e. 1 micro DALY per person per annum) under CSO impacts from the outfalls OA1 and OA3 are more stringent than what is required in case of events from the outfall OA2 for both *Cryptosporidium* and *Giardia*. Although OA1 and OA2 are located close to each other, the frequency of the CSO events at OA1 is higher than OA2 (5 times greater). Therefore, the difference in frequency of events influences the removal requirement as there is almost a 1-log difference in removal requirement between the events discharged through OA1 or OA3 and OA2. The pattern observed here is actually compatible with the result of Quebec's threat assessment for A2 where OA1 and OA3 are considered as the same level of threat (i.e. very high risk) with OA2 in one level lower (i.e. high risk). Employing the simulation results of the river model as the inputs of CSO-based QMRA revealed the underlying role of CSO microbiological-related impacts on the intakes in terms of removal requirements while quantitatively taking into account the number of CSOs rather than a simple definition of the frequency that is being used in the definition of the term in the Quebec's threat methodology. This can help better redefine the different classes of frequency of the event upon which the threat assessment is based.

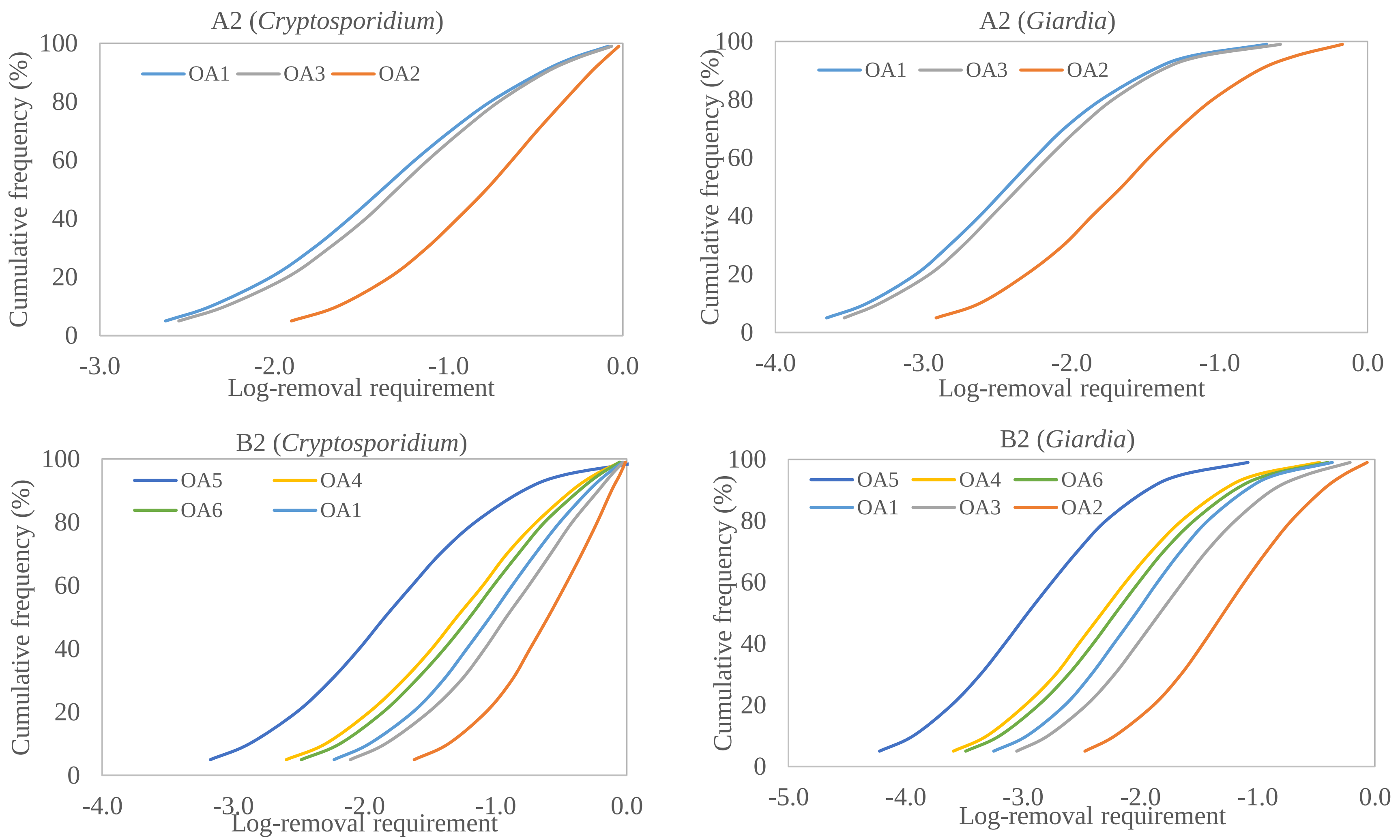


Figure 6.3: Log-removal requirement in the plants under the impacts of CSO discharges.

B2 was under the influence of all six CSO outfalls. Impacts from the outfall OA2 continues to correspond to the lowest removal requirement while those of OA1 and OA3 reflect almost the same level of treatment needed to meet the health target criteria. The overall treatment requirements at B2 for the events from OA1, OA2 and OA3 are almost similar to those at A2. For the more downstream outfalls, OA4, OA5 and OA6 are roughly located in the same vicinity but with different frequency of occurrences. Impacts of CSO discharges from OA5 requires more than 3 and 4 log-removal of *Cryptosporidium* and *Giardia*, respectively. Generally, the treatment requirement imposed by the CSOs farthest downstream (i.e. OA4, OA5 and OA6) is larger than those of upstream ones, due to the proximity of the downstream outfalls to the plant B2 as well as more frequent events. Comparing the range of treatment requirement in the plant B2 for discharges from all 6 outfalls, the difference in removal level required can vary particularly between OA5 and other outfalls. However, OA5 is still classified in the very same risk level (results of the threat assessment according to the Quebec and Ontario approaches, See Table 6.3) as other threats while there is a difference of more than 1 log removal requirement. Therefore, the provincially-developed threat assessment may not quantitatively differentiate between events of the same class of frequency. For example, OA4 and OA5 are both classified as frequent and defined as “very high risk” while their treatment requirements are not the same. Therefore, application of event-based QMRA to prioritize the potential risk with regards to treatment requirement can provide supplementary information to the current threat assessment.

As seen, different classes of vulnerability or threat level may result from adopting two provincial source water protection approaches even for one case study could be an example of fragmented governance of water in Canada previously noted by Bakker and Cook (2011). It is possible to improve the assessment of threats by considering the level of treatment they will require and using this information for prioritization of mitigation measures. The threat assessment conducted in Quebec and Ontario merely classifies the threats quantitatively and does not necessarily correspond to treatment burden those threat may impose on the treatment process. The event-based analysis provides a framework in which each threat could be assessed according to their associated treatment requirement while quantifying the magnitude of the microbiological impacts and the frequency of the events rather than qualitatively-based classification of the events. This is the first study to consider the location and the frequency of the outfalls at the same time for prioritizing the threat to drinking water intakes. Ontario’s approach is very general and Quebec’s approach is more qualitative. However, the approach proposed in this study can undertake the role of both parameters for threat evaluation and the corresponding mitigation strategies. However, one important caveat is that this study was based on the availability of a hydrodynamic model for the drinking water intakes and a first-pass prioritization of CSOs. Many other sources of contamination exist in a drinking water source. The approach proposed here could be used for refinement of current source water protection vulnerability and threat assessments in both provinces.

6.4 Conclusions

This research compares SWP strategies currently applied in Quebec and Ontario, Canada. Every municipality is required to provide an assessment report for the drinking water intakes under service. The framework employed to assess the vulnerability and threats to the intakes and their classification differ in important ways. Considering a river as case study on a transboundary line of the two provinces, two drinking water plants located on the river downstream of CSO outfalls were assessed according to the two proposed vulnerability and threat characterization methods. Moreover, an event-based (CSOs) analysis was conducted to quantify the potential impacts of threats in term of treatment requirement as a supplementary component to the approaches. The suggested analysis was performed by using hydrodynamic and water quality model of the river combined with QMRA. The following findings can be concluded from the aforementioned tasks:

- Vulnerability assessment proposed by Ontario corresponds to delineation of areas of intakes based on the hydraulic characteristics of the water body such as 2 hour travel time and the physical specifications of the intake.
- The vulnerability assessment required by Quebec is based on the intake concentration measurements and not the surrounding areas. The vulnerability of intakes can be analyzed for 6 indicators defined in the regulation, particularly vulnerability to microorganisms based on *E. coli* concentrations.
- Ontario-regulated threat assessment is directly dependent of the IPZ delineation as well as vulnerability assessment. Threats to drinking water intakes are sorted in 3 levels of low, moderate and significant depending on the position of threats within the IPZs.
- Quebec instructions for threat assessments to DWIs is based on the severity as well as the frequency/probability of that activity/condition. Threats are categorized in six levels; very low, low, moderate, high and very high. Compared with the Ontario approach, the proposed

threat assessment by Quebec is more driven by nature of threat, allowing a better understanding of the potential threat.

- CSO-type threat evaluation for the intakes A2 and B2 proposed by the two provinces showed that the assessment results are variable even for one intake, emphasizing on the need to adopt a unified framework so that mitigation measures can include the needs of out of province threats and a mapping from one system to another for prioritization of threats.
- Analysis of log-removal requirement within drinking water treatment related to the occurrence of threat can be introduced as reliable ground for threat classification. Event-based analysis of threat would enable water managers to more objectively characterize threats while considering microbiological impacts as well as recurrence of the threats.

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6.6 Supplementary Materials

6.6.1 Vulnerability assessment

6.6.1.1 Ontario's approach

In Ontario, municipalities must carry out vulnerability assessments for their drinking water intakes every 5 years. It is a mandatory process through which the vulnerable areas (of a drinking wtaer intake) to contamination are determined and assigned a vulnerable score from 1-10; the higher the score is, the more vulnerable the area will be. The vulnerability assessment typically compromised of 3 sections: 1) intake classification, 2) delineation of Intake Protection Zone (IPZ) and 3) vulnerability scoring. In Ontario, the vulnerability approach is a score-based system in which it is the area surrounding the intake is assigned a score rather than the intake. Based on the type of the intake and its location within a waterbody, the IPZ of the intake would be established according to the fixed distance, travel time and potential contribution to the intake. Definition of each IPZ is provided in Table 6.6. 1. IPZ1 recognized as the areas immediately adjacent to the intake within which minimum dilution of contaminant would be assumed. IPZ2 delineation is based on a 2-hour water flow travel time to the intake, during which treatment plant operator has sufficient time to shut down the intake in the event of spill accident. Having delineated the three types of IPZs, the vulnerability of each area (V) is calculated according to susceptibility of the area to contamination (expressed as area vulnerability factor (B)) as well as the location-based characteristics of the intake in water body (expressed as source vulnerability factor (C)). Key factors in defining the vulnerability score is provided in Table 6.6. 2. The vulnerability score obtained in this step is applied to evaluate the risk of a threat within an IPZ. The Ontario vulnerability assessment focuses mainly on the physical and hydrodynamic conditions of the intakes regardless of the contamination type.

6.6.1.2 Quebec's approach

Quebec's intake vulnerability assessment approach entirely relies on the intake itself while the method of determining the level of vulnerability of surface water intake is unique and based on 6 criteria including 1) physical vulnerability of the site, 2) vulnerability to microorganisms, 3) vulnerability to fertilizers, 4) vulnerability to turbidity, 5) vulnerability to inorganic substances, 6) vulnerability to organic substances. Unlike Ontario's assessment, the type of contamination in the Quebec framework is explicitly identified.

Although, delineating IPZs in Quebec's approach has some similarities with Ontario's, there are different terminologies and definitions with regard to the intake type and extent of each IPZ (See Table 6.6. 1). In equivalence to IPZ1, IPZ2 and IPZ3 introduced in Ontario approach, there are areas of inner, intermediate and outer featured in Quebec IPZ classification. There is no area delineated by the travel time according to the Quebec approach but rather a distance upstream (and partially downstream) of the intake. The concentration-based comparison of each contamination type measured at the intakes of drinking water sources forms the basis of this approach to assign different vulnerability classes. The vulnerability of surface water intakes to microorganisms (described in Table 6.6. 3) is generally expressed in terms of being high, medium or low based on the median values or 95th percentile of *E. coli* concentrations at the intake (Method 1). The reason behind the selection of the fixed values, i.e. 15, 150 and 1500 CFU/100mL (in Method 1) is due to the fact that the Quebec drinking water requirement is based on the fecal indicator bacteria concentration, i.e. *E. coli* in raw waters for microbial contaminant removal. In other words, the amount of treatment required to remove the microbial contaminant is determined based on the mean value of *E. coli* concentrations at intakes (MDDELCC, 2014). The vulnerability of an intake to microorganisms can be interpreted as an indication of log-removal requirement. Therefore, the vulnerability assessment of an intake would enhance the understanding the treatment process required for safe drinking water recommended by the guidelines. There is also another method (Method 2) which is independent of microbiological status level measured at the intake and more relies on the location of the outfalls. Method 2 qualitatively accounts for the potential contribution of those outfalls to the microbiological water quality level at the nearby intake by characterizing the intake as highly vulnerable considering the presence of a CSO outfall within inner or intermediate areas of the intake in an urban environment.

6.6.2 Threat assessment

The threat assessment is a shared directive by the regulations of both provinces. The concept typically relies on recognizing drinking water issues within the IPZs that contributes to quality and quantity of water. Then the current or potential activities/conditions that are or would be worsening the problem are considered as threats to drinking water quality and quantity. Ultimately, the level of threats to drinking water intake would be determined. The method of threat classification differs from Ontario to Quebec, a summary of which is provided in the following sections.

6.6.2.1 Ontario's approach

In Ontario, there is a list of 22 pre-described activities that are considered as drinking water threats among which storage, application and discharge of chemicals or pathogenic materials have been addressed Ontario regulation 287/07 (Clean Water Act, 2006). Depending on the type of threat (microbiological), the level of threat is defined as high, moderate or low (Tables of Drinking Water Threats, as a part of Clean Water Act (2006) is based on the current/potential location of the threats within the IPZ of an intake along with associated vulnerability score (Table 6.6. 4). Depending on the vulnerability scoring of areas around the intake where the threat is/would be located, the level of threat is determined. Ontario's threat assessment is directly dependent on the vulnerability assessment of IPZs and the position of a threat within those areas.

6.6.2.2 Quebec's approach

Quebec threat assessment approach is based on a more qualitative technique where the level of threat depends on the magnitude of impacts of an activity/a condition (i.e. severity) and its frequency/probability of occurrence. Prior to threat assessment (or potential risk evaluation) an inventory is required of anthropogenic activities and potential events within the inner and intermediate areas of the intake. With the inventory, the approach qualitatively takes into account the characteristics of a threat including the type and the amounts of contaminant to be released to the environment. Four classes of severity of a threat are allocated as minor, serious, severe and catastrophic (Table 6.6. 5). The frequency/probability of an activity/event is also considered (Table

6.6. 5). The combination of severity of consequence and the frequency/probability of an activity/event would result in 6 classifications of the risk of a threat; very low, low, moderate, high and very high. Unlike Ontario's threat assessment, Quebec's approach considers the nature of the threat in terms of magnitude of negative effects as well frequency of the phenomena while it is somewhat independent of vulnerability assessment.

Table 6.6. 1: Intake classification and definition of intake protection area proposed in Ontario's (adapted from Clean Water Act, 2006) and Quebec's (adapted from MDDELCC, 2014) approaches.

Intake type	**Ontario's approach**			
	Description	**Protection areas around the intake**		
		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 1km 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

Table 6.6. 1: Intake classification and definition of intake protection area proposed in Ontario's (adapted from Clean Water Act, 2006) and Quebec's (adapted from MDDELCC, 2014) approaches (cont'd).

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 and 50 m downstream of the intake	

Table 6.6. 2: Vulnerability scoring of the areas around the intake (Ontario's approach) (adapted Clean Water Act, 2006).

Vulnerability score (V=B×C)					
	Parameters of the factor	**Description**	**IPZ1**	**IPZ2**	**IPZ3**
Area vulnerability factor (B)	Percentage of land area	Based on weight-average, to be calculated for each IPZ	B=1	7 <B< 9	1 <B< 9
	Land use				
	Imperviousness				
	Percentage of land area drained by stormwater				
Source Vulnerability factor (C)	Depth of intake	Constant for all IPZ, dependent on the type of intake	Type A	0.5-0.7	
	Distance from river bank		Type B	0.7-0.9	
	Presence of drinking water issue		Type C	0.9 or 1	
			Type D	0.8-1	

Table 6.6. 3: Classes of vulnerability of an intake to microorganism (Quebec's approach) (adapted from MDDELCC, 2014).

Quebec Vulnerability of the intake					
Vulnerability indicator	**Description**		**High**	**Medium**	**Low**
Vulnerability to microorganisms	A consecutive enumeration of *E. coli* over a period of five years	Method 1	Median greater than 150 cfu/100 mL or value of 95th percentile exceeds 1500 cfu/100 mL	Neither low nor high	Median less than 15 cfu/100 mL or value of 95th percentile less than 150 cfu/100 mL
	When method 1 not applied	Method 2	Banks of the inner protection areas located entirely in an urban environment or at least one item of an overflow network likely to discharge wastewater in an inner or intermediate area	Neither low nor high	i: sampling site is located in a lake,ii: no combined sewage discharge upstream

Table 6.6. 4: Ontario's threat assessment of CSO outfalls (adapted from Tables of Drinking Water Threats, Clean Water Act, 2006).

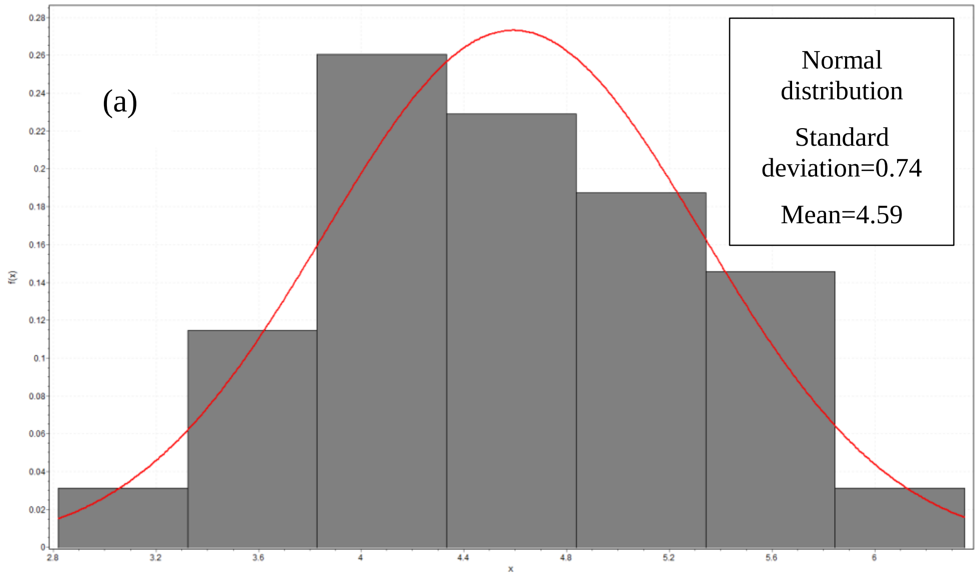
Reference Number	**Description**	**Significant threat if located within the area with vulnerability score of**	**Moderate threat if located within the area with vulnerability score of**	**Low threat if located within the area with vulnerability score of**
1947	The system is a combined sewer that may discharge sanitary sewage containing human waste to surface water The discharge may result in the presence of one or more pathogens in surface water	8-10	6-7.2	4.2-5.6

Table 6.6. 5: Quebec's threat classification (adapted from MDDELCC, 2014).

		Level of threat			
Level of severity [a]		**Minor**	**Serious**	**Sever**	**Catastrophic**
Frequency of occurrence [b]	Very frequent	Moderate	High	Very high	Very high
	Frequent	Low	Moderate	High	Very high
	Occasional	Very low	Low	Moderate	Very high
	Rare	Very low	Very low	Low	High
Probability of occurrence [c]	Almost certain	Low	Moderate	High	Very High
	Possible	Very low	Low	Moderate	High
	Unlikely	Very low	Very Low	Low	Moderate

[a] Level of Severity	Minor: Aesthetic water quality problem, acceptable by the consumers
	Serious: Aesthetic water quality problem, inacceptable by the consumers
	Sever: Health issue as a result of long-term exposure (chemical contamination representing risk of chronic toxicity)

	Catastrophic: Health issue as a result of short-term exposure (microbiological or chemical contamination representing risk of acute toxicity)
[b] Frequency classification	Very frequent (≥ one time/week): Discharge of contaminant at least one time per week
	Frequent (≥ one time/year): Discharge of contaminant at least one time per year or month etc but not in the category of "very frequent"
	Occasional (> one time/5 years): Discharge of contaminant more than one time in course of 5 years, but not in the category of "frequent"
	Rare (≤ one time/5 years): Discharge of contaminant almost one time in course of 5 years, or even less
[c] Probability classification	Almost certain: It is almost certain to happen at least once in the next 5 years
	Possible: It is possible to happen in the next 5 years
	Unlikely: It is imaginable to happen, but very unlikely to happen in the next five years



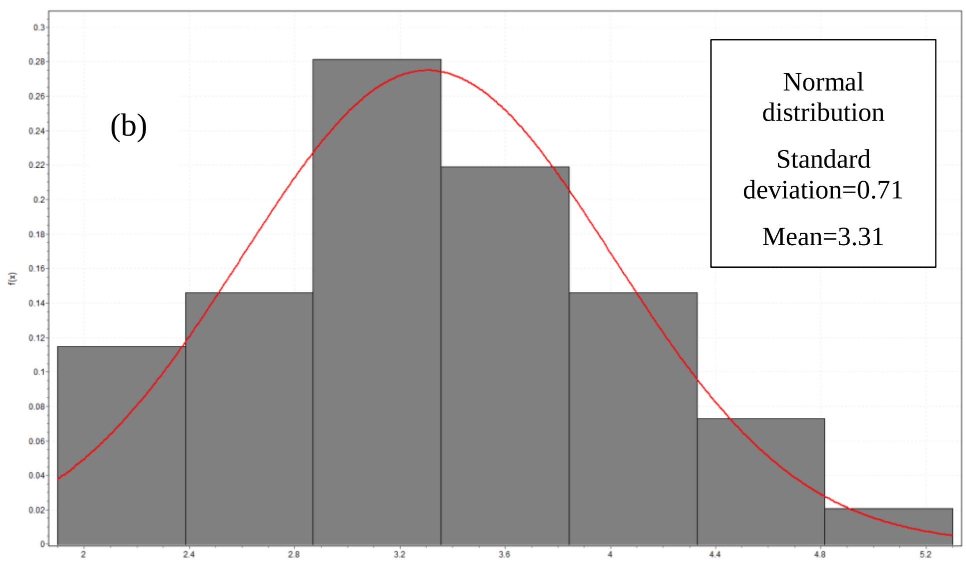


Figure 6.6. 1: Probability distribution function of the ratio (in log values): (a) *E. coli* to *Cryptosporidium*, (b) *E. coli* to *Giardia* adapted from Taghipour et al. (2019a) and Sylvestre et al. (2018).

CHAPTER 7 SUMMARY AND GENERAL DISCUSSION

This chapter summarizes the main findings from the present research project. The general objective was to analyze the impacts of wet weather flow discharges, i.e. CSOs, in terms of microbial risk of drinking water supplies based on not only a single event but also a range of probable CSO occurrences. The main idea originates from the fact that CSOs are deteriorating the microbiological quality of receiving water as they contain high amount of untreated wastewater. Given that receiving waters are used as drinking water supplies, CSOs can cause periods of high microbial contamination at drinking water intakes. Therefore, ensuring safe water supplies is a priority of water authorities, which requires detailed characterization of such events from the loading conditions at the point of discharge to the transport of contaminants from the source to the drinking water intake and the risk it poses to consumers.

7.1 Step one: CSO load model developement

7.1.1 Characterization of dynamics of CSO discharges

In order to study the intra-event variability of CSO discharges in terms of flowrate and concentration, obtaining a detailed sets of data measured in course of CSO events was the primary requirement. Two sets of data were used for this purpose. The first dataset was used for drawing conclusions about the general patterns of CSO discharges. The second dataset was retrieved from the published literature of both stormwater and CSOs studies, for verification of the findings obtained from the first dataset. Through transforming the scale-related parameters (i.e. flowrate, concentration and discharge duration) to the normalized parameters by their respective peak values, a uniform scale ranging from 0-1 was established so that different CSOs could be compared regardless of the scale of the events. As a result, any scale-related dependency of discharge behavior of CSO events was eliminated. When considering normalized flowrate and concentration parameters against the normalized time of occurrence (Figure 4.2), similar patters were seen for each individual event. Normalized peak flowrate occurred within the 2nd decile for 6 out of 8 events. The peak flowrate in other two events occurred in the 1st (for intense summer event) and 3rd decile (as the result of co-occurrence of snowmelt and rainfall), one decile before and after the 2nd decile, respectively. Occurrence of peak flowrate for the events of verification dataset was shown to be within the 2nd decile as well. Therefore, a general model can consider peak flows as occurring during the 2nd decile. In addition, it was observed that normalized flowrate was linearly correlated with the normalized time while reaching to the peak flowrate (Figure 4.3), as so called ”rising limb” period for both datasets.

While double-peak and triple peak overflow (up to $0.7Q_p$) were observed from the normalized hydrographs in some events of the first group of data after the occurrence of the initial peak (as seen in A1 and A5), it would not alter the general pattern of overflows as the main peak flowrate of the whole discharge duration occurred within the 2nd decile. Occurrence of double-peak and triple peak overflow during an event may cause some discrepancies between the model predictions and actual flowrates. This could be regarded as one of the proposed model limitations in capturing temporal flowrate increase after the main peaks. However, CSO events considered in this study were basically defined as mass-limited and occurrence of higher flowrates beyond the main peak flow period would be the main concern in terms of loading contributions.

Following the peak period, the flowrate showed logarithmical decreasing trend for the remainder section of the events, in both datasets. Therefore, for CSOs, the dynamic behavior of flowrate, as having a linear rising limb and a logarithmic recession can be characterized in accordance with the normalized time of occurrence. In fact, the information on the normalized flowrate behavior with regard to normalized time is attributable to events of different scales, filling out the gaps for adaptable definition of periods of rising limb, peak and recession. Based on the patterns observed for increasing and decreasing limb, and the trendlines established for different percentile values of the normalized flowrate (Figure 4.4), the resulting correlation for the 75th percentile values was selected to represent dynamics of normalized flowrate (Equation 4.1).

CSO discharge dynamics in terms of contaminant concentration were investigated by considering the variability of concentrations of TSS, *E. coli*, CAF and ACE within each decile. The period of 1st decile was shown to most likely correspond to occurrence of peak concentrations for all four contaminants, followed by a period of lower concentrations in both datasets (except for the event with precipitation during snowmelt). While the pattern of contaminant concentrations for each decile of CSO events should be considered for modeling CSO discharge event, identifying the period of peak concentration is a key step towards monitoring discharge-based events with the aim of capturing the peak concentrations. Contaminant concentration dynamics was best modeled with probability distributions of concentrations within the 1st decile, 2nd decile, and remaining portion of the events. Normalized concentrations were found to follow a variety of probability distributions for each studied portion (Table 4.2), given that the stochastic model was more appropriate for highly variable concentrations than a deterministic one.

7.1.2 CSO load model and application

Using information resulted from analysis of dynamics of discharges concerning the occurrence time of peak flowrare and contaminant concentrations, normalized loading terms were obtained by multiplying the normalized flowrate (expressed in deterministic form) with the normalized concentration (expressed in stochastic form) through a Monte Carlo iteration process (Figure 4.1). The resulting normalized loading (Figure 4.6) of TSS and CAF showed an increasing trend from the 1st decile to the 2nd and a decreasing trend from the 2nd decile to the end of discharge duration, as the loading behavior was mostly driven by the flowrates. However, normalized loading characteristics of *E. coli* and ACE were less influenced by flowrate dynamics and no sudden increase in loading values was observed from the 1st decile to the 2nd decile considering median values. *E. coli* loading characteristics were highly variable and this is now recognized by the proposed loading model.

One of the advantages of the proposed loading model is that it provides the capacity to model of events of different scales without resorting to a detailed hydraulic model such as SWMM. Considering normalized loading characteristics and adjusting the scale of events defined by a peak flowrate, peak concentration and discharge duration, CSO loading conditions can be produced reflecting various ranges of potential loading values upon which management strategies should be based. Moreover, the outputs of such semi-probabilistic CSO loading approach can be treated as the inputs of a hydrodynamic and water quality model. An example scenario generated for this purpose was shown in Figure 4.7. The loading profiles generated by the proposed approach can serve as a tool to investigate different loading conditions to receiving waters. Successful application of such an approach can ultimately address the needs of municipalities to more efficiently explore mitigation policies for discharge-based phenomena.

The CSO loading model was developed based on a very limited data set that were available in the literature. However, the diversity of the CSO events from the data sets used in this study helped in generalization of the patterns, as 8 CSO events from 2 outfalls, representing two watersheds combined with 5 individual CSO and stormwater events results in the development of such loading model. The CSO loading model requires further validations to include complex conditions of discharges if more data on the dynamic behavior of the CSO events are available. It is also of great interest to further investigate extreme summer events as well as snowmelt event where co-occurrence of rainfall and snowmelt is likely, whose dynamic behavior has not been properly addressed in the proposed model.

7.2 Step two: Hydrodynamic and water quality model

7.2.1 Model selection

In order to simulate the transport and fate of microbial contamination from discharge sources to any points of interest (e.g. drinking water intakes) and investigating different loading conditions, a suitable model capable of capturing the dominant physical characteristics of the water body and discharge points is of great importance. In this project, a two-dimensional hydrodynamic and pollutant transport model, MIKE 21 FM by Danish Hydrodynamic Institute (DHI) was chosen for simulating free surface flows. Utilizing a flexible mesh grid, MIKE 21 enables users to select greater resolution in the regions of interest and less resolution in other areas. A range of factors (accounting for site characteristics, type of point source discharges, computation time and financial budget) were considered for model selection. Besides, City B had used MIKE 21 to study *E. coli* transport for the downstream section of the river. However, it is important to note that uncertainties always exist due to the simplified assumptions, numerical techniques used to solve the governing equations, model grid result ion and quality of data and many other factors. Many of the uncertainties discussed in Jalliffier-Verne (2017) for a downstream portion of the river apply here as well and include uncertainties of flowrates, dispersion, inactivation, CSO loads, etc.

The modeling system is based on the numerical solution of the 2-dimensional incompressible Reynold average Navier-Stokes equations subject to the assumptions of Boussinesq and of hydrostatic pressure. Therefore, the model consists of continuity, momentum, temperature, salinity and density equations. Model inputs consist of various parameters including computational mesh and bathymetry data, time step and simulation length, calibration factors such as bed resistance and initial and boundary conditions. For instance, setting up the mesh includes the appropriate selection of the area to be modelled, adequate resolution of the bathymetry, flow, wind and wave fields. The sub-module of Mike 21, Eco-Lab is coupled with the result of hydrodynamic model to simulate the spreading and the fate of a substances under the influence of the fluid transport, dispersion process and kinetics.

7.2.2 Model calibration and validation

Based on the available hydrometric data provided to us by the City B, the hydrodynamic model was calibrated and validated by comparing the results of model simulations (i.e. transactional flow velocity profile) with those of measurement at different sections of the river in two different hydrodynamic river conditions. (Figure 5.2 and Figure 5.3). The hydrodynamic model was able to predict the general hydraulic nature of the river reasonably well considering the scope of this study, extent of the river modeled, and the accuracy required. The flow regime as the outputs of the validated hydrodynamic model satisfactorily represented the flow distribution in the river, which was then used with the water quality model.

For the water quality model calibration and validation, the study domain was split in half to include only the reaches of the river where *E. coli* data were available based on daily measurements. The water quality model (Eco-Lab) was calibrated and validated by simulating *E. coli* concentrations for a period of 8 days (no CSO events) and for a period of 2 days (with a CSO event), respectively. The simulation results (i.e. *E. coli* concentrations) fall within the range of concentrations measured at B2 by adjusting the *E. coli* decay rate and dispersion coefficient as water quality model set up parameters. It was found that the model results show a better agreement with the measurements (i.e. within an order of magnitude) when the decay rate and dispersion coefficient constant were set to 0.22/d and 1 m^2/s, respectively (Figure 5.4).

Although all the CSO outfalls were considered as surface discharges in the studied area, there might be cases of submerged discharges where the plume may exhibit a three-dimensional structure in the water column, possibly due to temperature variations between the effluent and ambient water body. In depth averaged model, the difference in density of effluent plume and background river flows is not recognized. Consideration must be given to these specific sources. A mixing model such as CORMIX may be required to evaluate the 3D mixing process in the near-field provided sufficient information is available to describe the temperature variation between the effluent and ambient water body.

The river model was sensitive to some parameters that influenced the model predictions. The hydrodynamic model was sensitive to size of the mesh used. Grid analysis was conducted to find the optimum grid size considering the accuracy required, scope of the study and the expected results. The flexible mesh grid used in this study allows for greater resolution (course mesh) in regions of interest and less resolution (dense mesh) in areas that are less important. As the objective was to evaluate the impact of point source discharges on the downstream water quality at drinking water intakes, relatively finer mesh size was implemented near the intakes location. The model calculation was also sensitive to boundary conditions as well as time step selected. For the water quality model, the results were mostly sensitive to the dispersion coefficient implemented in the simulations. The results of water quality model were also dependent of the *E. coli* decay rate, but were not as strongly influenced by as dispersion coefficient. These two parameters were considered for calibration and validation of the water quality model.

7.2.3 Scenario development and simulation results

CSO scenarios were produced according to the CSO loading framework developed in the first step. 6 CSO outfalls upstream of drinking water intakes were considered and their potential *E. coli* loads based were estimated to be representative of monthly CSO discharges. The scenarios were then incorporated into the hydrodynamic and water quality model to evaluate the potential impacts for the months from March to October. Based on the correlation established between CSO discharge duration and the volume of discharge, probability distribution functions of CSO discharge volume were determined in each month based on a range of discharge duration recorded. Four types of scenarios were defined considering the 10^{th}, 50^{th}, 90^{th} percentile values of the volume probability distributing functions and one extreme scenario representing events of high discharge volume (90^{th} percentile) within a short period of time that is equivalent to the 10^{th} percentile of discharge period in each month (Table 5.3).

Simulation results showed that two intakes were impacted by the upstream discharges (i.e. A2 and B2). Periods of peak *E. coli* concentration were identified by considering a series of potential CSO discharges instead of one single loading condition. Different loading scenarios led to different peak *E. coli* concentrations at the intakes that were characterized by assigning probability distribution functions (Figure 5.6. 7). The probability distribution of *E. coli* concentrations caused by CSOs not only reflects a wide range of possibilities of upstream loading conditions (i.e. considering inter-event as well as intra-event variability), but also provides information on the associated extent of variation of concentrations at the source of drinking water intakes (Table 5.4).

The modeling results obtained from the integration of the semi-probabilistic CSO model and hydrodynamic and water quality models are intended to include the short term microbiological impacts of CSOs. Drinking water treatment must handle these periods of peaks from CSO events by reducing the incoming microbiological contamination to an acceptable level, while human health targets must be respected considering several peak periods throughout a year. Results will help water managers efficiently operate the drinking water treatment plants under the impacts of upstream CSOs by estimating travel times of the contamination plumes or predicting a range of potential microbial contaminant concentrations occurring at the intakes.

7.2.4 Probability distribution of the *E. coli* to *Cryptosporidium* ratio

E. coli was the selected as an indicator of microbiological contaminant to be included in our simulation scenarios. Due to the availability of data on *E. coli* concentration dynamics during CSOs, an *E. coli*-based CSO load model was developed. The water quality model of the river was based on *E. coli* concentrations because of greater data availability measured at the studied intakes. Therefore, resulting concentrations from scenario simulations were expressed in *E. coli* concentration, while QMRA was established based on pathogen (e.g. *Cryptosporidium*) concentrations. In order to derive information on the potential *Cryptosporidium* level based on a range of *E. coli* concentrations (obtained from simulation), different ratios of *E. coli* to *Cryptosporidium* have been reported previously. Rather than considering a single ratio value, a probability distribution of ratio values was used in this study to include different possibilities. *E. coli* and *Cryptosporidium* concentration values at the intakes of B1 and B2 combined with four other urbanized drinking water intakes in large rivers were used to obtain the distribution of the ratio value. Employing the probability distribution of ratio value (Figure 5.6. 4) and that of *E. coli* concentration led to a rage of *Cryptosporidium* (probability distribution) at the drinking water intakes. Accordingly, modeling results in terms of *E. coli* concentrations could be used to guide QMRA inputs in terms of pathogen concentrations.

7.3 Step three: CSO-associated microbial risk

Having simulated the impacts of CSOs in terms *Cryptosporidium* concentrations, the associated risk of drinking water sources was calculated. By considering a shorter reference period such as daily instead of yearly risk, the health target of 2.73E-9 DALY per person per day was selected. The short-term risk of CSO discharges was evaluated for mean concentration during the periods of peak obtained from the river model simulation results under two treatment performance conditions (i.e. 3 log removal and 4 log removal) (Figure 5.5). It was shown that 4 log removal condition would satisfy the daily health target in 80% and 90% of the time at A2 and B2 intakes, respectively. Under 3 log removal conditions, daily health target would be respected just in 40% and 55% of the time, which is a significant reduction compared to that of 4 log removal condition. The role of treatment efficiency (i.e. difference of 1 log removal) in terms of associated risk have been quantified for the first time in this study. The contribution of short-term risk (daily) on the longer-term risk (i.e. mean annual risk) was also evaluated. This information could be practical to estimate the risk of peak concentration following a CSO event without having it continuously measured to delineate the related peak concentrations. It should be mentioned that the scope of the modeling framework and the microbial risk assessment in this study is limited to CSO events only. There are many other non-point sources of contamination that are of probabilistic nature and may contribute to the adversity of the river water quality, including stormwater discharges, surface runoff from surrounding areas (including manure-applied surface runoff) and presence of migratory birds near the intakes. Therefore, it is of interest to investigate the probabilistic contribution of such sources and evaluate how the resulting microbial risk would be affected, which is beyond the scope of this research study.

The CSO-associated risk discussed so far was based on the assumption of co-occurrence of 6 CSOs at the same time and the results reflected their cumulative effects. Assumption of synchronized and similar CSO events from these 6 outfalls was made basically due to the lack of data on CSO occurrences. One of the limitations of the results could be related to this assumption while multiple CSOs with different time lags and delays may potentially occur. In order to overcome this challenge, a detailed hydrological study within the watershed of the intakes is suggested to fill up the gap on the response time at each outfalls. The number of CSO events in a year is an influencing parameter in defining the level of risk in course of a year. Obviously, the more CSOs discharge to the river, the greater the number of peak periods. In this study, the mean annual risk of CSOs was estimated based on baseline condition, daily risk profile and the number of potential occurrence of discharges at 6 outfalls in a year (Figure 5.5). The mean annual risk of CSOs under two operating treatment performance were different, leading to distinctive outcomes. The mrean annual risk did not violate the annual health target during a year with CSO evetns in case of 4 log removal condition at both inakes. However, in case of 3 log removal, the annual health target is not respected at all. The mean annual health risk is more dependent on the treatment performance of the plant rather than the number of CSOs per year.

The frequency of water quality measurements at the intakes plays an important role in determining the mean annual risk profile considering CSO events and baseline conditions combined. The mean risk profile (considering baseline condition and CSO events) at B2 is not drastically different from the baseline condition. At A2, the risk profile from baseline condition and that of baseline condition and CSO events combined is slightly different, implying that the weekly measurement of raw water quality at intakes (A2) might not be enough to reflect the impacts of CSOs within the present modeling framework and that more frequent monitoring to reduce the uncertainty of the estimate of the mean concentrations could be considered.

This is the first study examining in detail the risk of CSO discharges with the removal efficiencies of drinking water treatment, which are important elements of urban source water protection strategies. The results of the proposed CSO-related QMRA could be used as a managerial tool to investigate the effectiveness of possible risk-reduction actions concerning the CSO occurrences. They can also be used to guide the sampling campaign at the intakes. Thus, the variation in treatment efficiency and the number of CSOs could be evaluated against their respective variation in risk level simultaneously. This information can be used to guide any boil water advisory declaration should difficulties in treatment occur during CSO events.

7.4 Step four: Importance of event-based QMRA in conventional vulnerability and threat assessment

7.4.1 Conventional threat and vulnerability assessment

As source water protection policies are within the authorities of provincial governments in Canada, there is a range of diversity in provincial legislation and strategies for water governance. For example, Quebec and Ontario have their own source water protection strategies in place to ensure safe drinking water. Both approaches have been in implemented aiming to evaluate 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 municipalities are required to produce assessment reports containing vulnerability and threat assessments of drinking water sources. While vulnerability assessments are the drivers of actions to protect drinking water sources, there are notable differences in the approaches of Quebec and Ontario.

The present study was the first to employ Quebec newly vulnerability assessment guideline on intakes of drinking water. It was also intended to include the microbiological impacts of discharge-based events like CSOs during periods of peak concentration in the vulnerability and threat assessments. The modeling approach established in the previous stages of this research provides an opportunity to consider the risk of drinking water under the impacts of CSOs and integrate such information in vulnerability and threat assessments. The study area is the part of a large river in the Outaouais region, Canada. The River is stretched through the boundary line of two Canadian provinces; Ontario and Quebec where four intakes of drinking water treatment plant are located. The study area provides such a platform to explore the application of two vulnerability and threat assessment practices, particularly when it comes to different policies for one body of water.

For conventional vulnerability and threat assessment, four intakes of drinking water treatment plants were considered (i.e. A1, A2, B1 and B2). Applying Quebec's vulnerability approach (vulnerability to microorganism), the vulnerability of A1, A2 and B1 were low while that of B2 was shown to be medium (Table 6.2). Based on the weekly raw water sampling for *E. coli* at the intakes of A1 and A2, their vulnerability may be underestimated as the sampling frequency fail to capture daily or within-a-week variation compared to vulnerability of B1 and B2. Threat assessment (microbiological contamination) was conducted for A2 and B2 (Table 6.3). The level of threat of OA1, OA1 and OA3 to the intake A2 were classified as very high, high and very high, respectively according to Quebec's approach where the difference in frequency resulted in different classification of the threats. However, the Ontario approach merely considers the location of a threat within the IPZs, the closer a threat to the intake is, the higher potential risk that threat is. Accordingly, OA1 and OA2 are grouped as moderate threat while OA3 is recognized as a significant threat to A2. There is a distinct difference between the two approaches. Unlike Ontario's approach, the frequency of the occurrences of threats are being into consideration in Quebec's approach by acknowledging the historical or potential records of the threat activity. For example, there is one level of risk difference (i.e. very high to high) between the threat OA1 and OA2 just because of the former is more frequent than the latter while they are both considered as similar threat in Ontario approach. Threat analysis of intake B2 showed that OA1, OA2 and OA3 would be still defined as very high, high and very high, respectively even though they are located within the outer protection area (Quebec's definition). In Quebec's framework, it was also noted that severity of activity had a larger influence on determining the level of threat than the frequency of the event. For example, OA4, OA5 and OA6 were all defined as very high threats while OA6 is less frequent than OA4 and OA5 because they were all of catastrophic severity. The results of such analysis would help more effectively investigate alternatives in reducing the level of threat such as lowering the severity of the activity against lowering the frequency of the event. According to Ontario approach, OA1, OA2 and OA3 were moderate threats to B2 while OA4, OA5 and OA6 were labeled as significant. The outcomes of threat assessment by Quebec and Ontario lead to variable results in terms of risk classification.

7.4.2 Event-based QMRA

Two intakes of drinking water were considered (A2 and B2) downstream of CSO outfalls under extreme event scenarios from March to October. Using the developed CSO stochastic load model (step one) and river model (step two), contributions of CSO events to *E. coli* concentration at the intakes were simulated individually in each month. The simulation results were combined with QMRA (developed in the step three) to estimate the level of treatment required to meet the health target of 1E-06 DALY per person per year was calculated (Figure 6.3). The results evaluates the different level of treatment requirements under the influence of upstream discharges. The frequency of CSO events upstream of intakes as well as vicinity of outfalls to intakes both play roles in determining the level of treatment requirement. For example, different frequency of CSO events may result in different removal requirement, a difference of 1-log removal required at A2 between the events discharged through OA1 and OA2. It is very interesting to note that while impacts from OA5 discharges were required more than 3 log-removal in the plant B2, it was still classified in the very same risk level with other threats (by Quebec's and Ontario's approach) that may require 1 log lower removal (i.e. OA4). This can be perceived as an example of the practical shortcoming of the provincial approaches in threat identification in terms of treatment requirements. The threats assessment could be improved by considering the level of treatment that may be required in the case of events.

Threat assessments conducted for Quebec and Ontario do not clearly connect to the availability of drinking water treatment in response to these threats. However, the Québec guide provides some suggestions and apparent latitude as to how this can be done (i.e. by adjusting the class of the threat based on the availability of treatment). CSO-based QMRA can assess threats according to their treatment requirements while quantifying the magnitude of the microbiological impacts and the frequency of the events rather than qualitatively-based classification of the events based on a simple definition of the frequency. The Ontario approach is very general and the Quebec's approach is largely influenced by qualitative definitions. However, event-based QMRA as a supplementary piece to the conventional and threat assessments could potentially improve assessments by quantifying the role of different criteria (i.e. location of threat or frequency) while mitigation strategies could be adjusted accordingly.

CHAPTER 8 CONCLUSIONS AND RECOMMENDATIONS

This research project sought to evaluate the microbiological impacts of CSO discharges on the downstream drinking water sources in a river. Variability (intra and inter-event) of discharges was considered and their associated risk were quantified and implemented within the context of source water protection practices conducted in Quebec and Ontario. The dynamic behavior of CSOs in terms of flowrate and contaminant concentration led to the development of a semi-probabilistic CSO load model. The proposed loading model was then incorporated into a calibrated and validated hydrodynamic and water quality model of the river, to simulate a series of potential loading conditions that may occur over a year. The risk of water supplies related to occurrence of CSOs was then quantified using simulation results at the intakes of drinking water sources. The required level of drinking water treatment to handle the incoming peak periods of microbial contamination was analyzed and compared with the elements of threat classification procedures that are commonly in practice.

8.1 Conclusion

The following conclusions were drawn from this research study:

1. <u>CSO loading model</u>

- Normalizing technique is a suitable tool to exclude the effect of the scale of the CSO events. Normalized flowrate, concentration and discharge duration data in a uniform scale of 0 to 1 facilitates the analysis of the variability within any portion of the events.
- Normalized flowrate in CSOs was shown to reflect common characteristics. The normalized flowrate linearly increases from the start of an event to peak flowrate, reaches its peak (generally) wihin the 2nd decile and decreases logarithmically.
- The 1st decile represented the period of peak concentrations of TSS, *E. coli*, CAF and ACE in which the chance of capturing concentrations at their peaks or near the peaks could be expected. It was also found that CSO discharges were mass limited.
- Instead of assuming a fixed value for CSO loading characterization, a semi-probabilistic loading term was developed not only to quantify the potential CSO loading rates throughout the

discharge period, but also takes into account the intra-event variability with respect to their peak values.

- The result of dynamic analyses of CSOs can be used to more objectively design sampling campaigns aiming to capture peak concentration during an event. The suggested modeling approach enhances the characterization of the events while illustrated where monitoring could be most useful.
- The outputs of such load model can used as the inputs of hydrodynamic and water quality models to improve the quality of impact studies.

2. CSO-based QMRA

- The application of a calibrated and validated hydrodynamic and water quality model of the river can: 1) determine a range of probable *E. coli* concentrations, 2) characterize the critical peak periods under a range of potential loading events, 3) identify travel time of the peak contamination to reach the intakes to adjust the responsive reaction in case discharges occur.
- Hydrodynamic and water quality modeling results used with QMRA can characterize the risk from a series of potential CSO discharges.
- A comparison of daily DALY risk obtained from 24-h averaged concentrations showed that 4 log removal performance would be adequate for respecting the health target in case of CSO discharges. In case less treatment at the plant was available, compliance with the health target at A2 and B2 was reduced to half of the time as compared to that of 4 log removal.
- CSO-associated risk is determined more by the treatment log removals at the intakes rather than number of events per year. The daily health target was respected for the entire year if 4 log removal efficiency was maintained. However, daily health target was not met for 3 log removal conditions.
- Microbial data of raw water quality that are being measured at drinking water intakes are critical for defining the overall microbial risk profile in case of considering CSO events. If the frequency of sampling is not sufficiently representative, the ultimate risk profile could be biased, or demonstrate large uncertainties. Therefore, the role of short-term risk on long-term risk estimates is dependent on the quality of data representing baseline conditions.

- Microbiological impacts of CSOs on the drinking water sources can be addressed by combining health-based QMRA approaches with the results of the fate and transport model. The associated impacts can be quantified in terms of short-term (daily) and mean annual risks comparable to those of acceptable risk levels. The results of the proposed approach could be used as an alternative assessement tool for the municipalities to make decisions about the effectiveness of potential mitigation strategies such as CSO discharge reduction against treatment improvements.

3. Microbial vulnerability and threat assessment, a transboundary case study

- Given that source water protection generally falls within provincial jurisdiction in Canada, there is a wide range of diverse strategies being implemented by provinces and thus local governments.
- Ontario's vulnerability is based on the hydraulic characteristics of the water body regardless of type of contaminant while that of Quebec is dependent on the contamination type and its concentration measurement.
- Threat assessment in Ontario defines three level of threat as low, moderate and significant depending on the intake protection zones and vulnerability assessment. However, that of Quebec is classified in six levels (very low, low, moderate, high and very high) and is recognized by severity and frequency/probability of that activity/condition. Unlike Ontario's, Quebec's approach was found to be driven by the nature of threat, allowing a better understanding of potential threat.
- Comparing Quebec's and Ontario's assessment methodologies on our case study showed that results were different even for a given intake. Therefore, a more approach that is less influenced by definitions and more based on quantitative analysis is needed for threat classification, so that the risk level of drinking water sources can be more easily compared and prioritized.
- Event-based threat analysis enables water managers to more objectively characterize threats while considering the microbiological impacts as well as the recurrence of the threats.

8.2 Contributions

The contribution of this research projects can be characterized as followings according to each step:

Step 1: Dynamic behavior of CSOs in the context of source water protection

- Discharge behavior of the events can be understood and fluctuations of CSO loads and CSO control measures can be more objectively evaluated.
- More efficient and comprehensive sampling campaigns are recommended for capturing peak concentrations in the source.

Step 2 and 3: Drinking water utilities and management

- Microbial risk estimates can be improved by conducting event-based monitoring of raw water as well as treatment performance during loading events.
- An important step in characterizing wet weather flow impacts on drinking water sources by assessing CSO-associated contribution in terms of microbial risk (short term and long-term).

Step 4: Event-based vulnerability and threat assessment of drinking water sources

- Application of event-based QMRA to prioritize the potential risk with regards to treatment requirement can provide supplementary information to the current vulnerability and threat assessment.

8.3 Recommendations

Based on these findings, recommendations for further investigation may include:

- A study of the dynamic behavior of CSO discharges in terms of pathogen concentrations (*Cryptosporidium* or *Giardia*) would provide useful information for the CSO-probabilistic load model.
- Discharge-based QMRA using hydrodynamic and water quality models should be conducted for other types of wet weather flows (e.g. stormwater or wastewater bypasses) to prioritize the events contributing to microbiological contamination of downstream drinking water intakes. By quantifying the health risk associated with wet weather discharge-based events, it would be possible to compare events of wet weather flows according to their level of risk and influence for respecting health targets.
- Investigate the influence of peak period duration on the daily and annual risk profiles. It would also be interesting to understand how microbial risk would be shaped by different concentration values representing the periods of peak and the linkage between the resulting

microbial risks with the baseline condition to assess the optimal frequency of raw water quality sampling.

- Vulnerability and threat assessments could be conducted as per regulations in Quebec and Ontario for other contaminants of concern (e.g. inorganic or organic chemicals) to investigate how results would be different. This also would provide a chance to investigate the sensitivity of methodologies to different contaminants in results of vulnerability level and threat classification.

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